

Enhancing Radiology Workflows: Semi-automated Cervical Cancer Reporting at the Cancer Diseases Hospital in Zambia

by

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Submitted to the Department of Computing and Informatics
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Abstract

Cervical cancer remains the most prevalent form of cancer among women in Zambia, contributing significantly to delayed treatment and high mortality rates. At the Cancer Diseases Hospital (CDH-UTH), radiologists face substantial workflow challenges, including prolonged turnaround times for report generation. This project proposes a semi-automated software solution to streamline radiology workflows and reduce reporting delays. The system integrates a structured checklist interface, FIGO staging support, and an editable AI-assisted report generator, all deployed via a web-based platform built with ReactJS and Express.js. A pilot evaluation involving radiologists at CDH demonstrated strong usability and workflow alignment, with positive feedback on interface clarity and reduced manual effort. The solution also incorporates metadata extraction, standardized reporting formats, and plans for integrating a fine-tuned machine learning model. By enhancing reporting efficiency and supporting clinical decision-making, the system aims to improve patient outcomes and contribute to scalable cancer care innovation in low-resource settings.

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List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CDH-UTH	Cancer Diseases Hospital - University Teaching Hospitals
CT	Computed Tomography
DICOM	Digital Imaging and Communications in Medicine
DL	Deep Learning
EMI x Z	Enterprise Medical Imaging in Zambia
FIGO	International Federation of Gynecology and Obstetrics
GenAI	Generative Artificial Intelligence
GUI	Graphical User Interface
IEEE	Institute of Electrical and Electronics Engineers
ML	Machine Learning
MoH	Ministry of Health
MVC	Model-View-Controller
NASA-TLX	National Aeronautics and Space Administration - Task Load Index
NLG	Natural Language Generation
NLP	Natural Language Processing
REST	Representational State Transfer
TAM	Technology Acceptance Model
UNZA	University of Zambia
UNZA BREC	University of Zambia Biomedical Research Ethics Committee

Chapter 1

Introduction

Cancer is a pertinent disease that plagues individuals from across the world. Among the 300 district centers that serve cancer patients in Zambia, cervical cancer is the most prevalent, accounting for more than 60% of cancer cases [1]. Making cervical cancer the most popular form of cancer in Zambia. For this reason, cervical cancer cases were chosen as an area of focus at the Cancer Diseases Hospital, University Teaching Hospitals (CDH-UTH) Lusaka, Zambia for our study. Additionally, because cervical cancer provides easy staging which is mainly based on the FIGO classification system.

Cervical cancer, if not treated in a timely fashion, leads to significant complications. In developing nations mortality rates are high, particularly affecting women of reproductive age. These complications can significantly impact a patient's quality of life and long-term outcomes.

Prior to diagnosing computed tomography (CT) scans of a patient, on average, it takes about thirty minutes for a Radiologist to manually type-out and generate a report at CDH-UTH. The aim of this study is to streamline the radiological workflow associated with report generation, so as to reduce the turnaround time it takes to attend to a single patient. By reducing the turnaround time, this could potentially reduce the time it takes for patients to receive their treatment and save lives.

1.1 Background of the Study

In Zambia, the scarcity of radiologists has resulted in significant delays in cancer treatment, with patients waiting up to three months for their first treatment after diagnosis. One of the primary contributing factors to this delay is the turnaround time, which refers to the period between a radiologist receiving images and sending back a

report. Our project aims to address this critical issue by leveraging software solutions to reduce the turnaround time, when the Radiologist receives the images to the time a report is sent back.

The project seeks to develop and implement innovative software solutions that streamline the workflow of radiologists, enabling them to interpret images and generate reports more efficiently. By automating routine tasks, our solution aims to reduce the turnaround time. This, in turn, will enable patients to receive timely treatment, improving their chances of recovery and enhancing overall healthcare outcomes.

Our project team will collaborate with local healthcare professionals, radiologists, and stakeholders at CDH-UTH to gain a deeper understanding of the challenges and requirements of the Zambian healthcare system. We will then design and develop tailored software solutions that address these specific needs, ensuring that our solutions are user-friendly, scalable, and sustainable. Through rigorous testing and evaluation, we will ensure that our solutions meet the highest standards of quality, security, reliability and compliance.

The successful implementation of our project has the potential to transform the healthcare landscape in Zambia, particularly in the field of cancer diagnosis and treatment. By reducing the turnaround time, we can help alleviate the backlog of cases, enable patients to receive timely treatment, and ultimately improve healthcare outcomes. Our project demonstrates the power of technology in addressing pressing healthcare challenges, and we are committed to making a positive impact on the lives of cancer patients in Zambia.

1.2 Problem Statement

Delayed treatment initiation significantly affects cancer patient outcomes. An experienced radiologist has observed that most cancer patients begin their first treatment three months after diagnosis. This delay is influenced by various factors, including the turnaround time for interpreting medical images and generating reports. Delayed initiation of cancer treatment due to prolonged medical image interpretation

and report generation significantly worsens patient outcomes, often leading to preventable deaths. Currently, at observed hospitals, the process takes approximately two hours, with 30 minutes dedicated to report generation alone. This project aims to develop a software-based solution to streamline and expedite the interpretation and reporting process, ultimately reducing delays and improving patient outcomes.

1.3 Aim of the Study

The aim of this study is to design and implement a software based solution that reduces the turnaround time, thereby improving the efficiency of radiology workflow.

1.4 Project Objectives

To reduce the turnaround time associated with report generation by Radiologists at the Cancer Disease Hospital.

- I. To demonstrate the understanding of the cervical cancer staging workflow.
- II. To design and implement a software that assists radiologists as they interpret images and generate reports.
- III. To evaluate the effectiveness and usefulness of the implementation.

1.5 Project Scope

The project scope involves thoroughly analyzing the workflow for cervical cancer staging to better understand the problem and identify user requirements. This ensures the proposed solution effectively addresses the needs of radiologists. The focus is on designing and implementing a tailored software application that automates repetitive tasks, utilizes a standardized format for medical reporting, and securely records and stores patient details and generated reports. To achieve this, a metadata extractor will be developed to retrieve patient details and store them in a database, along with generated reports and other critical information. Additionally, a report document generator will be implemented to automatically populate patient reports and details into standardized document formats.

The project also includes training a machine learning (ML) model to generate cervical cancer reports. Instead of creating a model from scratch, a pre-trained ML model will be used and tuned to tailor it to the specific requirements of this project. This approach leverages existing ML advancements while customizing the solution for radiologists' workflow.

The software will feature a graphical user interface (GUI) designed for radiologists, enabling them to interact with the system easily and access previous patient reports for reference and continuity. Finally, the solution will be evaluated to ensure its effectiveness in reducing report turnaround times, enhancing usability for radiologists, and improving the overall efficiency of their workflow. Feedback will be gathered to refine the software and machine learning solution further, ensuring both meet their objectives effectively.

Key features include:

- **Metadata Extraction:** Retrieves patient details for streamlined data management.
- **Report Document Generation:** Creates standardized medical reports by automatically inserting patient details and findings.
- **Pretrained Machine Learning Model Integration:** Employs a tuned ML model to generate cervical cancer reports tailored to the project's requirements.
- **Graphical User Interface (GUI):** Provides a user-friendly interface for radiologists to interact with the system and access patient data easily.
 - **Standardized Medical Reporting Format:** Ensures all generated reports maintain a consistent and professional format.

Chapter 2

Literature Review

This section contains related work focusing on techniques in medical image reporting as it relates with the global south, the extent to which these processes are automated and the current limitations and opportunities. By synthesising existing literature, this section aims to identify existing gaps in order to contribute to ongoing research in automated report generation for medical reports.

2.1. Radiology Reports in Southern Africa

2.1.1. Shortage of Qualified Radiologists

In Zambia, the scarcity of radiologists has resulted in significant delays in cancer treatment, with patients waiting up to three months for their first treatment after diagnosis [1]. One of the primary contributing factors to this delay is the turnaround time, which refers to the period between a radiologist receiving images and sending back a report [2].

Research shows that cancer continues to be one of the leading causes of death worldwide [3]. Cervical cancer in Zambia is the most popular form of cancer, accounting for 41.1% in females and 23.8% in overall cases nationwide. Additionally, among the various forms of cancer, cervical cancer is ranked first as causing the most deaths in Zambia at 23.4% [4].

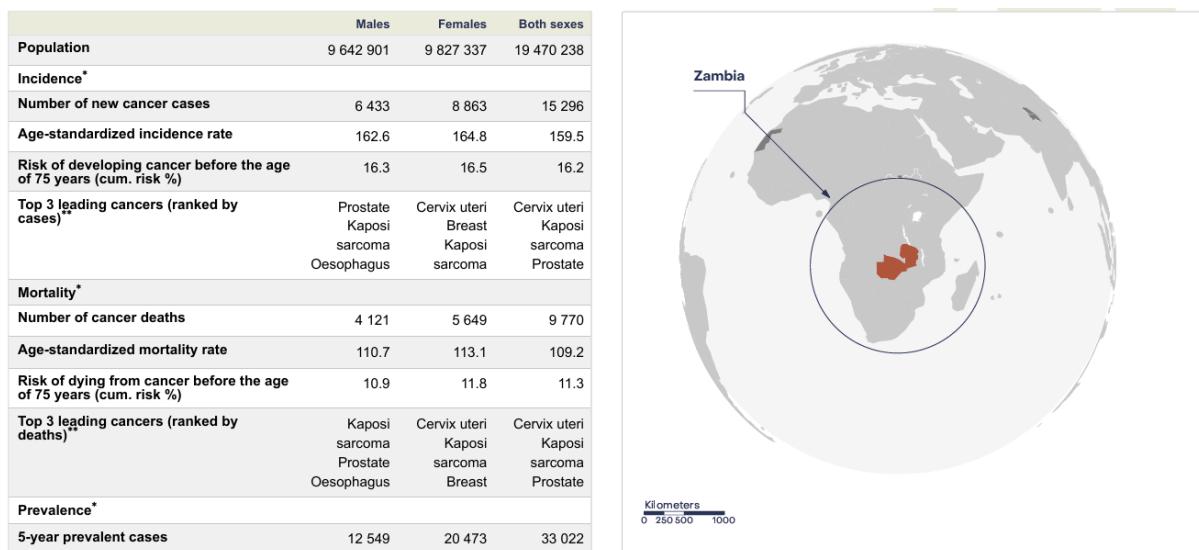


Figure 1. Zambia cancer statistics at a glance [4].

Although cancer is widely spread across Zambia, it is more prevalent in the southern region than the northern region. Southern regions such as Lusaka and Eastern Provinces form a high prevalence region in districts such as Luangwa, Katete, Chipata and Lusaka [3]. As such, we centered our study at the CDH-UTH being the country's premier healthcare center that serves cancer patients.

