A SECURITY-GOVERNED, AUDITABLE SYSTEM DYNAMICS MODEL FOR LUNG CANCER CASE LOAD MANAGEMENT IN KENYA: INTEGRATING PATTERN ANALYSIS WITH COMPLIANCE CONTROL

MAYIEKA JARED MARANGA

A Thesis Submitted to the Institute of Postgraduate Studies of Kabarak University in Partial Fulfilment of the Requirements for the Award of Doctor of Philosophy in Information Technology Security and Audit

KABARAK UNIVERSITY

NOVEMBER, 2025

DECLARATION

1. I do hereby declare that:

   i. This thesis is my original work, and to the best of my knowledge, it has not been presented for the award of a degree in any university or college.

   ii. That the work has not incorporated material from other works or a paraphrase of such material without due and appropriate acknowledgment.

   iii. That the work has been subjected to processes of anti-plagiarism and has met Kabarak University's 15% similarity index threshold.

2. I do understand that issues of academic integrity are paramount and therefore, I may be suspended or expelled from the University or my degree may be recalled for academic dishonesty or any other related academic malpractices.

Signed: ____________________________ Date: ____________________

Mayieka Jared Maranga

GDS/M/0374/01/19

RECOMMENDATION

To the Institute of Postgraduate Studies:

The Research thesis entitled **"A Security-Governed, Auditable System Dynamics Model For Lung Cancer Case Load Management In Kenya: Integrating Pattern Analysis With Compliance Control** and written by **Mayieka Jared Maranga,** is presented to the Institute of Postgraduate Studies of Kabarak University. We have reviewed the research thesis and recommend it be accepted in partial fulfillment for the Award of Doctor of Philosophy in Information Technology Security and Audit.

Signed: ______________________ Date: 15th December, 2025

Dr. Ruth Oginga

Department of Computer Science and Information Technology

Kabarak University

Signed: ______________________ Date: 15th December, 2025

Prof. Vincent Omwenga

Department of Information Technology

Strathmore University

COPYRIGHT

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my supervisors, Prof. Vincent Omwenga and Dr. Ruth Oginga, for their invaluable guidance, patience, and constructive critiques throughout this research project. I am grateful to the Institute of Postgraduate Studies at Kabarak University for providing the academic framework and support. Special appreciation goes to the Ministry of Health, Kenya, for providing access to secondary data, and to colleagues and peers who offered insightful discussions. Above all, I thank God for the strength and wisdom that sustained me in this journey.

DEDICATION

This doctorate is dedicated to the pillars of my strength and the sources of my inspiration. To my beloved wife, Esther Mwango, your unwavering support, constructive feedback, and constant encouragement have been a guiding light throughout this journey. Your resilience and dedication kept me grounded and propelled me forward, especially during the most challenging moments.

To my sons, Britto Jerry, Brittan Emmanuel, and Bryant Ignazio, our boundless energy and joy have filled our home with warmth and purpose. Though your lively presence often blended work with play, it is your zest for life that continually renewed my determination and reminded me why I strive for excellence. To my parents, Evans and Mondesta Mayieka, your sacrifices, love, and enduring wisdom laid the foundation for all I have achieved. You instilled in me the values that shaped my character and nurtured my aspirations, always believing in my potential even when I doubted myself.

To my late father-in-law, Simeon Nyamwega, and my late uncle, Elder Samuel Raini, your firm belief in the value of education and your encouragement to pursue higher learning remain an enduring legacy. You were mentors whose guidance and example continue to inspire me. This achievement belongs to all of you, whose love, guidance, and steadfast support have been the anchor and driving force behind every step of this journey.

ABSTRACT

Lung cancer remains one of the leading contributors to cancer mortality globally and in Kenya, accounting for approximately 18% of cancer-related deaths as reported by the Kenya National Cancer Registry and GLOBOCAN 2024. This study developed and evaluated a security-governed, auditable System Dynamics Model (SDM) for lung cancer caseload management, conceptualised as the coordinated control of patient volumes across healthcare levels, facilities, and referral pathways. Guided by four objectives, the study assessed the structural configuration, facility distribution, and reporting patterns influencing caseload management; examined ICT integration and secure data architecture within existing systems; designed and simulated a System Dynamics Model incorporating referral delays, facility capacity, and feedback structures; and evaluated the model's forecasting accuracy and decision-support capability. A mixed-methods design was employed. Quantitative data were obtained from the Kenya National Cancer Registry, the Kenya Health Information System, and GLOBOCAN datasets, while qualitative insights were drawn from a Delphi panel comprising oncologists, ICT managers, and healthcare policymakers. Analytical procedures integrated pattern analysis techniques using Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models for referral delay and trend prediction, complemented by Vensim for model construction, simulation, and sensitivity analysis. Security validation applied the Security Maturity Index (SMI) and a probability-of-breach metric consistent with the Kenya Data Protection Act (2019/2022). The findings indicated that more than 65% of patients were diagnosed at advanced stages, with diagnostic and treatment capacity heavily concentrated in national referral hospitals and reporting processes remaining inconsistent in lower-level facilities. The SDM achieved a prediction accuracy of 98.1% (MAPE = 1.9%) and demonstrated that strengthening referral linkages, enhancing ICT integration, and adopting secure data practices significantly improves caseload coordination, forecasting reliability, and data integrity. The study concludes that combining pattern analysis with System Dynamics provides a practical, secure, and evidence-driven decision-support tool for healthcare managers and policymakers, enabling more efficient resource planning and strengthened caseload management within Kenya's cancer control framework.

Keywords: *Lung Cancer, Caseload Management, System Dynamics Model, Pattern Analysis, Security Governance, Auditability, Compliance Control, Kenya.*

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

AES	Advanced Encryption Standard
AFCRN	African Cancer Registry Network
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BETA	Beta Coefficient (statistical parameter)
CA	Cancer
CDC	Centres for Disease Control and Prevention
CEC	Chief Executive Committee
CLD	Causal Loop Diagram
COVID	Coronavirus Disease
CT	Computed Tomography
DOI	Digital Object Identifier
DSR	Design Science Research
EBM	Evidence-Based Management
EMR	Electronic Medical Records
GATS	Global Adult Tobacco Survey
GDPR	General Data Protection Regulation
GDS	Global Data Systems
HBM	Health Belief Model
HIE	Health Information Exchange
HIPAA	Health Insurance Portability and Accountability Act
HIV	Human Immunodeficiency Virus
HR	Hazard Ratio
IARC	International Agency for Research on Cancer
ICD	International Classification of Diseases
ICT	Information and Communication Technology
IDS	Intrusion Detection System
IEC	Information, Education and Communication
IQR	Interquartile Range
ISO	International Organization for Standardization
KHIE	Kenya Health Information Exchange
KHIS	Kenya Health Information System

KNCCS	Kenya National Cancer Control Strategy
KNCR	Kenya National Cancer Registry
KNH	Kenyatta National Hospital
KTRH	Kisii Teaching and Referral Hospital
KUREC	Kabarak University Research Ethics Committee
LSTM	Long Short-Term Memory
MCDA	Multi-Criteria Decision Analysis
MFL	Master Facility List
MIT	Massachusetts Institute of Technology
MTRH	Moi Teaching and Referral Hospital
NBTS	National Blood Transfusion Service
NCD	Non-Communicable Disease
SHA	Social Health Authority
NHS	National Health Service
NPCR	National Program of Cancer Registries
NQCL	National Quality Control Laboratory
NSIRH	National Spinal Injury Referral Hospital
OWASP	Open Worldwide Application Security Project
PET	Positron Emission Tomography
PLE	Participatory Learning and Evaluation
RBAC	Role-Based Access Control
SD/SDM	Secure System Dynamics Model
SDT	System Dynamics/System Dynamics Theory
SHA	Social Health Authority
STS	Socio-Technical Systems
TAM	Technology Acceptance Model
UHC	Universal Health Coverage
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

CONCEPTUAL AND OPERATIONAL DEFINITION OF TERMS

Causal Loop Diagram (CLD: A visual representation used in system dynamics to illustrate feedback loops and the causal relationships among variables (Sterman, 2000). In this study, diagrams created in Vensim are used to represent feedback loops that influence lung cancer patient flows, referral delays, and resource allocation in Kenya's healthcare system.

Data Protection Act (2019): A Kenyan law that establishes legal principles for the collection, storage, and processing of personal data, ensuring the right to privacy (Kenya Parliament, 2019). In this study, it guides the design of the secure data architecture within the SDM, including encryption, role-based access, and compliance audits for lung cancer patient information

Encryption: The process of converting data into a coded format to prevent unauthorised access (Stallings, 2017). Here, it refers to the application of secure encryption algorithms within the SDM to protect lung cancer patient records during storage and transmission

Healthcare Resource Allocation: The process of distributing healthcare resources including human, financial, and infrastructural to achieve efficiency, equity, and improved health outcomes (Finkler, Kovner, & Jones, 2013; WHO, 2010). In this study, it refers to the distribution of oncology-specific resources such as radiology equipment, oncology specialists, chemotherapy units, and funding across Kenya's healthcare system to meet lung cancer care demands.