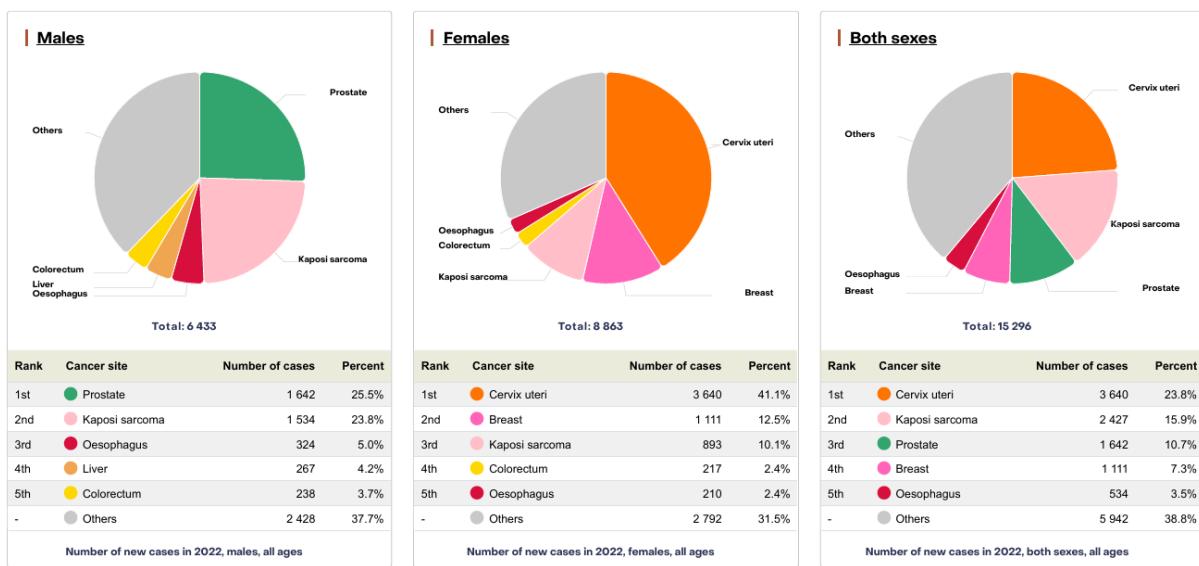


Figure 2. Overview of typical radiological workflow [4].

2.1.2. Standard Reporting for Radiology Reports

There is no narrative standard for Zambia radiology reports, because of this, there was a need for metadata to be annotated in existing reports to determine characteristics of

good reports [5]. Additionally, there is no agreed upon metadata standard designed with Southern Africa in mind. Z. Mahlaza et al, sought out to answer the research question, “*what categories of information ought to be included in radiology reports?*”[5]. Their research led them to create the first comprehensive list of radiology terminology that is not biased towards a specific region (e.g. North America). They demonstrated the utility of the dataset via a hypothetical use case, i.e., instead of using published structured reports that are partially suitable for Southern African countries, the dataset can be used to design archetypes for report templates thus potentially improving patient outcomes.

2.1.3. Classical Radiology Workflow

Primarily, the task of authoring radiology reports in Zambia has been tasked to the radiologist. Due to the extensive training that certified radiologists go through and the shortage of these radiologists to the population of Zambia [1], the Government of the Republic of Zambia sought to train radiographers and extend their role toward aiding the authoring of these reports [1, 11]. A survey indicated that 95% of radiographers are positive about extending their roles to include image reporting, with 93% willing to pursue postgraduate training [11]. Radiographers believe that this role extension will enhance the delivery of imaging services and improve patient outcomes [12]. Though Zambian Radiographers showed a positive attitude toward extending their role to report generation and some towards image interpretation, the lack of post graduate coursework in this speciality was a concern. This method of extending the radiographer's role in the cervical cancer workflow, requires an extensive amount of effort and time to teach the radiographers. There is a need to expand the scope of this and further investigate alternative methods to assist the radiology workflow that is both effective and inexpensive. Beyond Zambia, on average there are 3.6 radiologists to one million people in Africa [13].

2.2. Common Radiology Report Software

A number of approaches have been taken in the form of health information systems to lessen the burden of cancer cases on radiologists. Most of the existing solutions involve

a combination of image interpretation and electronic report systems based on national standards with regards to cervical cancer control [14]. Literature shows that Generative AI (GenAI) has the potential to add value to the radiology reporting [15].

2.2.1. Rad AI

Rad AI is a company based in San Francisco, California in the year 2018. It was co-founded by Dr. Jeff Chang, one of America's youngest radiologists. It was founded with a focus on workflow automation in healthcare. The company's mission is to empower physicians with AI - saving physicians time, reducing burnout, and improving the quality of patient care.

Their area of focus is centered around harnessing AI to automatically generate reports. Their products and problem solving approach towards this problem was divided into two main segments, which are further sub-divided as follows:

- Radiologist Workflow
 - Rad AI Reporting
 - Rad AI Impressions
- Follow-Up Management
 - Rad AI Continuity

Rad AI Reporting

Rad AI reporting employs advanced machine learning algorithms and generative AI (GenAI) to create comprehensive and accurate reports with remarkable speed. The process of report generation using Rad AI can be summarized as follows into three simple steps, by dictating findings followed by utilising GenAI to decrease cognitive load and finally the radiologist would then review and sign the final report. The typical of Rad AI reporting is summarised in the figure below

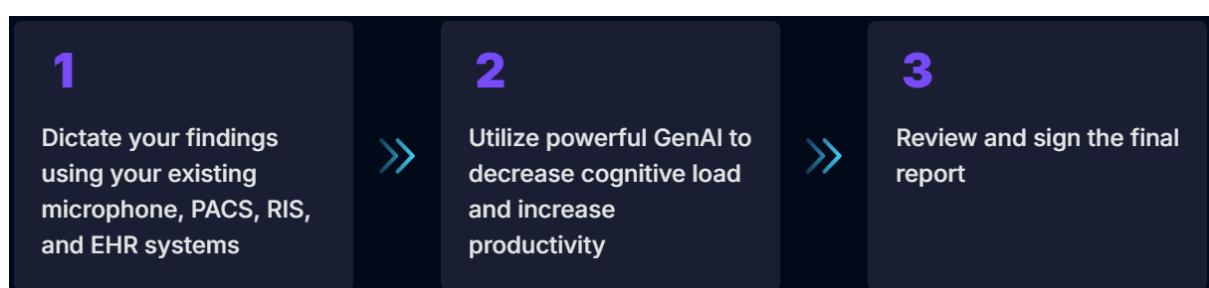


Figure 3. Rad AI Reporting summarised as a sequence of three steps that seamlessly integrates into an existing radiological workflow.

This approach reduces cognitive load and allows the radiologist to focus on image interpretation.

Rad AI customizes reports for each radiologist by using advanced neural networks to customize reports according to the exact language and style preferences. It takes cues from the radiologist's past reports and freely dictated findings to generate a complete templated report that the radiologist can quickly review and finalize.

With regards to security, Rad AI holds a SOC 2 Type II HIPAA+ certification and strictly follows confidentiality and data security policies. This ensures patient data and reports stored in their online radiology reporting software are protected.

Rad AI Impressions

Rad AI impressions automatically generate report impressions from dictated findings. The impression language is individually customised to each radiologist and practice. This was achieved with zero-click automation. Additionally, impressions generated in 0.5 to 3 seconds depending on complexity for all specialties and modalities. The typical Rad AI reporting is summarised in the figure below.

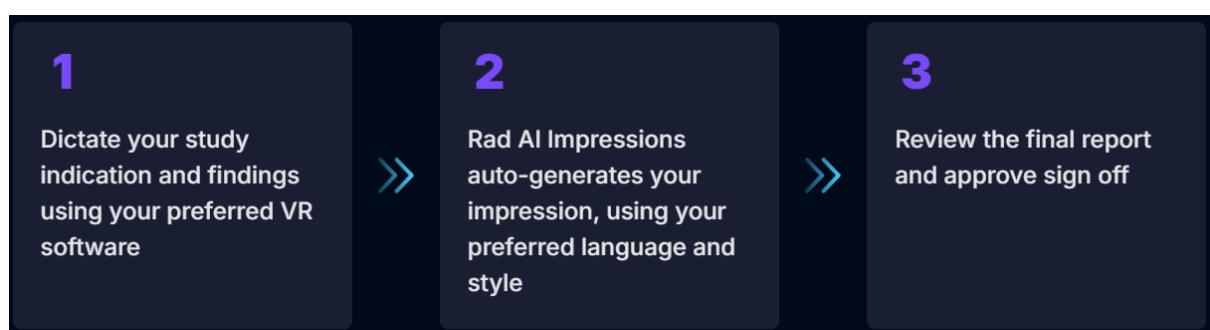


Figure 4. Rad AI Impressions summarised as a sequence of three steps that seamlessly integrates into an existing radiological workflow.

It was found that LucidHealth increased radiologist productivity by 11% and reduced CT exam turnaround time by 6% with Rad AI impressions [16].

Rad AI Continuity

Rad AI continuity uses AI - driven patient follow-up for significant actionable findings using automated detection and communication. Their deployed and advanced AI model trained on half a billion reports. It then applied NLP to identify the category and anatomy. Finally it utilises a central dashboard on one platform for comprehensive visibility & tracking.

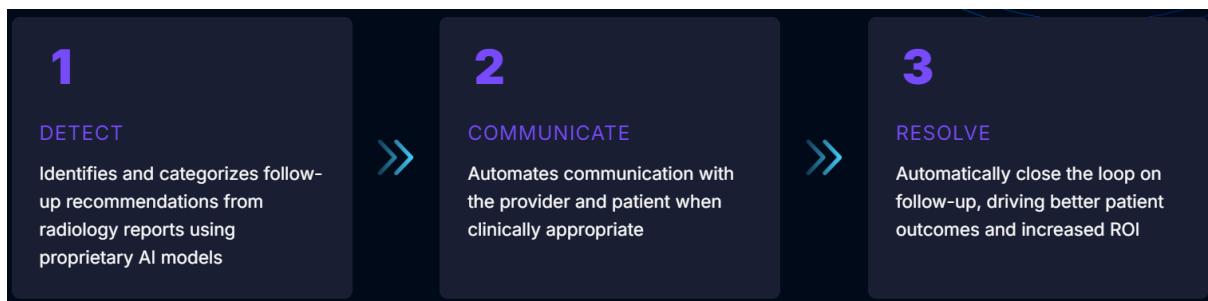


Figure 5. Rad AI automated detection + communication summarised as a sequence of three steps.

Colorado Imaging Associates' experience with Rad AI Impressions demonstrates the significant impact generative AI can have in radiology. With an 80% reduction in dictated words per impression and a 30% reduction in time spent on impressions, CIA's radiologists are working more efficiently while maintaining high report accuracy [17].

- 80% reduction in impression words dictated per report (from 67 to 15 words per impression).
- 30% reduction in overall time spent on impressions (from 30 to 21 seconds per report on average).
- 40% reduction in MRI impression times (from 50 to 29 seconds on average).
- 30% reduction in CT impression times (from 52 to 37 seconds on average).
- 20% reduction in Ultrasound and CR impression times.

2.2.2. RadioReport® Automatic AI

RadioReport® uses guided reporting, which is a way of rethinking structured reporting. Key to the development of Guided Reporting is the idea of digitally mapping the thinking of experienced radiologists. The resulting software provides a structured framework that helps guide users through the analysis process, offering flexibility while ensuring key considerations are addressed [18]. A web-based platform to achieve this with a free demonstration option on their website [18]. The weaknesses of current reporting are as follows:

- Rising Imaging Demands, Stretched Radiology Teams
- Time Lost in Reporting
- Unclear Referrals and Inconsistent Reporting Fuel Redundant Imaging.

How guided reporting can address current weaknesses in radiology:

- Guided reporting provides a structured reporting framework supporting radiologists by streamlining high-volume workflows and reducing cognitive load.
- Intuitive selection tools and pre-defined fields eliminate repetitive tasks and reduce time spent generating reports.
- Standardized, comprehensive output ensures clarity and consistency, improving communication and reducing unnecessary follow-ups.

2.2.3. RADPAIR

RADPAIR is an advanced AI-powered radiology platform designed to streamline radiology reporting with cutting-edge generative AI. This innovative, web-based solution enhances efficiency, accuracy, and workflow automation for radiologists. As a leader in clinical AI technology, RADPAIR is transforming the future of medical imaging and diagnostic reporting [19]. Key features of RADPAIR include:

- **Completely Web Based:** No installation. Zero footprint.
- Just sign up and go.
- **Full Gen AI Reporting:** Fine tuned models out of the box.
- No complicated training processes.
- **All-In-One Solution:** Dictation and reporting platform.
- Integration available.

- **Dynamic Editing:** Simple click and drag report
- editing for minor revisions.
- **PAIR INSIGHTS:** Near real-time report generation.
- including findings and impressions.
- **WINGMAN:** AI Co-Pilot

2.3. Artificial Intelligence in Automated Medical Report Generation

2.3.1. Natural Language Generation

Natural Language Generation (NLG) is a subfield of Natural Language Processing (NLP) concerned with converting structured data into coherent, human-readable narratives. The growing demand for efficiency and consistency in domains such as healthcare, finance, and public administration has positioned NLG as a critical technology for automating routine report writing tasks. Yagamurthy, Azmeera, and Khanna [8] provide a comprehensive overview of NLG techniques and their applicability in automated reporting across diverse fields. They outline a typical NLG pipeline consisting of data analysis, data-to-text mapping, sentence planning, and surface realization, which collectively transform structured inputs into natural-language outputs. Approaches are typically divided into rule-based or template-driven systems on one hand, and machine learning-based or neural models on the other. Rule-based and template methods prioritize accuracy and predictability but produce repetitive text, while neural methods such as transformers generate more natural prose but risk factual inconsistencies and “hallucination” of unsupported content [8].

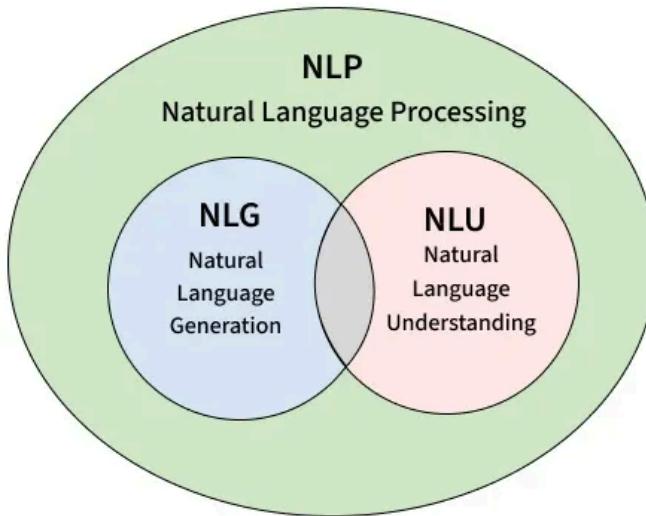


Figure 6. Natural Language Generation as a subset of Natural Language Processing and Natural Language Understanding.

In healthcare, the paper emphasizes that structured, domain-specific data dramatically improves the factual reliability of NLG outputs. Consequently, hybrid models that combine templates with machine learning offer a balance between fluency and factual control. Such models also enable the personalization of reports, adaptability to institutional preferences, and efficiency gains in clinical workflows. However, Yagamurthy et al. highlight several persistent challenges: the requirement for high-quality structured data, difficulties in capturing domain-specific nuances, and the ethical implications of automated text generation, especially in high-stakes contexts like medicine [8].

These observations resonate strongly with clinical radiology, where reports must not only be factually accurate but also use consistent terminology, support longitudinal patient tracking, and communicate findings clearly to both clinicians and patients. In this respect, NLG provides the foundation for automating report generation, but its adoption in radiology requires adaptation to domain-specific challenges.

2.3.2. Deep Learning Approach

Deep learning (DL) is a branch of machine learning that leverages multilayer neural networks to automatically learn hierarchical feature representations from complex data such as medical images and clinical records. Its ability to detect subtle patterns and correlations has made DL a cornerstone of modern medical image analysis and computer-aided diagnosis. Vazquez *et al.* [10] provide a comprehensive scoping review of machine- and deep-learning applications in cervical cancer, covering studies on diagnosis, prognosis, and treatment planning. Their review highlights the rapid adoption of convolutional neural networks (CNNs), transformer-based models, and multimodal fusion strategies across diverse cervical cancer tasks, from automated Pap smear screening to survival prediction.

The authors identify a typical DL pipeline that begins with data acquisition and preprocessing, followed by feature extraction through CNNs or Vision Transformers (ViTs), representation learning, and task-specific prediction layers. Models are commonly trained using transfer learning, where weights pretrained on large natural-image datasets are fine-tuned on cervical imaging data to mitigate data scarcity. Approaches can be broadly divided into unimodal image-based systems and multimodal frameworks that integrate imaging with clinical metadata. CNN-based systems excel at lesion detection and segmentation in Pap smear and colposcopy images, while transformer variants capture long-range dependencies in high-resolution histopathology slides. Multimodal methods combine image embeddings with patient information (e.g., HPV status, age) to improve prognostic modeling and treatment-response prediction.

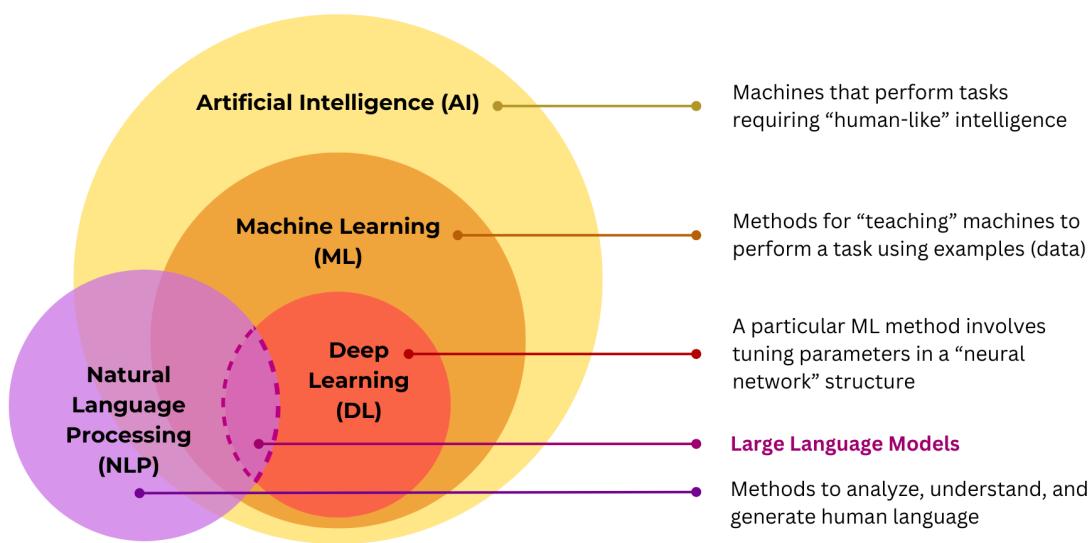


Figure 7. Deep learning as a subset of machine learning and Natural Language Processing in the context of Artificial Intelligence.

A key advantage of DL approaches is their capacity for high diagnostic accuracy and automated feature discovery, reducing reliance on handcrafted descriptors. This has enabled state-of-the-art performance in tasks such as lesion classification and treatment-outcome forecasting, even in low-resource settings. However, the review underscores persistent challenges: the need for large, well-annotated datasets; the risk of overfitting in small or imbalanced cohorts; and limited generalizability to new imaging modalities or local reporting styles. Moreover, most existing cervical cancer studies output structured predictions—such as lesion labels or segmentation masks—rather than full narrative reports, leaving a gap for systems that can generate clinician-ready text.

These findings are highly relevant to radiology report automation. DL techniques supply powerful visual encoders and language decoders for transforming medical images and structured findings into narrative reports. Yet, as Vazquez *et al.* note, explainability and clinical trust remain critical obstacles. Incorporating structured checklist inputs, as proposed in the current project, addresses several of these concerns by providing explicit semantic guidance to the generation model, reducing hallucinations, and enabling provenance tracking of each generated statement.

Consequently, deep learning serves not only as a tool for automated image interpretation but also as a foundation for checklist-conditioned report generation that can meet the accuracy, consistency, and transparency demands of clinical radiology.

2.4. Medical Image Report Generation through Standard Language Models

Leonardi, Portinale, and Santomauro [9] present a practical approach to medical image report generation by fine-tuning existing pre-trained language models rather than building large models from scratch. Their method combines an image encoder, tested with both CheXNet and a Vision Transformer (ViT), and a decoder-only language model (GPT-2) to produce radiology reports from chest X-ray images. Using the MIMIC-CXR dataset, the authors applied preprocessing tools to clean reports, reduced class imbalance, and evaluated the system with BERTScore and token-level precision, recall, and F1 metrics. Results showed that the ViT + GPT-2 setup with beam search achieved the best performance ($F1 \approx 0.78$), demonstrating that modest computational resources can still deliver clinically relevant outputs. This work is valuable because it shows how healthcare teams with limited data and compute capacity can reuse general language models for medical purposes. However, the study is limited to chest X-rays, lacks evaluation with radiologists, and relies mainly on automated metrics that do not fully capture clinical correctness. It also does not address domain adaptation to other anatomical regions or local reporting styles. While the paper highlights the strength of fine-tuning standard language models for efficiency, it leaves open the question of how such systems generalize to other domains such as cervical cancer reporting. For the current project, this research is highly relevant in demonstrating the feasibility of resource-efficient fine-tuning, but the checklist-driven approach proposed here goes further by ensuring explainability, reducing hallucinations, and adapting the output to the reporting standards used at CDH-UTH.

2.5. Automatic Medical Report Generation

Automatic Medical Report Generation (AMRG) has emerged as a promising approach to alleviate the increasing workload on radiologists and improve diagnostic accuracy. In

a comprehensive review, Guo et al. [6] analyzed AMRG methods developed from 2021 to 2024, identifying critical advances and challenges across imaging modalities such as X-ray, CT, MRI, and ultrasound. Their study outlines how computer vision (CV) and natural language processing (NLP) are combined—typically via pretrained convolutional neural networks (CNNs) and Transformer-based architectures—to generate descriptive, clinically relevant reports. A key finding is that fine-tuning pretrained models significantly enhances performance, particularly in terms of coherence and semantic alignment with medical terminology.