Information and Communication Technology (ICT): Technologies that provide access to information through telecommunications, including hardware, software, and networks (UNESCO, 2021). In this study, it refers to digital health systems, cancer registries, EMRs, and secure communication platforms used for lung cancer caseload reporting, analysis, and decision-making in Kenya.

Lung Cancer Caseload Management: The coordinated and systematic process of monitoring, regulating, and optimising the number of lung cancer patients in a healthcare system to ensure efficient use of resources, timely service delivery, and improved outcomes (WHO, 2020; American Cancer Society, 2020). In this study, it refers to the structured processes used in Kenya's healthcare facilities from primary to tertiary levels to record, track, and manage lung cancer patient volumes, including diagnostics, treatment scheduling, inter-facility referrals, cross-border referrals, and follow-up care

Machine Learning (ML): A subset of artificial intelligence that enables computer systems to learn patterns from data and improve performance without explicit programming (Bishop, 2006; Goodfellow et al., 2016). In this study, it refers to the use of algorithms such as LSTM and CNN to detect trends, classify data, and forecast lung cancer patient volumes from historical caseload datasets

National Cancer Registry (Kenya National Cancer Registry – KNCR): A centralised system for the collection, storage, analysis, and dissemination of data on cancer incidence, mortality, survival, and prevalence (Bray et al., 2018; WHO, 2018). Here, it refers specifically to the KNCR as the main source of secondary data on lung cancer incidence, demographics, staging, and facility-level reporting in Kenya.

Pattern Analysis Approach: A data mining and analytical process that identifies, interprets, and models recurring relationships or trends in datasets to support decision-making (Han, Kamber, & Pei, 2011). This study applies statistical pattern recognition and machine learning algorithms to lung cancer caseload data to detect trends, forecast demand, and support predictive planning in oncology service delivery.

Predictive Analytics: The application of statistical algorithms and machine learning techniques to historical and current data to forecast future events or outcomes (Shmueli et al., 2020; Witten et al., 2011). In this study, it denotes the use of predictive modelling tools to estimate future lung cancer patient volumes, resource demands, and referral flows within Kenya's health system.

Role-Based Access Control (RBAC): A method of restricting system access to authorised users based on their roles within an organisation (Sandhu et al., 1996). In this study, it refers to the access management system embedded in the SDM, ensuring that only authorised healthcare staff can view or modify specific categories of patient data.

Secure Systems Dynamics Model (SDM: A simulation-based systemdynamics framework integrated with security protocols to protect the confidentiality, integrity, and availability of sensitive data (Morecroft, 2015; Stallings, 2017). In this study, it refers to a Vensim-based system dynamics model enhanced with encryption, RBAC, and data integrity checks to simulate and secure lung cancer caseload data across Kenya's healthcare system.

Sensitivity Analysis: A modelling technique used to determine the impact of variations in input parameters on the outputs of a system under defined conditions (Saltelli et al., 2008). In this research it involves adjusting parameters in the SDM such as patient inflow rates, diagnostic turnaround times, and treatment capacity to assess their influence on projected lung cancer caseload outcomes.

Stock-and-Flow Diagram: A system dynamics tool that models the accumulation (stocks) and movement (flows) of resources or entities over time (Sterman, 2000). In this study, it represents the patient pathways, resource capacity, and treatment processes within the SDM for lung cancer care in Kenya.

System Dynamics: A methodological framework for understanding the structure and behaviour of complex systems over time, using feedback loops, accumulations, and time delays (Sterman, 2000; Forrester, 1961). Here, it refers to the use of causal loop diagrams and stock-and-flow simulations in Vensim to model the interactions between referral patterns, facility capacity, resource allocation, and patient flow in Kenya's lung cancer care system.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Lung cancer remains one of the leading causes of cancer mortality globally and in Kenya. According to the Kenya National Cancer Registry (KNCR, 2024) and GLOBOCAN (2024), lung cancer accounts for approximately 18% of all cancer-related deaths, with more than 900 new cases and over 820 deaths reported in 2022, and a steady rise through 2024. Despite advances in early detection and treatment worldwide, most Kenyan patients continue to be diagnosed at advanced stages. This late presentation is attributed to limited public awareness, scarce diagnostic infrastructure, and fragmented referral pathways between lower-level facilities and specialized oncology centres such as Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and the newer Kenyatta University Teaching, Referral, and Research Hospital (KUTRRH).

Effective management of lung cancer cases depends not only on clinical interventions but also on the healthcare system's capacity to track, coordinate, and balance patient flows across levels of care. This broader process, known as caseload management, involves controlling and optimizing patient numbers within and across facilities, ensuring timely diagnosis, efficient referral, and equitable access to oncology services. In Kenya, weaknesses in caseload management are evident in inconsistent reporting from sub-county hospitals, a lack of integrated digital records, and delayed decision-making resulting from poor information flow. These challenges lead to overcrowding in tertiary hospitals, duplication of effort, and loss of critical patient data during inter-facility transfers.

The digitisation of health information through systems such as the Kenya Health Information System (KHIS) and the Kenya National Cancer Registry (KNCR) was designed to improve data quality and coordination. However, these platforms still face interoperability gaps, limited real-time sharing, and data security concerns. Studies such as those by Omotoso et al. (2023) and the WHO (2024) demonstrate that data protection breaches, inconsistent coding, and manual reporting undermine the reliability of health information systems in low- and middle-income countries. In Kenya, the enforcement of the Data Protection Act (2019/2022) has brought renewed focus to the need for secure, auditable, and compliant digital architectures in the healthcare sector. Yet, most hospitals continue to rely on fragmented or semi-manual systems with minimal encryption, authentication, or audit capabilities.

In response to these challenges, the Ministry of Health’s National Cancer Control Strategy (2023–2027) prioritises the integration of digital cancer registries, electronic medical records, and surveillance tools. The strategy emphasizes the use of data analytics and system modeling to inform early detection, service planning, and resource allocation. Despite these policy efforts, however, a persistent disconnect remains between national-level information systems and facility-level decision-making. This gap necessitates an integrated, dynamic framework that can model patient movement, predict service demand, and deliver secure, decision-grade insights for planners and managers.

The use of System Dynamics (SD) provides a powerful approach to capturing the complex feedback relationships that drive caseload accumulation, diagnostic delays, and resource constraints. Through causal-loop and stock-and-flow modelling, SD can simulate patient flows, test policy interventions, and visualise bottlenecks across the healthcare continuum. When coupled with pattern analysis techniques such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), it becomes possible to forecast referral delays and patient trends with high accuracy. Embedding these analytical capabilities within a secure and auditable framework ensures that patient data are protected, integrity is maintained, and every data transaction remains traceable thus aligning with principles of security governance, risk assurance, and compliance control in Information Systems Security and Audit.

Consequently, this study was grounded in the understanding that strengthening lung cancer caseload management requires more than descriptive reporting. It calls for a security-aware, data-driven systems model that combines dynamic simulation, machine intelligence, and secure data governance. Such a model not only supports real-time decisions in cancer control but also contributes to Kenya's broader health informatics and cybersecurity frameworks under Universal Health Coverage (UHC) and the Social Health Authority (SHA). By developing and evaluating a secure, auditable System Dynamics Model integrated with pattern analysis, this study addressed both a societal health need and a technological assurance gap within Kenya's digital health ecosystem.

1.2 Statement of the Problem

Lung cancer remains a major public-health burden in Kenya, with cases increasing steadily and more than two-thirds of patients diagnosed at advanced stages. Although the Kenya National Cancer Registry (KNCR 2024) and GLOBOCAN 2024 provide aggregated statistics, these data have not yet been translated into efficient management of patient flows across healthcare levels. Caseload information remains fragmented among sub-county hospitals, county referral facilities, and tertiary oncology centers, such as KNH, MTRH, and KUTRRH. The absence of an integrated, dynamic framework for tracking, forecasting, and securing patient data continues to undermine planning and timely care delivery.

Existing digital systems, including the Kenya Health Information System (KHIS) and KNCR, capture cancer-related data but lack interoperability, automated analytics, and comprehensive security governance. Reporting delays, incomplete submissions, and inconsistent use of digital tools weaken decision support. Moreover, many facilities still rely on manual or semi-automated entry processes that expose sensitive patient information to privacy risks and audit gaps, contrary to the requirements of the Kenya Data Protection Act (2019/2022).