The review classifies AMRG solutions into several categories: bridging the image-text modality gap through global and local alignment techniques; enhancing lesion-focused image encoding via classification and segmentation networks; augmenting text decoders with retrieved reports, knowledge graphs, or memory modules; and refining output using traceback mechanisms and reinforcement learning. These methods improve the model's ability to generate high-quality medical text, but most are tailored to chest radiography using datasets like MIMIC-CXR and IU-Xray. This creates a notable limitation for applying AMRG to other domains, such as cervical cancer imaging, which remains underexplored [6].

Moreover, the study reveals a lack of region-specific model tuning, especially for low-resource environments such as Zambia. This echoes the findings of Mahlaza et al. [5], who identified inconsistencies in radiology reporting terminology and the absence of standardized templates in Southern Africa. Guo et al. [6] also emphasize the impact of dataset limitations, such as small sample sizes, noisy annotations, and minimal representation of specialized imaging types, which hinder the development of generalized AMRG systems.

2.6. Explainable-AI in Medical Report Generation

A notable advancement is the integration of Explainable AI (XAI) in medical report generation. Ahmed et al. [7] introduced an explainable deep learning framework for chest X-ray analysis, combining image-to-text systems with XAI techniques. Their work underscored the importance of interpretability and transparency, ensuring that

AI-generated reports can be trusted by clinicians. The study demonstrated how visual explanations, such as attention maps, could help radiologists understand which image regions influenced the generated textual findings. However, their research focused exclusively on chest X-rays, with limited applicability to other imaging modalities such as CT and MRI used in cervical cancer staging.

2.7. Summary of Literature and Gaps in the Study

Summarised in TABLE I is the literature relevant, the gaps identified and the proposed solutions our Study aims to address.

TABLE I. Summary of Literature and Gaps in the Study.

Ref	Name of Authors	Year	Title	Findings	Methods	Proposed solutions	Gaps
[5]	Z. Mahlaza, E. O. Zulu, and L. Phiri	2024	Radiology report terminology to characterise reports in Southern Africa	Found inconsistencies in terminology and structure across radiology reports in the region. Highlighted the need for standardized templates.	Qualitative analysis of report samples from multiple Southern African hospitals.	Qualitative analysis of report samples from multiple Southern African hospitals.	Lack of automated integration of standardized templates into radiology workflows.
[6]	L. Guo, A. M. Tahir, D. Zhang, Z. J. Wang, and R. K. Ward	2024	Automatic Medical Report Generation: Methods and Applications	Reviewed AI-based approaches for generating medical reports. Identified effectiveness of fine-tuning pretrained models.	Systematic literature review of report generation methods and technologies.	Use of deep learning and pretrained transformer models in clinical NLG.	Most studies are based in high-income settings; lack of localization for resource-limited environments like Zambia.
[7]	S. B. Ahmed, R. Solis-Oba, and L. Ilie	2022	Explainable-AI in automated medical report generation using chest X-ray images	Introduced explainable AI techniques to improve interpretability and trust in AI-generated radiology reports.	Integration of explainable models (XAI) with deep learning-based image-to-text systems.	XAI-enabled medical report generators.	Focused on chest X-rays only; no application to cervical cancer or Zambian healthcare context.

Ref	Name of Authors	Year	Title	Findings	Methods	Proposed solutions	Gaps
[8]	D. N. Yagamurthy, R. Azmeera, and R. Khanna,	2023	Natural Language Generation (NLG) for Automated Report Generation	Demonstrated how NLG improves consistency and efficiency in clinical documentation. Emphasized hybrid systems (template + ML).	Development of NLG system using rule-based and ML components.	Hybrid NLG model for medical reporting.	Limited insight into radiologist workflow adaptation and deployment in low-resource hospitals.
[9]	G. Leonardi, L. Portinale, and A. Santamaria	2023	Enhancing Medical Image Report Generation through Standard Language Models: Leveraging the Power of LLMs in Healthcare	Found that fine-tuned LLMs can produce coherent and accurate medical image reports.	Use of GPT/BERT-like models in medical image captioning tasks.	Leveraging LLMs to generate professional-grade medical reports.	General focus; no evidence of region-specific fine-tuning for African healthcare scenarios.

Chapter 3

Methodology

3.1. Introduction

This chapter outlines the methodology used in the design, development, and evaluation of the project, an intelligent cervical cancer radiology reporting platform. It explains the research design, system development approach, tools and technologies, data handling methods, and evaluation strategies. The study involved multiple aspects, understanding the cervical cancer reporting workflow, designing the system, and evaluating its effectiveness.

3.2 Research Design

This study adopted a mixed methods research design to explore radiologists' workflow challenges and evaluate the potential of an AI-assisted reporting system at the Cancer Diseases Hospital (CDH-UTH). The approach combined qualitative and quantitative techniques to capture both contextual insights and structured user feedback.

Qualitative data was collected through semi-structured interviews and focus group discussions with radiologists and clinical staff. These methods were chosen to uncover workflow inefficiencies, user expectations, and attitudes toward AI integration. Participants were selected using purposive sampling to ensure relevance and depth of insight. Thematic analysis was applied to identify recurring patterns and inform the design of the proposed system.

To complement these findings, quantitative data was gathered during the evaluation phase using Likert-scale questionnaires. Participants rated their agreement with statements related to system usefulness, interface clarity, and adoption intent. This structured feedback provided measurable indicators of user perception and helped validate the system's conceptual design.

Due to the AI model not being trained, performance metrics such as accuracy and efficiency were not assessed in this phase. The focus remained on user-centered evaluation, laying the foundation for future technical validation once the model is fully trained.

3.3. System Design and Implementation

3.3.1 Project Model

The spiral model was adopted as the development methodology for this project, ensuring an iterative, adaptive approach. This model enabled continuous stakeholder engagement throughout the development lifecycle, ensuring that evolving system functionalities remain aligned with user needs.

Through multiple development cycles, stakeholders provided feedback for refinement, ensuring the system was both technically sound and user-centered. By leveraging the spiral model, this project ensured continuous improvement, efficient risk management, and the delivery of a high-quality, user-centered solution that accelerates decision-making and enhances diagnostic precision.

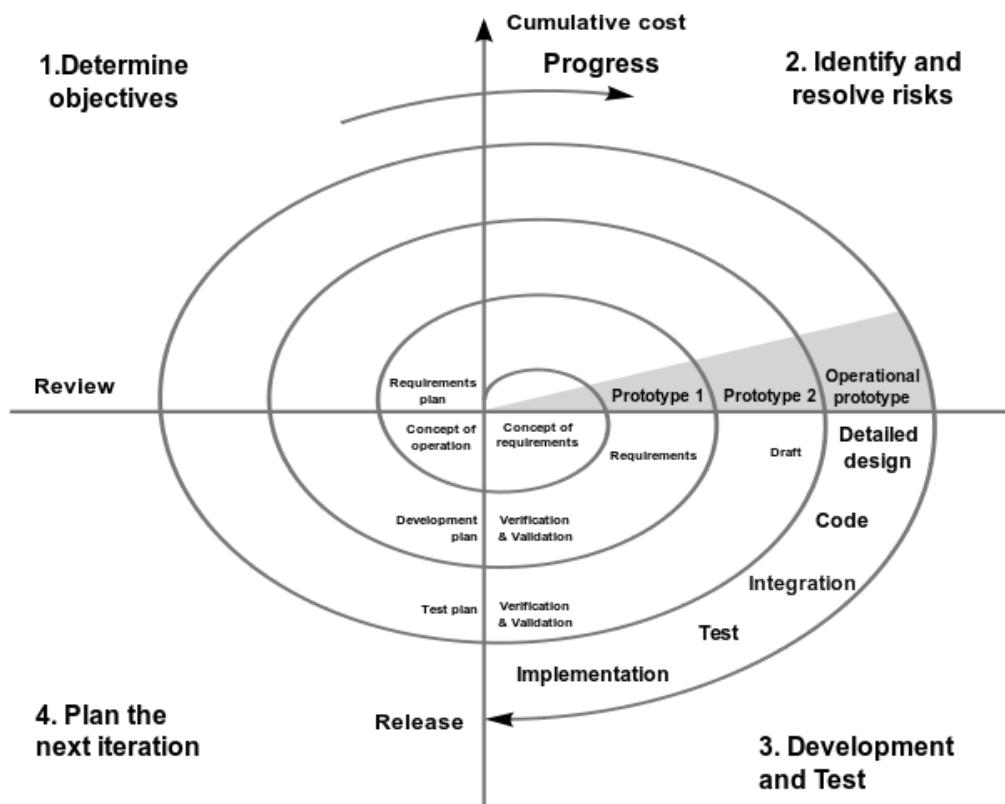


Figure 8. Spiral model of software engineering.

3.3.2. Spiral Model in Project Development

The development of the project followed **four major spiral iterations**, as shown conceptually in Figure 9.

Planning Phase

During the planning phase, system goals, requirements, and constraints were identified.