Previous research in Kenya has focused largely on descriptive reporting of cancer incidences and on strengthening registries, with limited attention to how system behaviour, feedback delays, and information-security weaknesses jointly affect caseload accumulation. There is little evidence of dynamic, auditable models that can simulate referral pathways, quantify security-related risks, and guide real-time managerial interventions.

Consequently, healthcare managers face recurring challenges, including overstretched oncology capacity, delayed referrals, and limited assurance of data integrity. Addressing these intertwined problems requires a secure, auditable System Dynamics Model capable of integrating clinical flow data, pattern-analysis predictions, and compliance control mechanisms. Such a model would enable the health system to forecast patient volumes accurately, manage referrals efficiently, and maintain the confidentiality, integrity, and accountability of cancer data in line with Kenya’s digital health governance framework.

1.3 Objectives of the Study

1.3.1 General Objective of the Study

The primary objective of this study is to design and evaluate a security-governed, auditable System Dynamics Model (SDM) for managing lung cancer caseloads in Kenya, integrating pattern analysis techniques and compliance control mechanisms.

1.3.2 Specific Objectives of the Study

i. To assess the current structural configuration, facility distribution, and reporting patterns of the healthcare system that influence lung-cancer caseload management and referral coordination in Kenya.

ii. To examine the integration, coverage, and challenges of Information and Communication Technology (ICT) systems in lung cancer caseload management, and to incorporate a secure data architecture and audit controls for protecting patient information within the proposed model.

iii. To design and simulate a System Dynamics Model that integrates caseload data, referral delays, facility capacity, and pattern-analysis feedback loops across healthcare levels and departments.

iv. To evaluate the effectiveness of the developed secure and auditable model in forecasting patient volumes, optimising resource use, and supporting real-time decision-making for healthcare managers in Kenya.

1.4 Research Questions

In alignment with the above specific objectives, this study was guided by the following research questions:

i. How do the structural configuration, facility distribution, and reporting patterns of Kenya's healthcare system influence lung-cancer caseload management and referral coordination?

ii. To what extent are Information and Communication Technology (ICT) systems integrated into lung cancer caseload management, and how can a secure data architecture and audit controls enhance the protection of patient information?

iii. How can a System Dynamics Model integrating caseload data, referral delays, facility capacity, and pattern-analysis feedback loops be designed and simulated to improve coordination across healthcare levels?

iv. How effective is the developed, secure, and auditable System Dynamics Model in forecasting patient volumes, optimizing resource use, and supporting real-time decision-making in lung-cancer care in Kenya?

1.5 Justification for the Study

Lung cancer continues to impose a growing clinical and economic burden on Kenya's healthcare system. The persistent rise in late-stage diagnoses, limited treatment capacity, and inadequate referral coordination underscores an urgent need for evidence-based management tools that can enhance service planning and resource allocation.

This study is justified on two complementary grounds: societal relevance and disciplinary contribution.

From a societal perspective, the study responds to Kenya's national call for technology-enabled cancer control, as outlined in the National Cancer Control Strategy (2023–2027) and the Universal Health Coverage (UHC) framework. By modelling patient flow and referral dynamics, the research provides health managers and policymakers with a simulation tool for forecasting service demand, minimising congestion, and enhancing equitable access to oncology care. Strengthening caseload management directly supports the Kenya Social Health Authority's (SHA) goals of efficiency, transparency, and timely care delivery.

From an academic and professional standpoint, the study extends the field of Information Systems Security and Audit (ISSA) by demonstrating how security governance, auditability, and compliance can be effectively embedded within a system dynamics environment. It contributes to the assurance domain by introducing a Security Maturity

Index (SMI) and a probability-of-breach metric, thereby linking control validation with predictive analytics. This fusion of pattern analysis, System Dynamics, and secure data architecture provides a replicable framework for healthcare systems that handle sensitive patient information.

Furthermore, the study strengthens Kenya's compliance with the Data Protection Act (2019/2022) by proposing a model that upholds confidentiality, integrity, and accountability in data handling. The results offer both practical insights for health system managers and theoretical advances for scholars in secure systems modeling, making the research valuable to government agencies, hospitals, ICT regulators, and academic institutions.

1.6 Significance of the Study

This study is significant at academic, policy, managerial, and operational levels, addressing a critical gap in how Kenya manages lung cancer caseloads within a secure and compliant digital health environment.

From an academic perspective, the study contributes to knowledge by being the first Kenyan application of a security-governed and auditable System Dynamics Model (SDM) for managing lung cancer caseloads. It advances scholarship beyond traditional epidemiological or facility-based analyses by integrating pattern analysis techniques—specifically Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN)—to forecast referral delays and caseload trends within a dynamic simulation framework. By embedding compliance control and data-security governance within the System Dynamics architecture, the study expands methodological frontiers in Information Systems Security and Audit (ISSA), health informatics, and public health systems modelling.

From a policy and managerial perspective, the research aligns with Kenya's National Cancer Control Strategy (2023–2027), Digital Health Act (2023), and Data Protection Act (2019/2022). It supports the Ministry of Health, the National Cancer Institute of Kenya (NCI-K), county governments, and regulatory agencies, such as the Office of the Data Protection Commissioner (ODPC) and the ICT Authority (ICTA), in building compliant and interoperable digital health ecosystems. The model provides a decision-support and compliance-monitoring tool that enhances accountability, strengthens reporting accuracy, and supports secure data exchange across the Kenya Health Information Exchange (KHIE) and the Social Health Authority (SHA) frameworks.

From a practical perspective, the study benefits healthcare managers, clinicians, and patients by providing real-time insights and improved coordination. It enables managers to anticipate patient volumes, balance referral loads, and optimise use of diagnostic and treatment resources across counties. Clinicians benefit from reduced diagnostic bottlenecks and timelier case routing, while patients experience earlier diagnosis, predictable service flows, and enhanced protection of their personal health information. The auditable design of the SDM also ensures that every data exchange and simulation action can be traced, reinforcing both operational transparency and regulatory trust. Furthermore, the model's simulation capability enables policymakers to virtually test cancer-care interventions and evaluate policy outcomes before implementing them in the real world, thereby reducing systemic risk and cost.

Overall, this study provides an integrated contribution to academia, governance, and practice. It delivers a security-governed, auditable, and compliant System Dynamics framework that not only improves caseload coordination and forecasting accuracy but also embeds legal, ethical, and technical safeguards into Kenya's evolving digital health infrastructure, advancing both the science and governance of cancer care management.

1.8 Scope of the Study

The study focused on the design, simulation, and evaluation of a security-governed, auditable System Dynamics Model (SDM) for lung-cancer caseload management within Kenya’s healthcare system. Its scope was defined by the interaction of four key domains: health system structure, ICT infrastructure, system dynamics modeling, and information security assurance.

Geographical scope: The study covered Kenya at the national level, focusing on data drawn from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS), and three major referral hospitals: Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching, Referral, and Research Hospital (KUTRRH). These institutions represent Kenya’s highest levels of oncology service delivery and data reporting structures.

Temporal scope: The analysis utilised data from 2018 to 2023, the most recent five-year period with consolidated national and facility-level cancer data available at the time of study completion. This timeframe captures trends before and after the implementation of the National Cancer Control Strategy (2023–2027).

Conceptual scope: The research examined the following: (i) the structure and distribution of lung-cancer services; (ii) the integration of ICT systems and secure data architecture; (iii) the design and simulation of a System Dynamics Model using Vensim; and (iv) the embedding of security and audit controls through the Security Maturity Index (SMI) and probability-of-breach (P_{breach}) indicators.

Exclusions: The study did not address clinical or biomedical aspects of lung cancer diagnosis and treatment outcomes. Instead, its focus remained on system-level modelling, data security, and policy decision support. The model’s predictive scope was limited to forecasting patient volumes, referral delays, and system feedback under different capacity and security scenarios.

1.9 Assumptions of the Study

This study was guided by several theoretical and methodological assumptions derived from System Dynamics theory and Information Systems Security and Audit (ISSA) principles:

i. The Kenya National Cancer Registry (KNCR) and Kenya Health Information System (KHIS) data from 2018 to 2023 accurately reflect lung cancer service utilization and reporting trends in Kenya.
ii. That oncology referral pathways and reporting hierarchies among county and national hospitals remain structurally stable during the study period, allowing reliable system simulation.
iii. The respondents in the Delphi panel (oncologists, ICT managers, policymakers) provided expert input consistent with professional experience and institutional practice.
iv. The integration of pattern analysis models (LSTM and CNN) into the System Dynamics simulation could reveal valid temporal patterns of caseload behavior.
v. That embedding security governance and audit metrics (e.g., Security Maturity Index and probability-of-breach) within the model accurately represents organisational compliance and control conditions under Kenya’s Data Protection Act (2019/2022).

These assumptions form the conceptual equivalence of hypotheses within the systems-modelling framework, positing that the interaction of structural, technological, and security variables determines caseload performance outcomes.