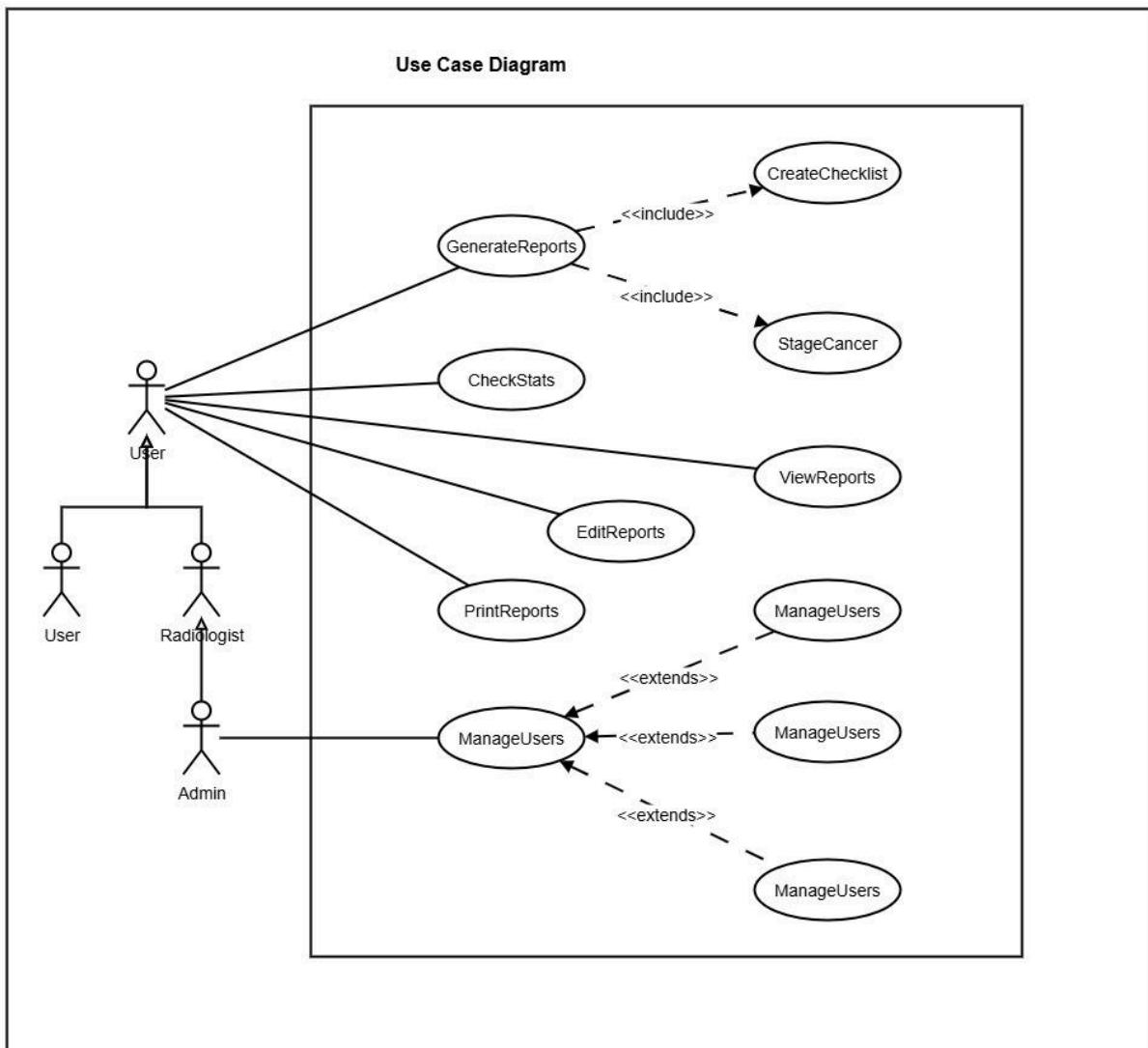


Figure 9. Use Case Diagram.

Requirements were gathered through:

- Literature review on radiology reporting standards.
- Informal interviews with medical professionals.
- Analysis of existing medical reporting systems.

The requirements were classified as:

Functional Requirements:

- Automatically extract metadata from Dicom formatted images
- Automatically generate structured reports.
- Manage user accounts and patient records.
- Retrieve historical reports.

Non-Functional Requirements:

- Secure data access.
- Fast response time.
- Ease of use and accessibility.

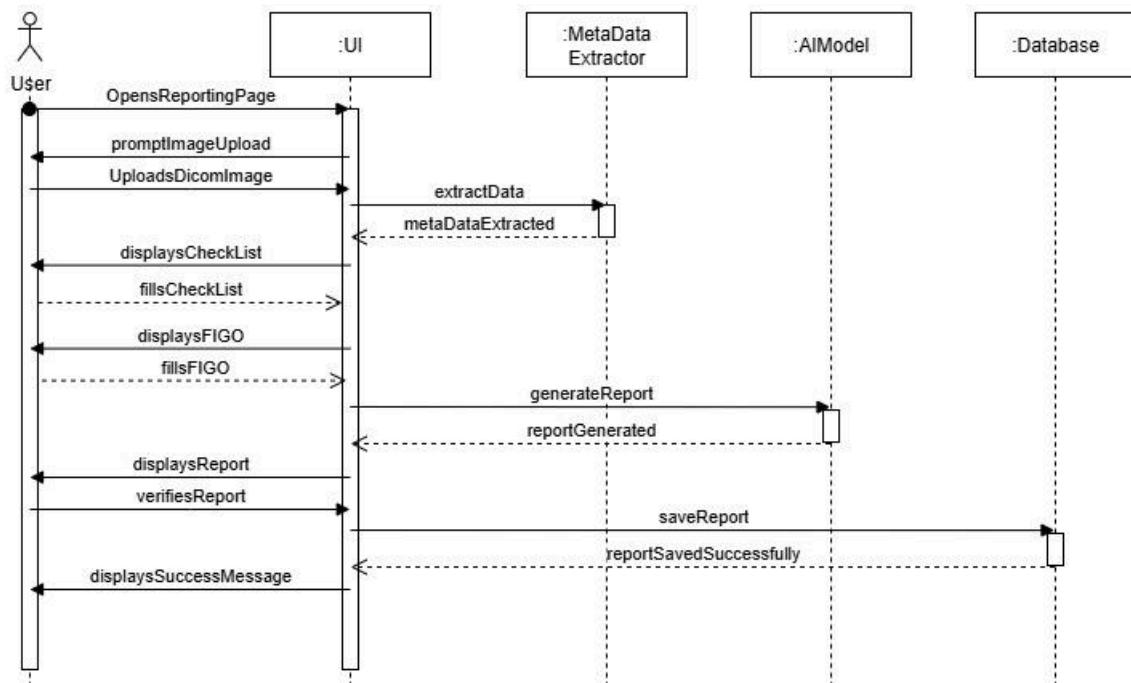


Figure 10. Sequence Diagram.

Risk Analysis Phase

This phase focused on identifying potential risks that could affect the successful development and adoption of the solution, as well as defining strategies to mitigate them.

One of the main risks identified was data quality, particularly since the system relies on checklist data provided by radiologists and metadata extracted from CT scan images. Inconsistent or incomplete input could compromise the accuracy of generated reports. To address this, data validation mechanisms and standardization of checklist formats were implemented to ensure reliable input for report generation.

A second risk involved report accuracy and reliability. Since the system automatically generates structured radiology reports based on the radiologist's input rather than direct image interpretation, there was a risk that generated outputs might not fully reflect the clinician's intended findings. This was mitigated by enabling radiologists to review, edit, and approve all AI-generated reports before finalization, ensuring human oversight and accuracy.

Security and privacy risks were also carefully addressed due to the sensitive nature of patient data. To ensure compliance with ethical and data protection standards, all patient identifiers were removed, and data was anonymized before being transmitted to the machine learning module for report generation. In addition, authentication, access control, and data encryption mechanisms were implemented to prevent unauthorized access and protect data integrity during storage and transmission.

Finally, user acceptance risk was recognized as a potential challenge, as radiologists and medical personnel may be hesitant to adopt an AI-assisted system for clinical documentation. To mitigate this, early demonstrations and user feedback sessions were conducted to align the system's interface and workflow with existing clinical practices, ensuring transparency and maintaining user trust in the final output.

Engineering (Development) Phase

The engineering phase focused on the actual implementation and integration of the system's components based on the design specifications and risk mitigation strategies identified in earlier phases. Development was conducted iteratively in line with the Spiral Model, allowing for progressive refinement of functionality, interface design, and performance based on user feedback.

The frontend of the system was implemented using React.js, chosen for its modular architecture and component-based structure, which facilitated the development of a dynamic and responsive user interface. The frontend provides radiologists with an intuitive platform to complete diagnostic checklists, view patient details, and review automatically generated reports. Emphasis was placed on ensuring usability and accessibility, with consistent styling achieved through Tailwind CSS to maintain a clean and professional interface.

The backend was developed using Express.js (Node.js), which served as the central communication layer between the frontend, database, and AI reporting module. The backend handled user authentication, request validation, and data routing. It also implemented secure RESTful APIs that enabled efficient data transfer while maintaining system modularity and scalability.

The database layer utilized MongoDB, a NoSQL database chosen for its flexibility and scalability in handling semi-structured medical data. The database stored user accounts, checklist inputs, and report data, with appropriate indexing and schema validation to ensure data consistency. Data security was prioritized through the use of authentication and controlled access privileges.

The AI report generation module was developed as a separate service in Python, responsible for generating structured radiology report drafts based on the checklist data submitted by the radiologist. The module received standardized input via RESTful API requests, processed the data using predefined templates and natural language generation logic, and returned the generated report text to the backend for review and approval by the radiologist.

During each development iteration, integration testing was performed to verify the seamless operation of the frontend, backend, and AI components. Feedback from test users and project supervisors informed successive refinements.

Evaluation Phase

The evaluation phase focused on assessing the usability, and perceived usefulness of the system. In alignment with the Spiral Model, this phase served as both a validation step for completed iterations and a source of feedback for subsequent refinements. Although the AI model was not trained, preventing quantitative measurement of correctness and efficiency, a qualitative evaluation was conducted to determine the system's potential value and impact on user workload.

The evaluation process involved demonstrating the functional prototype to potential users, followed by the administration of a short questionnaire designed to capture user perceptions. Participants rated statements on a five-point Likert scale, including:

- “The system appears useful for solving the intended problem.”
- “The interface and process are clear and easy to follow.”
- “I would consider using such a tool if it were fully implemented.”

The results indicated that users found the concept of provided solution both useful and relevant, particularly in its ability to automate and standardize parts of the radiology reporting workflow. Participants highlighted the system's potential to reduce manual effort and streamline report preparation.

The evaluation phase validated the usefulness and feasibility of the solution concept and confirmed that the system meets its core design goals. The findings provided valuable insights that informed subsequent design refinements and highlighted areas for future work, particularly in enhancing AI accuracy and real-time interaction feedback.

3.4. System Architecture and Design

The overall system consists of three major components: the frontend (React.js) for user interaction, the backend (Express.js) for handling business logic and API communication, and the database (MongoDB) for data storage. Additionally, the system integrates an AI-based report generation module that uses the anonymized checklist data to generate structured reports.

These components interact seamlessly through RESTful APIs, ensuring scalability, maintainability, and separation of concerns.

3.4.1. System Architecture

The system adopts a **Layered Architecture** to organize system responsibilities into distinct layers: **Presentation**, **Application/API**, **Business Logic**, and **Data Access**. This structure promotes modularity, facilitates testing, and simplifies maintenance.

The architecture is further guided by the **Model–View–Controller (MVC)** pattern and **Component-Based Design principles**, ensuring logical separation between data models, control logic, and user interfaces.

The presentation layer forms the user interface through which radiologists interact with the system. It allows users to log in, fill out radiology checklists, submit data, and review the AI-generated reports. The interface is responsive, dynamic, and designed using React's component-based architecture to promote modularity and reusability.

The API/interface layer handles communication between the frontend and the backend. It exposes RESTful endpoints for actions such as checklist submission, report retrieval, and authentication. Controllers validate input data and delegate tasks to the business logic layer.

The business logic layer contains the system's core logic and service functions that process data, manage report generation requests, and coordinate communication with the AI model. It ensures that all rules governing report generation and data validation are enforced consistently.

At the data access layer all database operations are managed. It uses **Mongoose models** to define schemas for entities such as users, checklists, and reports. The data access layer provides an abstraction over MongoDB, ensuring secure, efficient, and structured data handling.

Within the layered structure, both frontend and backend subsystems adhere to the **MVC architecture**:

- **Model:** Implemented through Mongoose models that define and manage MongoDB collections.
- **View:** Implemented through the React frontend, which renders dynamic user interfaces.
- **Controller:** Handled by Express route controllers that process client requests and respond accordingly.

The **React frontend** further follows a **Component-Based Architecture**, where each interface element (e.g., form fields, buttons, tables, and cards) is developed as a self-contained component. This approach enhances **reusability, maintainability, and consistency** across the application. Similarly, Express middleware and services are structured as modular components with clearly defined interfaces, ensuring clean separation of functionality.