1.10 Limitations of Study

i. The study relied primarily on secondary datasets from KNCR and KHIS, which may contain reporting inconsistencies or omissions, particularly from sub-county facilities with limited digital infrastructure.

ii. The simulation model was calibrated using Kenyan data and contextual parameters; therefore, its predictive outputs may not generalise directly to other health systems without local adaptation.

iii. While the model incorporated security maturity and breach-probability indices, real-world enforcement of data-protection controls may vary across institutions, potentially influencing the accuracy of security-level estimations.

iv. Computational performance and validation outcomes were limited by the constraints of the modelling environment (Vensim) and available computing resources.

v. Delphi-panel opinions, although valuable, reflected subjective professional judgments that may not accurately represent the perspectives of all stakeholders.

Despite these limitations, methodological triangulation through pattern analysis, expert validation, and simulation verification ensured that the findings are robust, reliable, and contextually meaningful for healthcare and ISSA applications.

1.11 Delimitations of Study

The study was delimited to the design and evaluation of a security-governed, auditable System Dynamics Model (SDM) for lung-cancer caseload management within Kenya's public healthcare system. The analysis focused on structural, technological, and security assurance dynamics influencing patient flow management, rather than on clinical or biomedical determinants of lung cancer outcomes.

The study specifically examined the operational levels of the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS), and three national referral hospitals Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching, Referral and Research Hospital (KUTRRH). County and sub-county facilities were considered only insofar as they contributed referral or reporting data to these institutions.

The research limited its timeframe to 2018–2023, corresponding to the most recent complete five-year cancer-reporting cycle available. Only data variables relevant to caseload trends, referral delays, facility capacity, and ICT security architecture were included. From an ISSA perspective, the study focused on information-security governance, auditability, and compliance control within the healthcare data environment. Broader aspects such as cybersecurity workforce policy, national budget allocation, or patient-behavioural analytics were outside its scope.

These boundaries ensured methodological focus and analytical coherence, allowing the research to concentrate on how System Dynamics and pattern-analysis techniques can enhance secure, auditable decision support in Kenya's oncology-care system.

1.12 Justification for the Use of Secondary Data

The study primarily relied on secondary data obtained from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS), and global repositories, including GLOBOCAN 2024. This approach was justified by three key considerations: comprehensiveness, reliability, and compliance assurance.

Comprehensiveness: Secondary datasets provided the only national-level longitudinal records on lung cancer incidence, mortality, and service utilization across Kenya's 47 counties. These sources consolidate reports from public and private health facilities, thereby ensuring broad coverage that would be unattainable through primary data collection within the scope and timeframe of this PhD study.

Reliability and triangulation: The KNCR and KHIS datasets are validated by the Ministry of Health's Division of Health Informatics and Data Management and routinely undergo data-quality audits in line with WHO standards. To strengthen validity, facility-level records from KNH, MTRH, and KUTRRH were cross-checked against registry summaries, and expert feedback from the Delphi panel helped interpret any observed discrepancies.

Compliance and ethical alignment: Using secondary data supported adherence to Kenya's Data Protection Act (2019/2022) and NACOSTI ethics requirements by minimising direct patient-level data handling. All datasets were anonymized and accessed under institutional authorization, ensuring the confidentiality, integrity, and accountability of the information.

From an Information Systems Security and Audit (ISSA) perspective, the use of secondary data allowed the researcher to evaluate existing digital health systems within their natural operational contexts. This enabled the assessment of reporting integrity, data security maturity, and audit-trail functionality without compromising patient privacy. Consequently, secondary data were not only practical but methodologically consistent with the study's objective of designing a secure, auditable, and policy-relevant System Dynamics Model for national-level lung-cancer caseload management.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter is to embed this study within the broader scholarly and policy discourse on healthcare systems, lung cancer management, ICT integration, and secure data architectures. A high-quality literature review must do more than summarize it should critically synthesize knowledge, expose deficiencies in theory and practice, and justify the need for the present research. Aligning with Kabarak University doctoral standards and global academic rigor, this chapter is structured into five sections: the theoretical foundation, empirical evidence aligned with objectives, a conceptual framework, and clearly articulated research gaps.

Globally, lung cancer remains the leading cause of cancer mortality accounting for nearly 18 % of cancer-related deaths (World Health Organization [WHO], 2022). High-income countries have seen improvements through integrated oncology networks, advanced diagnostic tools, and interoperable electronic health records (EHRs); yet, referral delays and equity gaps persist, signaling the necessity of systems-level models like System Dynamics to unravel patient flow complexities and resource bottlenecks (Sterman, 2000; Forrester, 1961).

In sub-Saharan Africa, systemic fragility is profound, with structural inequities hindering access to prevention, early detection, and treatment (Omotoso et al., 2023). Kenya, in particular, has traditionally centralized cancer treatment in Nairobi; however, recent decentralization to regional cancer centers promises expanded access—a policy shift that is deeply relevant to caseload management and referral dynamics (Johns Hopkins/NCCP report, 2023). Simultaneously, the 2023–2027 National Cancer Control Strategy emphasizes the digitalization of cancer services and the bolstering of strategic information systems a clear policy foundation for modeling and ICT integration (MoH Kenya, 2023).

In Kenya, lung cancer continues to present late, with very high mortality compared to incidence: approximately 794 new cases and 729 deaths were reported in 2019—a fatality ratio exceeding 90 % (KESHO, 2019). At the same time, reports from Kenyatta National Hospital indicate 221 diagnosed cases of lung cancer between 2018 and 2020, with survival outcome studies now emerging to inform modelling efforts (SAID & DEGU, 2022). Moreover, the Ministry of Health's 2025 partnership with IARC and Oxford University to strengthen cancer registry data systems signals a critical turning point towards robust, real-time data sharing (MoH Kenya, 2025). The Kenya Data Protection Act (2019) further imposes legal imperatives for secure data architecture and patient privacy compliance.

Positioned at the convergence of Health Systems Management, System Dynamics modelling, ICT/digitalization, and secure data structures, this review will therefore:

i. Critically assess theoretical frameworks System Dynamics Theory, Technology Acceptance Model (TAM), Information Systems Success Model (ISSM), along with socio-technical perspectives.

ii. Examine empirical research aligned with the study's four objectives: healthcare system structure and reporting patterns, ICT integration and secure data handling, system dynamics modeling of lung cancer caseloads, and evaluation of secure clinical decision-support systems.

iii. Present a Conceptual Framework (diagram and narrative) that links key variables (caseloads, referrals, ICT systems, security parameters).

iv. Identify and articulate research gaps knowledge, methodological, and contextual that justify and sharpen this study's contribution.

This structured, multi-layered approach ensures that the study is not only theoretically and empirically grounded but also deeply contextualized within Kenyan policy and global best practices thereby setting a strong foundation for modelling and innovation in caseload management.

2.2 Theoretical Review

The theoretical review provides the intellectual foundation for this study. It situates the research within established scholarly traditions while critically examining the adequacy of existing models in addressing the complexities of lung cancer caseload management in Kenya. Theories are not only discussed in terms of their origins and assumptions but also critiqued for their limitations and relevance to the current research objectives. The following frameworks are particularly pertinent.

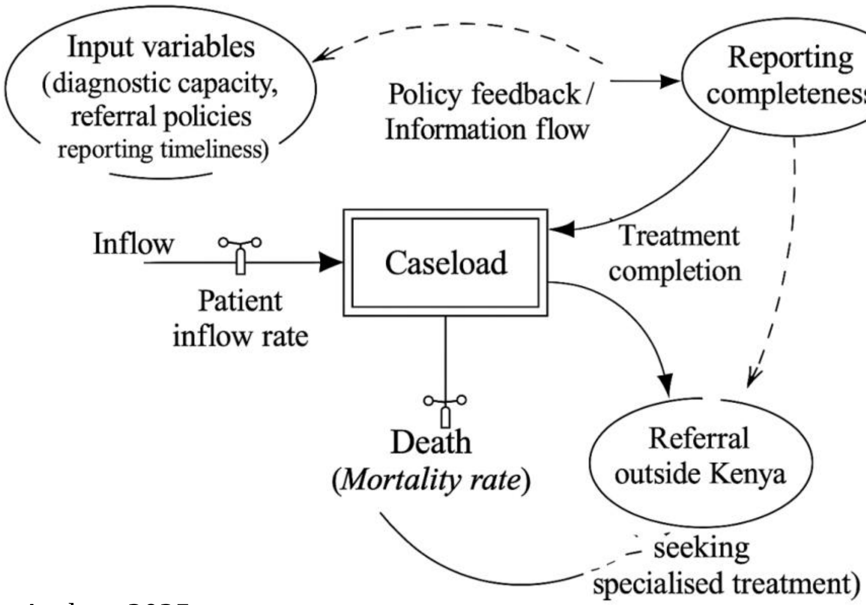
2.2.1 System Dynamics Theory

System Dynamics Theory (SDT) was first introduced by Jay W. Forrester in the late 1950s at the Massachusetts Institute of Technology as a methodology for examining the behaviour of complex systems over time (Forrester, 1961). Unlike traditional linear cause–and–effect models, SDT is grounded in the principle that systems evolve through the interaction of stocks (accumulations), flows (rates of change), feedback loops, and time delays. These features, as Sterman (2000) emphasised, are particularly valuable in contexts where interventions may produce counter-intuitive or delayed outcomes, making the theory especially relevant to health systems research.

Healthcare is characterised by dynamic interactions among patient flows, referral patterns, resource constraints, and policy interventions. Reinforcing feedback loops can amplify challenges; for example, delayed diagnosis may increase late-stage cases, further burdening already limited treatment capacity. In contrast, balancing loops act to stabilize systems, such as through improved reporting mechanisms that redistribute resources more effectively. Time delays, a core feature highlighted by Meadows (2008), are evident in oncology, where the benefits of screening, treatment initiation, or policy reforms may only become observable months or years later. This ability to account for both reinforcing and balancing dynamics underlines why SDT has been widely applied to modelling patient flows, hospital resource allocation, and system-level policy evaluation (Homer & Hirsch, 2006; Brailsford & Hilton, 2019).A defining tool within SDT is the stock–flow structure, which visually represents how patients or resources accumulate within a system and exit through multiple pathways. Figure 1 illustrates a generic stock–flow structure adapted to caseload management. Here, inflows, such as new diagnoses or referrals, add to the caseload, while outflows occur through treatment completion, mortality, or referral outside Kenya for specialized services. Input variables, including diagnostic capacity, referral policies, and reporting timeliness, influence inflow rates, while treatment efficiency and workforce levels shape outflow patterns. Feedback loops then connect system outcomes back into policymaking processes, providing information that can guide adjustments in policy or resource allocation.

Figure 1

Generic Stock–Flow Structure for Caseloads with Inflows, Outflows, and Feedback



Source: Author, 2025

Note. *Rectangles represent stocks, arrows with valves represent flows, ovals represent auxiliary variables, and dashed arrows represent feedback loops.*

The principal strength of System Dynamics Theory (SDT) lies in its flexibility to integrate both quantitative and qualitative inputs, thereby allowing policymakers to test alternative policy, capacity, and compliance scenarios before implementing them in practice. Brailsford and Hilton (2019) demonstrated that System Dynamics models in healthcare are particularly effective for identifying bottlenecks, exploring "what-if" scenarios, and projecting the long-term consequences of reforms. Similarly, SDT enables the synthesis of heterogeneous data streams clinical, operational, and regulatory into a coherent structure that reveals how feedback loops shape overall system performance.

However, as Lane (2000) cautions, simplification within System Dynamics is both its strength and its limitation: it makes complex systems tractable yet may overlook subtle relationships when parameters are uncertain or data incomplete. This limitation is especially salient in low- and middle-income contexts, such as Kenya, where data fragmentation, underreporting, and inconsistent security assurance reduce simulation precision.

Despite these challenges, SDT provides the methodological backbone for this research. It directly supports Objective 3, which focuses on designing and simulating a security-governed, auditable System Dynamics Model for lung cancer caseload management. The framework maps inflows, outflows, and feedback loops across diagnostic, treatment, and referral subsystems, capturing how patient movement interacts with institutional capacity and policy levers. When integrated with pattern-analysis techniques, notably Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) algorithms, the model extends traditional SDT by embedding predictive intelligence for caseload forecasting and referral delay estimation.

Moreover, by incorporating secure data flows, audit trails, and compliance indicators consistent with the Kenya Data Protection Act (2019/2022) and the Digital Health Act (2023), the model transcends conventional forecasting. It becomes a tool for trustworthy, transparent, and legally compliant decision support, strengthening both the reliability of health system reporting and stakeholder confidence. In this way, SDT augmented by pattern analysis and compliance control—provides the conceptual clarity, analytical depth, and governance assurance required to capture the complexity of lung-cancer caseload management in Kenya.

2.2.2 Technology Acceptance Model (TAM) / UTAUT2

The Technology Acceptance Model (TAM) was developed by Davis (1989) to explain the determinants of individual acceptance and use of information systems. According to the model, two key perceptions —perceived usefulness and perceived ease of use — shape behavioral intention to adopt a system, which ultimately predicts actual usage. This parsimonious framework has since been widely applied and extended, with

Venkatesh and Davis (2000) refining its constructs and validating its predictive power in organisational contexts. In healthcare, where clinicians often juggle multiple demands, TAM provides an accessible way to understand why certain technologies are adopted quickly, while others face persistent resistance.

Empirical studies demonstrate that TAM has been influential in explaining adoption patterns of electronic medical records (EMRs), telemedicine platforms, and mobile health applications. For instance, Holden and Karsh (2010) noted that the model consistently predicts clinician attitudes toward health ICT, particularly under conditions of high workload and time pressure. Evidence from Africa suggests similar dynamics. Were et al. (2019), studying the implementation of the Kenya Health Information Exchange (KHIE), observed that many health workers resisted full utilisation of the system because it was perceived as complex and insufficiently beneficial to clinical workflows, despite policy-level enthusiasm for digital integration. These findings resonate with broader critiques of health ICT adoption across low- and middle-income countries, where infrastructure constraints and limited support often outweigh individual perceptions of usefulness.

The continuing relevance of TAM lies in its clarity and its empirical robustness, but this strength is also its weakness. As Legris et al. (2003) observed, the model’s focus on individual cognitive perceptions neglects broader organisational, cultural, and infrastructural factors that are equally critical for adoption. In practice, health workers in resource-constrained environments may value a system yet still struggle to use it effectively due to network outages, limited training, or administrative barriers. More recently, researchers have argued that TAM in its original form fails to capture the rising importance of trust, data protection, and security in influencing technology acceptance (Amoako et al., 2022). These omissions are particularly relevant in Kenya, where the

Data Protection Act (2019) requires all health ICT systems to safeguard patient information, and where clinicians are increasingly aware of the reputational and professional risks associated with data breaches.

Despite these limitations, TAM remains an essential theoretical lens for this study because it helps explain the behavioural aspects of ICT adoption in lung cancer caseload management. Its application extends beyond predicting whether healthcare workers will use an electronic reporting system; it also reveals how perceptions of system security, reliability, and clinical benefits influence adoption. This is particularly relevant for Objective 2, which focuses on integrating ICT and securing data architecture. By extending TAM to incorporate constructs such as trust and compliance, the study situates adoption behaviour within Kenya’s evolving policy and legal frameworks, ensuring that secure caseload management systems are not only technically functional but also acceptable to the professionals who must depend on them.

2.2.3 Information Systems Success Model

The Information Systems Success Model (ISSM), first articulated by DeLone and McLean (1992) and later updated in 2003, provides a multi-dimensional framework for evaluating the effectiveness of information systems. According to the model, six interrelated constructs system quality, information quality, service quality, use, user satisfaction, and net benefits determine whether an information system can be considered successful. As DeLone and McLean (2003) argued, these dimensions offer a comprehensive basis for assessing both technical and behavioural aspects of system performance, a feature that explains the model’s enduring relevance in healthcare contexts.

Applications of ISSM in healthcare are well documented. Petter et al. (2008), for example, highlighted how the model has been used to measure the effectiveness of clinical decision support systems and electronic health records (EHRs), while Alalwan et al. (2020) applied it in evaluating digital health platforms in low-resource settings. In Africa, studies have shown that the model is particularly useful for examining the performance of EMR systems within HIV/AIDS programmes, where issues of data quality, user satisfaction, and system sustainability intersect (Amoakoh-Coleman et al., 2016). Kenya has also witnessed similar evaluations, with researchers noting that data quality inconsistencies and insufficient training in the District Health Information System (DHIS2) often reduce user trust and limit the system's decision-support value (Mutale et al., 2020). These findings reinforce the model's utility in revealing not only the technical soundness of ICT systems but also their capacity to generate actionable benefits.

The strength of ISSM lies in its holistic evaluation approach, capturing multiple dimensions of system performance that extend beyond simple usage statistics. By incorporating both objective indicators, such as data accuracy, and subjective perceptions, like user satisfaction, the model provides a balanced framework for assessing system outcomes. However, as Seddon (1997) pointed out, the model can appear static, focusing on measuring outcomes rather than explaining the dynamic processes that shape adoption or sustainability. This limitation is particularly relevant in rapidly evolving healthcare environments, where systemic feedback loops and behavioural shifts are critical to understanding how systems actually perform over time. Moreover, ISSM has been critiqued for insufficiently addressing issues of data security and privacy, dimensions that have become central under frameworks such as Kenya's Data Protection Act (2019).