The system's overall architectural style combines **Layered**, **MVC**, and **Component-Based** principles. This hybrid approach enables the separation of concerns between presentation, logic, and data management while maintaining flexibility and modular design. It also simplifies debugging, scalability, and future enhancements.

3.4.2. Main Components

The intelligent cervical cancer radiology reporting platform integrates three core modules that collectively automate and streamline the report generation process: the **Metadata Extractor**, the **AI Model**, and the **Document Generator**. These components interact with the backend services, database, and user interface to ensure accurate data handling, efficient report generation, and professional document formatting.

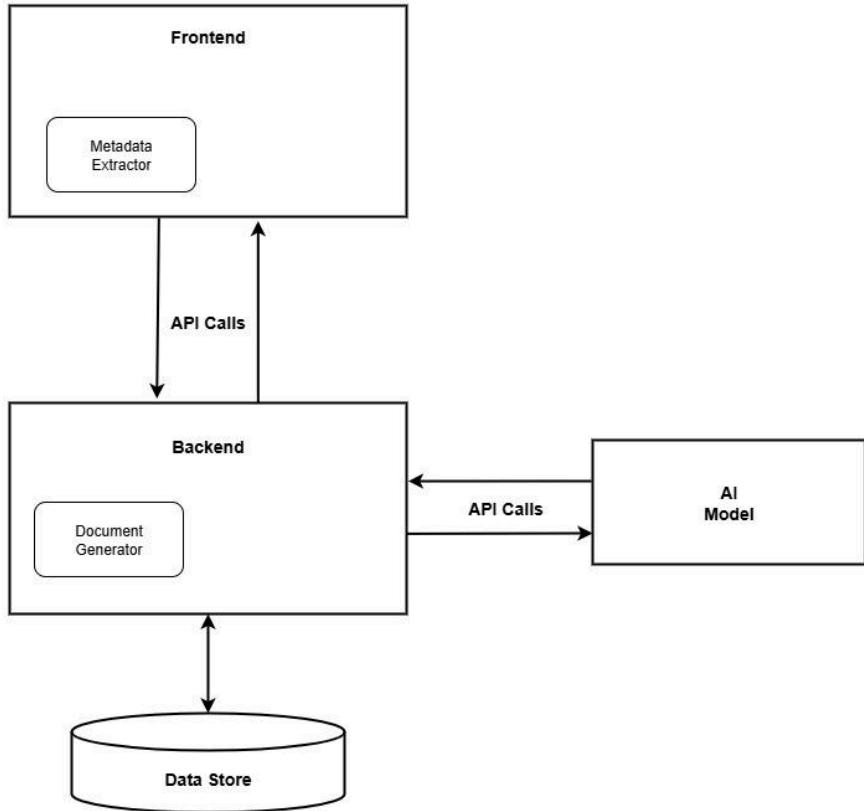


Figure 11. Architectural Diagram.

The **Metadata Extractor** processes DICOM-formatted imaging files uploaded by radiologists. Its primary function is to extract and store key metadata related to the patient and imaging study, including anonymized patient identifiers, study details, modality type, and technical parameters such as slice thickness and image dimensions. This metadata serves two purposes: it ensures traceable and secure record-keeping, and it enables automatic prefilling of patient and study information in the reporting interface and final report template, reducing manual entry errors. The module is implemented in JavaScript using the **dicom-parser** library and runs on the frontend, where it parses the uploaded DICOM files and returns a structured JSON object to the backend. The backend stores this data in MongoDB, and only de-identified metadata is transmitted downstream to comply with ethical and privacy standards.

At the core of the system is the **AI Model**, which transforms structured input—specifically the radiology checklist and selected FIGO stage—into a coherent,

narrative report body. The model used is **LLaMA 3 (8B)**, a pretrained large language model developed by Meta AI. It was selected for its strong performance in medical and scientific text generation, balanced with moderate computational requirements suitable for local or on-premise deployment. The backend collects the radiologist's completed checklist and FIGO stage, formats them into a prompt template, and sends this to the model. The AI then generates a structured report body following professional radiology tone and format. Radiologists review and edit the AI-generated draft to ensure clinical accuracy before finalization, maintaining human oversight and accountability.

Once the report body is approved, the **Document Generator** assembles and formats the complete radiology report. Unlike the AI Model, this module does not generate text; it focuses on document construction and layout. It creates a structured Word (.docx) report template with predefined sections such as Patient Details, Study Information, Findings, and Impression. It inserts metadata and the AI-generated report body into their respective sections and applies consistent formatting—fonts, spacing, headers, and institutional branding—for professional presentation. The module is implemented in JavaScript, integrated into the frontend to generate downloadable Word or PDF files for archiving and printing.

Together, these components form a cohesive pipeline. The finalized report is stored in the database and made available for clinician review or export, completing the automated reporting workflow.

3.4.3. Database Design

The RepoGen system utilizes MongoDB, a NoSQL document-oriented database, to manage user, patient, and report data. MongoDB was selected for its flexibility in handling semi-structured medical records and its seamless integration with JavaScript-based backend development using Node.js and Mongoose. This choice supports rapid development, schema adaptability, and efficient data querying in a clinical context.

The database architecture is organized into four primary collections: Users, Patients, Reports, and Appointments. Each collection is designed to reflect real-world entities and their interactions within the radiology workflow.

The Users collection stores information about system users, including radiologists, administrators, and supervisors. Each user document contains personal details (name, email, phone), professional identifiers (license ID, department), and assigned system roles (e.g., user, admin, super admin). Unique constraints on fields such as email and licenseId help prevent duplication and ensure data integrity.

The Patients collection holds basic demographic data such as patient name, sex, and a unique patient ID. Each patient document maintains an array of associated report IDs, establishing a direct link between patients and their imaging reports. This structure supports longitudinal tracking of patient history and facilitates efficient retrieval of related reports.

The Reports collection serves as the central repository for all generated radiology reports. Each report document includes references to the patient (patientId) and study details (studyId, studyDate, examType, studyType). It also contains the final structured report text, segmented into findings, impressions, and metadata about the radiologist responsible for authoring or reviewing the report. Version control is supported through createdAt and updatedAt timestamps, enabling traceability and auditability of report revisions.

The Appointments collection manages scheduling information, including patient name, appointment date, and optional notes. This module assists in coordinating imaging sessions and follow-up visits, contributing to workflow continuity and patient care planning.

The database design reflects key relationships within the system:

- A **one-to-many relationship** exists between Patients and Reports, allowing each patient to be associated with multiple reports.
- A **one-to-many relationship** also exists between Users and Reports, enabling radiologists to author or review multiple reports over time.

To ensure secure and efficient data operations, each collection uses unique identifiers such as patientId, studyId, and licenseId. Validation rules and timestamping mechanisms are embedded within each schema to maintain consistency, support audit trails, and uphold ethical standards for medical data handling.

A conceptual diagram (Figure X) illustrates the relationships between the core collections, highlighting how Users, Patients, and Reports interact within the system.

3.4.4. UI Design

The user interface for the RepoGen system was designed to support radiologists through a structured, multi-stage reporting workflow. Developed using ReactJS and styled with TailwindCSS, the UI emphasizes clarity, responsiveness, and alignment with clinical tasks. Each stage corresponds to a distinct phase in the reporting process, guiding users from image upload to report finalization and statistical review.

The design follows a progressive disclosure model, presenting only the relevant controls and information at each step to reduce cognitive load. Interactive components such as toggles, tabbed panels, and editable fields streamline data entry and review. Navigation is handled through a sidebar menu, providing access to core modules such as Dashboard, Patients, Appointments, Statistics, and Report. Role-based access controls ensure that administrative and clinical users interact with appropriate features.

TailwindCSS utility classes enforce a clean and modular design system, while React's component-based architecture supports reusability and dynamic state management. Overall, the UI prioritizes usability, workflow integration, and clinical relevance.

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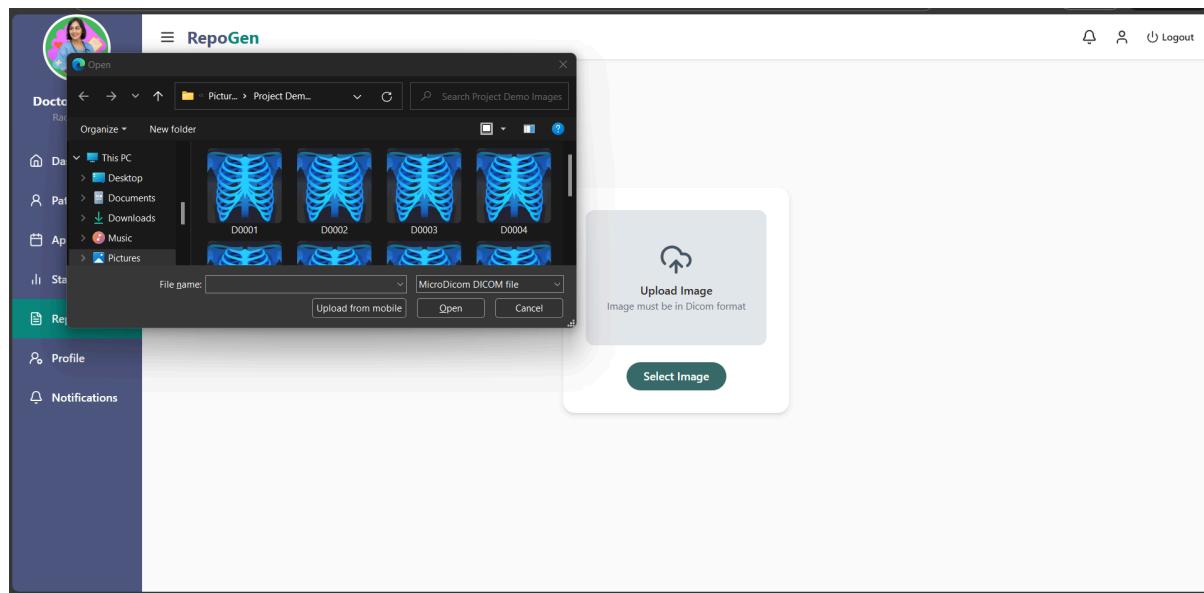


Figure 12.a. DICOM Formatted Image Upload Interface.

Initial screen prompting the radiologist to upload a medical image in DICOM format. This stage initiates the reporting workflow and supports metadata extraction.