For this study, ISSM is highly relevant to both Objective 2 and Objective 4. In examining ICT integration and secure data architecture, the model provides a lens for evaluating whether the proposed caseload management system achieves quality, reliability, and user satisfaction. At the same time, it informs the evaluation of the Security-Governed, Auditable System Dynamics Model by offering criteria—such as data quality, perceived usefulness, and net benefits-that can be applied in determining the effectiveness of the system in supporting healthcare managers. By extending ISSM to include explicit measures of security and compliance, this study ensures that system success is not only judged by functionality and satisfaction but also by adherence to Kenya's legal and ethical requirements for patient data protection.

2.2.4 Diffusion of Innovations Theory

The Diffusion of Innovations (DOI) Theory, developed by Rogers (1962) and refined in later editions of his work (2003), explains how new technologies, ideas, or practices spread within a population over time. According to the theory, adoption follows a predictable sequence through categories of innovators, early adopters, early majority, late majority, and laggards. Five perceived attributes of innovations, relative advantage, compatibility, complexity, trialability, and observability, shape the rate and extent of diffusion. As Greenhalgh et al. (2017) noted in their systematic review, these attributes are particularly influential in healthcare, where adoption decisions are embedded within professional norms, resource constraints, and organisational culture.

Evidence from global and African contexts demonstrates the utility of DOI in understanding the uneven uptake of health innovations. For instance, Nguyen et al. (2021) observed that while mobile health technologies have been widely piloted, their scaling has been slow due to infrastructural limitations and inconsistent policy support. In sub-Saharan Africa, diffusion patterns often reveal strong interest from innovators and early adopters but stagnation at the majority stages, a problem that has been linked to systemic barriers such as limited internet penetration, training gaps, and fragile supply chains (Omotoso et al., 2023). Kenya provides a vivid example: the staggered adoption of the Kenya Health Information Exchange (KHIE) and DHIS2 modules reflects how relative advantage and compatibility with existing workflows encouraged uptake in some counties, while perceptions of complexity and limited support slowed diffusion elsewhere.

One of the strengths of DOI is its ability to highlight how social systems and communication channels influence adoption behaviour. The categorisation of adopters and the identification of innovation attributes provide policymakers with practical entry points for designing strategies to accelerate diffusion. At the same time, however, the theory has been critiqued for being overly linear and insufficiently attentive to systemic feedback and non-adoption dynamics. Rogers himself acknowledged that adoption is not always permanent; innovations may be discontinued, reversed, or adapted in unexpected ways. This limitation is particularly significant in healthcare systems, such as those in Kenya, where resource shortages, intermittent funding, and concerns over data security can cause promising digital systems to stall or regress after initial implementation (Amoako et al., 2022). Moreover, DOI in its traditional form pays limited attention to institutional trust and regulatory compliance, factors that are increasingly critical under Kenya's Data Protection Act (2019).

Despite these limitations, DOI remains an important theoretical lens for this study because it situates individual adoption within a broader social and organisational context. For Objective 2, which examines ICT integration and secure data architecture, DOI explains how secure data systems can be disseminated across healthcare facilities and what factors might accelerate or hinder their mainstream adoption. When combined with models such as the Technology Acceptance Model, DOI enables a more comprehensive understanding of adoption by linking individual perceptions with systemic patterns of diffusion. This integration is particularly useful in the Kenyan context, where reforms under the Social Health Authority (SHA) aim to standardize ICT platforms across counties. However, success will ultimately depend on how innovations are perceived, communicated, and sustained across diverse institutional settings.

2.2.5 Health Belief Model (HBM)

The Health Belief Model (HBM), originally developed by Rosenstock in the 1950s and later expanded by Becker (1974), provides a psychological framework for understanding why individuals adopt or avoid specific health-related behaviours. The model posits that behaviour is influenced by six constructs: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy. According to Rosenstock, individuals are more likely to take preventive or therapeutic action if they believe they are personally at risk, if the consequences are severe, if the benefits outweigh the barriers, and if they feel capable of taking action. This model, as Champion and Skinner (2008) observed, has been widely applied in cancer screening and early detection research, where personal risk perception strongly influences patient decision-making.

HBM has proven particularly relevant in cancer contexts, as late presentation is often shaped by how patients perceive symptoms and interpret risk. For instance, Jones et al. (2014) demonstrated that patients who underestimated their susceptibility to lung cancer were less likely to seek early diagnosis, even when symptoms persisted. In sub-Saharan Africa, cultural beliefs, limited awareness, and stigma have been shown to influence perceived severity and create barriers to care, leading to delayed treatment initiation (Moodley et al., 2021). In Kenya, similar findings have emerged: studies have noted that low levels of cancer literacy and reliance on traditional medicine can delay formal diagnosis. At the same time, lack of trust in public health systems further reduces self-efficacy in seeking timely treatment (Ministry of Health [MoH], 2022). These behavioural dimensions directly impact referral patterns and, by extension, caseload management.

The strength of HBM lies in its ability to capture individual-level decision-making, offering insight into why patients may or may not engage with healthcare systems. It provides explanatory power for understanding referral delays and late-stage presentation, both of which are critical in lung cancer outcomes. However, critics such as Janz and Becker (1984) have argued that the model is overly individualistic and insufficiently attentive to structural and systemic determinants of health behaviour. In resource-constrained environments like Kenya, even if patients perceive a high susceptibility and severity, barriers such as cost, geographical access, and weak health infrastructure may still prevent them from receiving timely care. Furthermore, HBM does not explicitly account for digital or systemic interventions such as ICT-enabled reporting or secure data flows, which are increasingly central to contemporary health systems.

Despite these limitations, HBM is useful for this study because it complements system-level theories by highlighting the behavioural factors that shape patient inflows and referral patterns. For Objective 1, which examines the structural configuration and reporting patterns of the healthcare system, HBM provides a lens for understanding why patients present late or fail to follow referral pathways. This, in turn, informs Objective 3, where patient inflows are modeled within the System Dynamics framework, ensuring that behavioral dimensions are not overlooked. By recognising that patient perceptions of risk, severity, and barriers influence caseload accumulation, the study integrates individual decision-making with systemic modelling, offering a more comprehensive view of lung cancer caseload management in Kenya.

2.2.6 Socio-Technical Systems Theory

Socio-Technical Systems Theory (STS) was pioneered in the 1950s by Trist and Emery at the Tavistock Institute to explain productivity outcomes in complex organisations (Trist & Bamforth, 1951). The theory posits that organisational effectiveness arises from the joint optimisation of social and technical subsystems, rather than focusing on technology or human actors in isolation. In healthcare contexts, this implies that the success of any digital-health intervention depends not only on the technical robustness of the system but also on its alignment with people, workflows, and institutional culture (Sittig & Singh, 2010).

STS has been extensively applied in digital-health research to explain variable outcomes in Electronic Medical Record (EMR) and Health Information System (HIS) deployments. Berg (1999) observed that even well-engineered systems may fail if they disrupt clinical routines or professional norms. Cresswell and Sheikh (2013) later argued that socio-technical perspectives are indispensable in evaluating large-scale health information rollouts, as such programs transform not only data processes but also patterns of power, accountability, and organizational behavior. In African settings, socio-technical misalignments have produced hybrid record-keeping, duplication, and user resistance (Amoako et al., 2022). Kenya’s own EMR experience illustrates this tension: several county hospitals reported clinician resistance due to poor system integration, limited technical support, and minimal short-term value for already overburdened staff (Were et al., 2019).

The strength of STS lies in its holistic view of technology and people as a coupled system, making it particularly valuable where policy reforms, resource constraints, and cultural expectations intersect with digital health initiatives. Nevertheless, operationalising STS remains challenging. Baxter and Sommerville (2011) noted that while the theory offers a rich conceptual lens, it lacks standardised metrics and can produce descriptive rather than predictive outcomes. Moreover, classical STS formulations seldom address data security, auditability, or compliance governance—aspects that have become fundamental in modern digital health ecosystems governed by legislation such as Kenya's Data Protection Act (2019/2022) and the Digital Health Act (2023).

Despite these limitations, STS is crucial to this study because it complements the technical and analytical perspectives by highlighting the human, organisational, and governance dimensions that determine whether secure digital solutions are successfully adopted and sustained. For Objective 2, it provides a lens for examining how staff attitudes, reporting workflows, and institutional accountability norms influence the integration of secure ICT platforms and compliance-controlled data architectures. For Objective 3, it informs the design of the security-governed, auditable System Dynamics Model by ensuring that variables such as workforce capacity, reporting culture, and organisational learning are represented within the feedback structure. When coupled with pattern-analysis insights and compliance indicators, the socio-technical lens ensures that the resulting model is not only technically robust but also socially adaptive, ethically compliant, and operationally sustainable within Kenya's healthcare system.