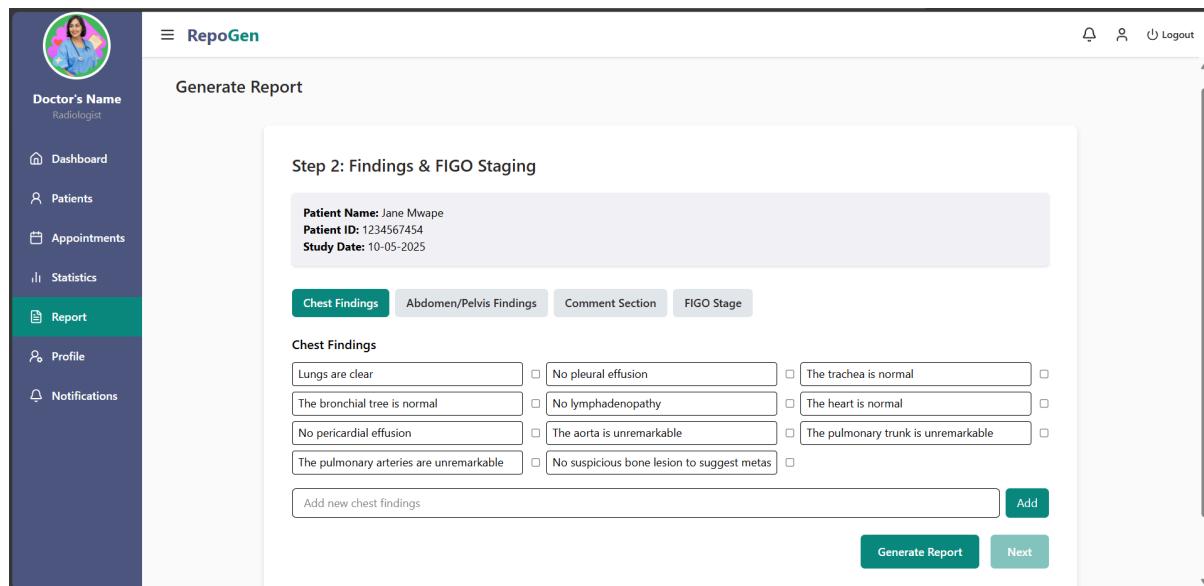


Figure 12.b. Structured Findings and FIGO Staging Interface

Checklist interface for entering structured diagnostic findings and assigning FIGO stage. Designed to streamline data entry and prepare inputs for AI-assisted report generation.

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The screenshot shows the RepoGen application interface. On the left is a dark sidebar with a doctor's profile picture at the top, followed by navigation links: Dashboard, Patients, Appointments, Statistics (highlighted in green), Report (highlighted in green), Profile, and Notifications. The main content area has a title "Generated Report (Editable)". It displays patient information: Patient Name: Jane Mwape, Patient ID: 1234567454, Study Date: 10-05-2025. Below this is a detailed report section with text about a cervical tumor, clinical findings, and treatment recommendations. At the bottom are three buttons: Back, Preview, and Save Report.

Figure 12.c. Editable AI-Generated Report Interface

Report editor displaying AI-generated findings and impressions. Radiologists can review and modify the draft before finalizing the report.

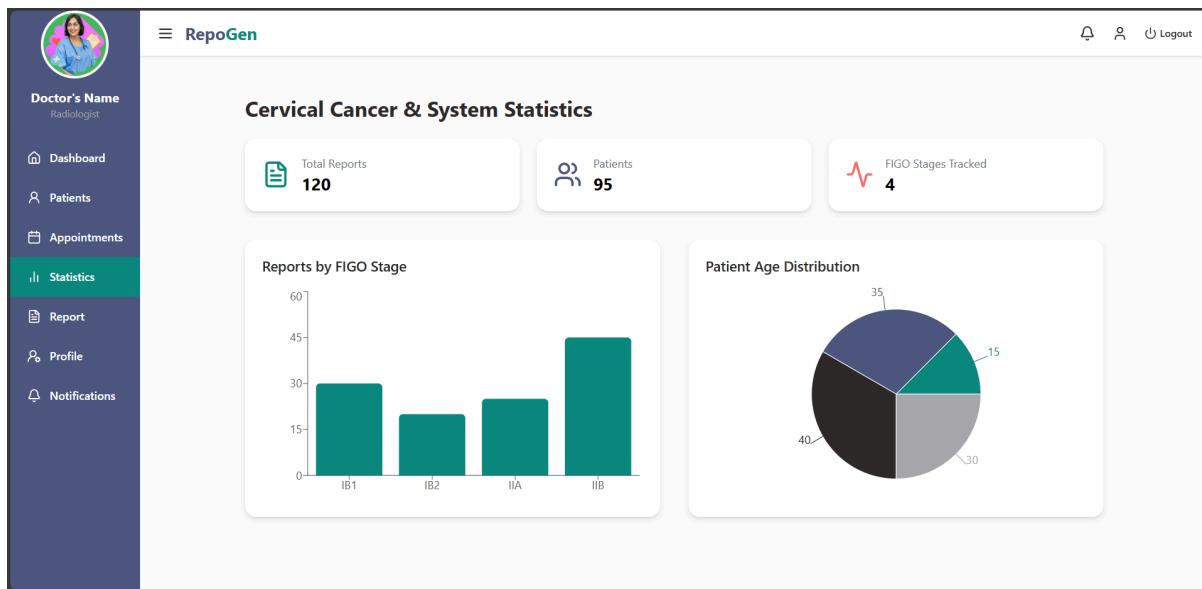


Figure 12.d. Cervical Cancer Statistics Dashboard

Administrative dashboard summarizing system usage and cervical cancer staging data. Includes visual charts and key metrics for clinical and operational insights.

3.5. Ethical Considerations

Although formal ethical clearance documents were not obtained due to time and other limitations, all necessary ethical principles were carefully observed throughout the study and system evaluation.

Participants involved in the evaluation were informed of the project's purpose and participated voluntarily. Basic participant information was collected for research record-keeping and demographic analysis (e.g., role, years of experience), but all personal identifiers were anonymized during data processing to protect privacy and confidentiality.

Despite the absence of formal clearance documentation, the project adhered to the principles of informed consent, confidentiality, and respect for participants, ensuring that no participant was personally identifiable or harmed during the research process.

3.6. Software Tools & Technologies

The system was implemented using programming languages, frameworks, storage, platforms and tools itemised in TABLE II.

TABLE II. Proposed tools and technologies.

S/N	Programming Languages	Frameworks	Storage	Platforms/tools
1.	Python	React	MongoDB	Github
2.	Javascript	Tailwind CSS		Git
3.		Express		

Chapter 4

Evaluation

4.1. Evaluation Framework

The evaluation of the system was conducted using a structured questionnaire designed to assess usability, interface clarity, and workflow integration. Although the AI model component is not yet implemented, the evaluation focused on the radiologist-facing interface and its ability to support clinical reporting tasks. The questionnaire was informed by principles from the Technology Acceptance Model (TAM), particularly the constructs of:

- Perceived Ease of Use: The degree to which users find the system intuitive, navigable, and free from technical friction.
- Perceived Usefulness: The extent to which the system supports task efficiency, reduces manual effort, and aligns with clinical workflows.

These constructs were operationalized through Likert-scale items and open-ended questions targeting interface usability, checklist clarity, DICOM upload experience, and overall satisfaction.

4.2. Participants and Procedure

Participants included three radiologists with clinical experience in cervical cancer imaging workflows. The evaluation began with a brief demonstration of the system's functionality, after which each participant was given the opportunity to interact directly with the pilot-deployed prototype hosted on Netlify. The system walkthrough covered three core stages: DICOM image upload, structured findings entry with FIGO staging, and editable report preview. Following their interaction with the prototype, participants completed an evaluation questionnaire. The questionnaire consisted of 7

Likert-scale items (rated from 1 = Strongly Disagree to 5 = Strongly Agree) and 3 open-ended questions.

4.3. Data Collection and Analysis

Quantitative data from the Likert-scale items were analyzed using descriptive statistics to identify trends in usability perception. Open-ended responses were thematically coded to extract qualitative insights into user experience, challenges, and suggestions for improvement.

The evaluation results are presented in Section 5, highlighting both numerical trends and user-reported themes.

4.4. Evaluation Results

Each participant had between seven and eight years of experience in radiology and reported no prior use of structured radiology reporting systems. The evaluation focused on key usability dimensions including interface clarity, checklist design, system responsiveness, workflow integration, and overall user confidence.

4.4.1. Quantitative Feedback

The table below summarizes responses from three radiologists who evaluated the system's usability. Each item was rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

TABLE III. Evaluation Results.

Evaluation Results	Mean Score	Interpretation
The system interface is intuitive and easy to navigate	4.7	Strongly Agree
The checklist and FIGO stage selection process is clear and well-structured	4.7	Strongly Agree
The app responds quickly and reliably	4.3	Agree
I feel confident using the app without additional help	4.	Agree
The app integrates well with my workflow	5	Strongly Agree
The system reduces manual data entry effort	5	Strongly Agree
I would consider using this system regularly if fully implemented	5	Strongly Agree

All participants rated the system interface as intuitive, with scores ranging from 4 to 5. The checklist and FIGO staging interface was consistently rated 5 by two participants and 4 by one, indicating strong clarity and usability. System responsiveness also received high marks, with scores between 4 and 5. Participants expressed confidence using the system without external assistance, averaging a score of 4. Workflow integration was rated highly across all responses, with unanimous scores of 5. Similarly, the system's ability to reduce manual data entry effort was affirmed by all participants, each assigning a score of 5. When asked whether they would consider using the system regularly if fully implemented, responses ranged from 4 to 5, suggesting strong adoption intent.

4.4.2. Qualitative Feedback

Participants highlighted the adaptability of the checklist interface, the usefulness of the reporting and appointment modules, and the overall clarity of the workflow. One radiologist noted that the checklist allowed for edits where needed and suggested that the statistics and appointment pages would significantly enhance workflow efficiency. Another participant appreciated the reporting module but pointed out the absence of functionality for uploading previous images. A third participant emphasized the importance of including clinical indications as part of the reporting interface.

Suggestions for improvement included expanding the report generation options, adding support for historical image uploads, and implementing the AI model to enhance reporting quality and efficiency. One participant recommended that the system be deployed in other facilities and re-evaluated post-implementation to gather broader feedback. Overall, the results indicate a positive reception of the system's usability and design, with constructive insights to guide future development.

4.4.3. Summary

The evaluation confirms the **usefulness and usability** of the system prototype. Although the AI report generation model was not yet active, participants expressed readiness to adopt the tool upon full integration. Future evaluations should include performance testing and user feedback after complete AI deployment.

Chapter 5

Results

5.1. Cervical Cancer Staging Workflows

The process of cervical cancer evaluation and staging follows a structured workflow. Once a patient is diagnosed with cervical cancer, a biopsy is performed to confirm the presence and characteristics of the disease. The biopsy results are then forwarded to the radiologist, who determines the appropriate imaging technique based on the clinical findings. Imaging is scheduled accordingly, and once completed, the scanned images are sent to the radiologist for analysis.



Figure 13. Overview of typical radiological workflow.

Upon receiving the images, the radiologist imports them from a compact disk into specialized imaging software. The radiologist meticulously examines each image, identifying abnormalities at various stages of disease progression. Using the FIGO staging system for cervical carcinoma and a predefined checklist-based template, the

radiologist generates a comprehensive report detailing the findings. This report is then sent back to the attending doctors, who use the information to guide treatment decisions and ensure optimal patient care.

Assessment of the existing cervical cancer reporting workflow at the Cancer Diseases Hospital (CDH-UTH) revealed that radiologists spend a considerable amount of time manually generating reports, averaging about thirty minutes per patient. The process was found to be repetitive and prone to inconsistencies due to the absence of standardized templates. This understanding informed the requirements for a more streamlined and semi-automated workflow aimed at reducing manual data entry and turnaround time.