Taken together, the theories reviewed in this section provide a multi-layered foundation for analysing lung-cancer caseload management in Kenya. Systems Dynamics Theory establishes the methodological backbone for modelling complex feedback, referral delays, and capacity constraints. The Technology Acceptance Model and Diffusion of Innovations Theory explain how organisations and professionals perceive and adopt secure ICT systems. The Information Systems Success Model adds evaluative criteria for information quality, user satisfaction, and decision-support value. The Health Belief

Model introduces patient-level behavioural determinants that shape presentation and referral flows. Finally, Socio-Technical Systems Theory reinforces that successful innovation demands the joint optimisation of technical, social, and regulatory subsystems ensuring that secure, auditable ICT frameworks and caseload-management models align with clinical practice, organisational culture, and Kenya's statutory compliance environment. By synthesising these perspectives, the study integrates structural, technological, behavioural, and governance dimensions into a coherent theoretical architecture, ensuring that the proposed security-governed, auditable System Dynamics Model is both technically rigorous and contextually grounded.

2.2.7 NIST Cybersecurity Framework (CSF) Theory

The National Institute of Standards and Technology (NIST) Cybersecurity Framework (CSF), first developed in 2014 and updated in 2024, provides an internationally recognised structure for security governance and compliance assurance within complex information systems. The framework organises cybersecurity activities into five continuous and interrelated functions Identify, Protect, Detect, Respond, and Recover that together form a cyclical model of risk management and resilience (National Institute of Standards and Technology [NIST], 2024). Each function contributes to a continuous assurance process that enables institutions to anticipate threats, safeguard critical assets, identify anomalies, respond effectively to incidents, and recover operations while maintaining accountability.

Within the field of Information Systems Security and Audit (ISSA), the NIST CSF has become a central reference for evaluating security maturity, governance alignment, and control auditability. Its structured approach allows for the mapping of controls to quantifiable metrics, making it particularly relevant for health information systems that handle sensitive personal data. In this study, the framework complements System

Dynamics Theory by embedding security-governance and audit principles into the dynamic behaviour of Kenya’s healthcare system.

In the model developed for this research, the Identify and Protect functions correspond to the recognition and safeguarding of patient data assets, facility networks, and information flows, as represented in the model’s stock-and-flow structure. The Detect and Respond functions parallel the model’s feedback loops, which identify inefficiencies, data anomalies, or referral disruptions and activate corrective actions. The Recover function mirrors the balancing mechanisms that restore optimal caseload levels and data integrity after perturbations or security breaches. In this way, the NIST CSF transforms abstract cybersecurity requirements into operational and measurable model components, ensuring that security and auditability are continuous processes rather than static features.

Integrating the NIST CSF into this study also strengthens alignment with both international best practices and Kenya’s statutory frameworks, including the Data Protection Act (2019/2022), the Digital Health Act (2023), and the Social Health Authority (SHA) digital-health standards. It provides the normative foundation for the compliance-control dimension of the model, ensuring adherence to the core pillars of confidentiality, integrity, availability, and audit traceability.

For Objective 4, which evaluates the effectiveness of the security-governed and auditable System Dynamics Model, the NIST CSF offers a benchmark for assessing model resilience, compliance maturity, and policy alignment. It transforms the secure SDM from a technical forecasting tool into a governance-oriented decision-support system that simultaneously enhances patient flow efficiency, enforces legal compliance, and institutionalizes a culture of continuous assurance. Through this integration, the NIST CSF extends the study’s methodological architecture by linking system dynamics, pattern analysis, and compliance control into a unified, auditable framework for sustainable healthcare governance in Kenya.

2.3 Empirical Review

2.3.1 Global and Local Lung Cancer Burden

Globally, lung cancer remains one of the leading causes of cancer mortality, responsible for an estimated 2.4 million new cases and about 1.9 million deaths in 2023, representing roughly 18 percent of all cancer-related deaths (World Health Organization [WHO], 2024; International Agency for Research on Cancer [IARC], 2024). According to the updated GLOBOCAN 2024 database, lung cancer has surpassed breast cancer as the most diagnosed malignancy worldwide.

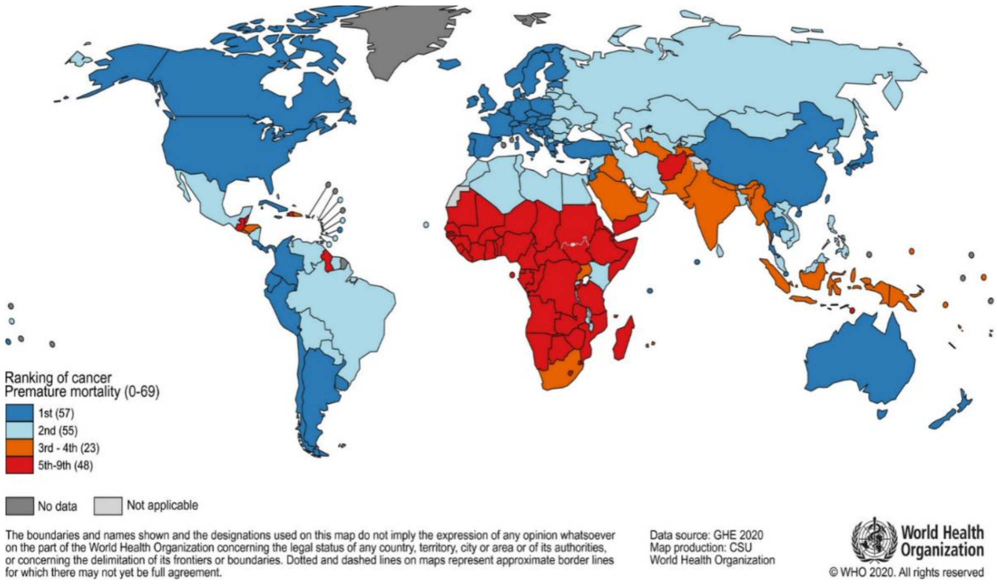
Bray, Ferlay, Soerjomataram, Siegel, Torre, and Jemal (2021) observed that while lung cancer was once concentrated in high-income countries because of smoking prevalence and industrial exposures, the burden has increasingly shifted toward low-and middle-income countries (LMICs), where rising tobacco consumption, environmental pollution, and occupational hazards coincide with fragile health infrastructure.

The mortality-to-incidence ratios reveal stark inequities. Sung, Ferlay, Siegel, Laversanne, Soerjomataram, Jemal, and Bray (2021) noted that although incidencesare highest in industrialised regions, LMICs record disproportionately high mortality due to late-stage diagnosis, fragile referral systems, and limited access to specialised care. These disparities highlight the structural weaknesses that complicate effective caseload management and underscore the importance of modelling patient flows in ways that capture delays and systemic bottlenecks.

As shown in Figure 2, regions with the highest mortality burden remain disproportionately concentrated in LMICs—particularly across sub-Saharan Africa. The figure further illustrates that cancer-mortality ranks are relatively lower in high-income regions such as Europe and North America, while most African countries, including Kenya, continue to fall within the highest categories of premature mortality.

Figure 2

Global Ranking of Premature Cancer Mortality (Ages 0–69 Years) in 2020



The figure reinforces empirical observations that structural weaknesses, rather than incidence alone, account for the disproportionate burden of cancer mortality in LMICs. For lung cancer, this implies that late presentation and fragile referral networks amplify caseload pressures and reduce survival outcomes. These systemic barriers make predictive modelling approaches, such as System Dynamics, critical for evaluating how patient inflows, diagnostic delays, and treatment pathways interact to produce observed outcomes.

In sub-Saharan Africa, lung cancer contributes a smaller proportion of total cancer incidence compared to breast and cervical cancers, yet mortality rates remain disproportionately high because of late detection and limited treatment options (*Jedy-Agba et al.*, 2022). The African Cancer Registry Network (*AFCRN*, 2024) continues to report a scarcity of population-based registries across the continent—a limitation that perpetuates under-reporting and constrains data accuracy (*Parkin et al.*, 2020). *Moodley et al.* (2021) further highlight the significance of environmental exposures, including the use of biomass fuel and air pollution, while the weak enforcement of tobacco control policies sustains preventable risks. Despite regional policy recognition of cancer as a major public health concern, surveillance systems remain fragmented, and data quality varies across facilities.

Kenya reflects these continental realities as it implements a series of strategic reforms. The Kenya National Cancer Registry (*KNCR*, 2024) estimated about 2,400 new lung cancer cases and approximately 1,900 deaths annually, yielding a case fatality ratio of more than 80 percent. The Ministry of Health (2024) acknowledges that diagnostic delays persist because advanced imaging and pathology services remain concentrated in urban tertiary hospitals. Rural populations continue to face long referral chains, financial constraints, and inconsistent reporting mechanisms.