5.2. Design and Implementation of the Solution

Based on the identified challenges, a semi-automated reporting system was designed and implemented using a web-based architecture. The system integrates a metadata extractor, an AI-assisted report generator and a document generator. Although the AI model was not yet trained during this phase, the functional prototype demonstrated strong alignment with clinical workflows and achieved the intended system design goals of standardization, usability, and reduced manual effort.

5.3. Evaluation of the Solution

Evaluation of the system with three radiologists showed highly positive feedback regarding usability, workflow integration. Participants found the interface intuitive, the checklist clear, and the reporting process well-structured. Although the reduction in turnaround time could not be quantitatively measured due to the untrained AI component, users strongly agreed that the system would significantly reduce workload once fully implemented. The evaluation thus confirmed the system's usefulness, feasibility, and potential to improve radiology reporting efficiency at CDH-UTH.

Chapter 6

Discussion

6.1. Demographics

The primary area of study setting for this experiment was at CDH-UTH, the focal point of cervical cancer cases not only in Lusaka, but Zambia as a whole. A small sample size was used to conduct the evaluation of the software. Four main cervical cancer service centers were identified in Zambia. Namely, Maina Soko Medical Hospital, Levy Mwanawasa Medical University, the University Teaching Hospitals and CDH. Three radiologists took part in the evaluation of the software.

6.2. Usability

The primary measurement instruments used in this study were Controlled Observation and the TAM. Controlled Observation was used because of the following reasons:

- It directly measured real user behaviour
- It provided a controlled and repeatable environment
- It revealed usability problems early
- It complimented quantitative and qualitative data

We were unable to measure the workload using measuring instruments such as NASA-TLX.

6.3. User Comments

With regards to future work, the team strongly advises to expand the evaluation of this software to the other three demographics mentioned earlier in Lusaka. This would allow for a broader sample size and a well rounded assessment of the overall software. Additionally, ethical approval was cardinal to the study and access to quality data to

train the model was observed to be a very important first step in the advancement of the next version of software. To observe overall usability, the same form used in the study would be reused to measure the perceived usefulness and the perceived ease of use of the software.

Chapter 7

Conclusion

In this study we proposed a method to reduce the turnaround time or cervical cancer reporting, we measure the usability of the software among the radiologists at CDH-UTH. Their positive attitude towards the piece of software proved to be useful, though the delayed ethical approval hindered a more in-depth quantitative analysis of the software. The key observation of this research was that once further enhanced using the proposed methodologies such as the spiral model to develop a fully fledged and powerful tool for the healthcare industry in Zambia. The initial area of focus for this research was cervical cancer, however, using the same design approach and principles, this solution could be extended to other forms of cancer in Zambia and Southern Africa as a whole.

Appendix A: Revised FIGO Classification

Revised FIGO staging of cervical carcinoma (2018)

- FIGO no longer includes stage 0 (Tis)
- **I:** confined to cervix uteri (extension to the corpus should be disregarded)
 - **IA:** invasive carcinoma only diagnosed by microscopy
 - **IA1:** stromal invasion <3 mm in depth
 - **IA2:** stromal invasion ≥3 mm and <5 mm in depth
 - **IB:** invasive carcinoma with measured deepest invasion ≥5 mm (greater than stage IA), lesion limited to the cervix uteri
 - **IB1:** invasive carcinoma ≥5 mm depth of stromal invasion and <2 cm in greatest dimension
 - **IB2:** invasive carcinoma ≥2 cm and <4 cm in greatest dimension
 - **IB3:** invasive carcinoma ≥4 cm in greatest dimension
- **II:** beyond the uterus, but has not extended onto the lower third of the vagina or to the pelvic wall
 - **IIA:** involvement limited to the upper 2/3 of vagina without parametrial invasion
 - **IIA1:** invasive carcinoma <4 cm in greatest dimension
 - **IIA2:** invasive carcinoma ≥4 cm in greatest dimension
 - **IIB:** with parametrial involvement but not up to the pelvic wall
- **III:** carcinoma involves the lower third of the vagina and/or extends to the pelvic wall and/or causes hydronephrosis or non-functioning kidney and/or involves pelvic and/or paraaortic lymph nodes
 - **IIIA:** carcinoma involves the lower third of the vagina, with no extension to the pelvic wall
 - **IIIB:** extension to the pelvic wall and/or hydronephrosis or non-functioning kidney (unless known to be due to another cause)
 - **IIIC:** involvement of pelvic and/or para-aortic lymph nodes, irrespective of tumour size and extent
 - **IIIC1:** pelvic lymph node metastasis only
 - **IIIC2:** para-aortic lymph node metastasis
 - with r (imaging) and p (pathology) notations to indicate how lymph nodes were identified
- **IV:** carcinoma has extended beyond the true pelvis or has involved (biopsy-proven) the mucosa of the bladder or rectum (bulloss oedema, as such, does not permit a case to be allotted to stage IV)
 - **IVA:** spread to adjacent organs
 - **IVB:** spread to distant organs ⁸

Figure 14. FIGO classification system used for cervical cancer staging.

Appendix B: CaCx Sample Report

CT NO:
Age:
Sex: F
Pt contact
No.....

COMPUTED TOMOGRAPHY REPORT

NAME OF PATIENT: DATE OF EXAM:
EXAMINATION: CT Chest/Abdomen/Pelvis without and with contrast
INDICATION: CaCx pre-treatment

Findings:

Chest

- Lungs are clear.
- No pleural effusion.
- The trachea and bronchial tree are normal.
- No lymphadenopathy
- The heart is normal, no pericardial effusion.
- The aorta, pulmonary trunk and pulmonary arteries are unremarkable.
- No suspicious bone lesions to suggest metastasis.

Abdomen/pelvis

- There is a mass in the cervix measuring x xmm, extending into theof the vagina inferior.
- There is mild surrounding fat stranding and parametrial invasion but no pelvic side wall extension.
- The rectal and bladder fat planes are.....and/but there is/no rectal or bladder wall thickening.
- Urinary bladder is regular with smooth outline.
- Both kidneys are normal in size, enhancement pattern and location. There are no identifiable masses, calcifications or calculi within either kidney.
- Bilateral renal collecting systems and ureters are unremarkable. No hydronephrosis or hydroureter.
- Liver, Gall bladder, Spleen, Pancreas and Adrenal glands are unremarkable.
- The stomach, small and large bowels are normal.
- The abdominal aorta, its main branches, IVC, Splenic and portal vein are unremarkable.
- No significant lymphadenopathy.
- No free fluid in the abdomen and pelvis.
- Degenerative changes of the lumbar spine. No suspicious bone lesion to suggest metastasis

Comment

- Known cervical cancer with disease extending into the of the vagina, with parametrial extension/ pelvic side wall andlymph nodes.
- No hydronephrosis.
- No liver, lung or bone metastasis.
- At least FIGO stage .

Date:

Radiologist

Figure 15. Cervical Cancer sample report used by CDH-UTH.

Appendix C: Ethical Clearance Approval



UNIVERSITY OF ZAMBIA BIOMEDICAL RESEARCH ETHICS COMMITTEE

Telephone: 260-1-256067
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Fax: + 260-1-250753
Federal Assurance No. FWA00000338

Ridgeway Campus
P.O. Box 50110
Lusaka, Zambia
E-mail: unzarec@unza.zm
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21st July, 2025.

Ref. No. 2731-2022.

Dr. Ernest Obbie Zulu,
University Teaching Hospitals,
Adult Hospital Department of Radiology,
P/Bag RW 1X,
Ridgeway,
Lusaka.

Dear Dr. Zulu,

**RE: APPLICATION FOR RENEWAL OF ETHICAL CLEARANCE APPROVAL:
“ENTERPRISE MEDICAL IMAGING FOR STREAMLINED RADIOLOGICAL
DIAGNOSIS IN ZAMBIAN PUBLIC HEALTH FACILITIES”
(REF. NO. 2731-2022)**

We acknowledge receipt of the request for renewal to the aforementioned study.

Renewal is hereby given for a period of two years from:

- i. 5th May 2024 to 4th May 2025 and from
- ii. 5th May 2025 to 4th may 2026

Yours sincerely,

A handwritten signature in black ink, appearing to read "Munsaka".

Prof. Sody Mweetwa Munsaka, BSc., MSc., PhD
CHAIRPERSON
Tel: +26099925304
E-Mail: s.munsaka@unza.zm

Figure 16a. Renewal of ethical approval by UNZA BREC with the EMI x Z project



**UNIVERSITY OF ZAMBIA
BIOMEDICAL RESEARCH ETHICS COMMITTEE**

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P.O. Box 50110
Lusaka, Zambia
E-mail: unzarec@unza.zm
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5th May, 2022

Your REF. No. 2731-2022

Dr. Ernest Obbie Zulu,
University of Zambia,
Department of Library and Information Science,
Lusaka.

Dear Dr. Zulu,

**RE: ENTERPRISE MEDICAL IMAGING FOR STREAMLINED RADIOLOGICAL
DIAGNOSIS IN ZAMBIAN PUBLIC HEALTH FACILITIES (REF. NO. 2731-2022)**

The above-mentioned research proposal was presented to the Biomedical Research Ethics Committee on 5th May, 2022. The proposal is **approved**. The approval is based on the following documents that were submitted for review:

- a) **Study proposal**
- b) **Questionnaires**
- c) **Participant Consent Form**

APPROVAL NUMBER : REF. 2731-2022

This number should be used on all correspondence, consent forms and documents as appropriate.

- **APPROVAL DATE : 5th May 2022**
- **TYPE OF APPROVAL : Fast Track**
- **EXPIRATION DATE OF APPROVAL : 4th May 2023**

After this date, this project may only continue upon renewal. For purposes of renewal, a progress report on a standard form obtainable from the UNZABREC Offices should be submitted one month before the expiration date for continuing review.

- **SERIOUS ADVERSE EVENT REPORTING:** All SAEs and any other serious challenges/problems having to do with participant welfare, participant safety and study integrity must be reported to UNZABREC within 3 working days using standard forms obtainable from UNZABREC.
- **MODIFICATIONS:** Prior UNZABREC approval using standard forms obtainable from the UNZABREC Offices is required before implementing any changes in the Protocol (including changes in the consent documents).
- **TERMINATION OF STUDY:** On termination of a study, a report has to be submitted to the UNZABREC using standard forms obtainable from the UNZABREC Offices.

Figure 16b. Initial ethical approval by UNZA BREC with the EMI x Z project - page 1/2.

Appendix C: Ethical Clearance Approval

- **NHRA:** You are advised to obtain final study clearance and approval to conduct research in Zambia from the National Health Research Authority (NHRA) before commencing the research project.
- **QUESTIONS:** Please contact the UNZABREC on Telephone No. +260977925304 or by e-mail on unzarec@unza.zm.
- **OTHER:** Please be reminded to send in copies of your research findings/results for our records. You are also required to submit electronic copies of your publications in peer-reviewed journals that may emanate from this study. Use the online portal: unza.rhinno.net for further submissions.

Yours sincerely,



Sody Mweetwa Munsaka, BSc., MSc., PhD

CHAIRPERSON

Tel: +260977925304

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Figure 16c. Initial ethical approval by UNZA BREC with the EMI x Z project - page 2/2.

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