The National Cancer Control Strategy (NCCS) 2023–2027 prioritizes digitalization, registry expansion, and data integration under the Kenya Health Information Exchange (KHIE) and the Cancer Information Management System (CIMS). Evidence from national implementation reports indicates modest but measurable gains in electronic data capture and facility-based reporting—especially within referral centres such as KNH, MTRH, and KUTRRH. However, as the current study confirmed, these improvements are uneven across counties. Peripheral and lower-tier facilities still rely heavily on manual registers, which hampers data timeliness, interoperability, and integrity. Furthermore, security and auditability gaps persist, as existing systems lack standardised encryption, access control, and automated audit trails.

Consequently, while the NCCS digitalisation agenda has enhanced visibility of cancer data at the national level, it has not yet translated into a secure, fully integrated caseload management ecosystem. This finding highlights the need for a System Dynamics model that incorporates secure data exchange, feedback loops, and audit controls, aligning with the Kenya Data Protection Act (2019) and the Social Health Authority (SHA) interoperability standards.

These patterns reinforce two implications for the present study. First, they validate the focus of Objective 1, which examines how structural configuration, facility distribution, and reporting patterns influence lung cancer caseload management in Kenya. Weak registries, late presentation, and fragile referral pathways are not merely epidemiological but systemic determinants that can be captured within a dynamic modelling framework. Second, the high mortality-to-incidence ratio substantiates Objective 4, which evaluates the effectiveness of predictive and decision-support models. Accurate forecasting of caseloads is crucial for anticipating demand, allocating resources equitably, and improving audit transparency. Addressing these digitalisation and security gaps, therefore, provides the rationale for the model developed in this thesis.

2.3.2 Structural Configuration, Facility Distribution, and Reporting Patterns

The configuration of healthcare systems plays a central role in shaping the management of cancer caseloads, as it determines the flow of patients, the distribution of specialised services, and the effectiveness of reporting mechanisms. Globally, health systems with decentralised oncology networks and robust referral pathways have demonstrated more equitable access to cancer diagnosis and treatment. For instance, the Organisation for Economic Co-operation and Development (OECD, 2021) reported that countries with well-structured cancer control systems such as the United Kingdom’s National Health Service achieve higher survival rates largely because of timely diagnosis, systematic referral coordination, and integrated cancer registries. By contrast, fragmented systems often produce duplications in reporting, bottlenecks in referrals, and uneven access to diagnostic and treatment services (Allemani et al., 2020).

In sub-Saharan Africa, health system structures remain highly variable but are frequently characterised by limited oncology infrastructure, centralised service provision, and weak inter-facility referral coordination. Jedy-Agba et al. (2022) highlighted that most cancer care facilities are located in urban centres,

creating geographic inequities for rural populations. The African Cancer Registry Network (AFCRN) has consistently reported that fewer than half of the countries in the region maintain functional population-based cancer registries, leading to a substantial underestimation of the true caseloads (Parkin et al., 2020). Moreover, as Okello et al. (2021) observed, cancer reporting in many African contexts is often paper-based, delayed, and incomplete, thereby undermining both surveillance and planning. These weaknesses not only limit epidemiological accuracy but also prevent effective modelling of patient flows across the health system.

Kenya's experience reflects many of these structural and reporting challenges while also revealing gradual reforms. The Kenya National Cancer Registry (KNCR, 2023) has expanded its coverage; however, reporting remains inconsistent across counties, with tertiary facilities, such as Kenyatta National Hospital and Moi Teaching and Referral Hospital, providing more comprehensive data than most county hospitals. The Ministry of Health (2022) has acknowledged that referral coordination is weak, often resulting in delayed or missed linkages between primary facilities, county hospitals, and tertiary cancer centres. Disparities in facility distribution exacerbate this fragmentation: according to the National Cancer Control Strategy 2023–2027, only a limited number of counties host comprehensive oncology centres, forcing patients to travel long distances for diagnostic imaging, pathology, or radiotherapy services. These patterns produce bottlenecks in tertiary hospitals while underutilising lower-level facilities.

The reporting architecture has also undergone digitisation efforts, with the Kenya Health Information System (KHIS/DHIS2) serving as the national platform for health data. However, as observed by Were et al. (2019), oncology modules within DHIS2 are not consistently adopted, and health workers often revert to parallel paper systems due to training gaps, system downtime, and limited clinical feedback. This has led to duplication, incomplete records, and delays in caseload reporting. Recent reforms under the Social Health Authority (SHA) aim to standardize financing and reporting across the health sector, but securing interoperability between county-level facilities, regional cancer centers, and national registries remains underdeveloped.

Taken together, the evidence highlights the structural and reporting weaknesses that directly influence lung cancer caseload management in Kenya. Centralised facility distribution, fragile referral networks, and inconsistent reporting practices not only inflate patient delays but also weaken the reliability of national caseload data. For this reason, Objective 1—which focuses on assessing the structural configuration, facility distribution, and reporting patterns of the Kenyan health system—remains foundational to this thesis. Without a clear understanding of these dynamics, it would be impossible to design a model capable of forecasting caseloads or supporting evidence-based planning.

2.3.3 ICT Integration and Secure Data Architecture

The integration of information and communication technology (ICT) into health systems has long been recognised as a critical enabler of effective caseload management, particularly for conditions such as cancer that require timely diagnosis, referral, and longitudinal monitoring. Globally, electronic health records (EHRs), health information exchanges, and digital decision-support platforms have been demonstrated to enhance reporting timeliness, reduce duplication, and improve continuity of care (Nguyen et al., 2021). According to the World Health Organization (WHO, 2020), countries with mature digital health ecosystems, such as Denmark and Estonia, have achieved significant efficiency gains by linking patient records across facilities, thereby enabling seamless referral coordination. However, even in advanced systems, challenges persist around interoperability and data security, with studies noting that weak governance of information flows can undermine trust and delay adoption (Adler-Milstein & Jha, 2017).

In low- and middle-income countries (LMICs), ICT integration has been uneven, with health information systems often fragmented across programmes and facilities. Braa et al. (2019) highlighted that while many African nations have adopted the District Health Information System (DHIS2) as a national platform, oncology-specific modules are rarely prioritised, leading to gaps in cancer surveillance. Omotoso et al. (2023) observed that, despite increasing investments in digital health, persistent barriers, such as unreliable internet connectivity, inadequate training, and parallel paper-based systems, limit the effectiveness of ICT adoption in sub-Saharan Africa. Security concerns further complicate integration; Mutale et al. (2020) found that health workers in Zambia expressed reluctance to enter sensitive patient information electronically due to concerns about confidentiality breaches, underscoring the need for robust and secure data architectures.

The security of healthcare ICT systems has therefore emerged as a central concern, given their status as high-value targets for cyberattacks. International frameworks such as the Health Insurance Portability and Accountability Act (HIPAA), the General Data Protection Regulation (GDPR), and ISO/IEC 27001 provide standards for safeguarding patient data through encryption, access controls, audit trails, and secure transmission

(Bărcanescu, 2020). In oncology, the stakes are even higher: as Shen et al. (2019) observed, breaches involving diagnostic and genetic information carry profound ethical and legal implications. These concerns highlight why security must be considered inseparable from the adoption of ICT in health systems.

In the Kenyan context, healthcare data security is primarily governed by the Data Protection Act (2019), which mandates technical and organizational measures to protect personal health information. Compliance, however, remains uneven. Odhiambo et al. (2020) found that many facilities rely on unsecured networks, weak authentication protocols, and lack robust backup or disaster recovery systems, exposing patient data to loss or misuse. These weaknesses are compounded by resource shortages and limited expertise, particularly outside major urban centres. The absence of secure interoperability has practical consequences. Without confidence in data confidentiality and integrity, clinicians are less likely to consistently use digital reporting tools, reverting instead to parallel paper-based systems. This erodes data completeness and timeliness, directly undermining caseload management.

Kenya has attempted to address these gaps through reforms, such as the Kenya Health Information System (KHIS/DHIS2) and the Kenya Health Information Exchange (KHIE), both of which are designed to support interoperability across counties and national systems. Yet adoption has been inconsistent. Were et al. (2019) reported that many facilities continue to duplicate reporting because of limited training and poor system reliability. The Ministry of Health (2022) has acknowledged that oncology data remain particularly fragmented, with delays in reporting from lower-level facilities undermining the completeness of the Kenya National Cancer Registry. Although reforms under the Social Health Authority (SHA) aim to standardise ICT reporting and financing structures, secure integration across platforms has not yet been achieved.

Embedding secure data architecture through encryption, role-based access controls, and interoperability safeguards creates an environment of trust that encourages system use. For this study, such architecture is integrated directly into the proposed lung cancer caseload management model, ensuring compliance with Kenyan law while enhancing user confidence. Despite incremental reforms, Kenya still lacks a fully integrated, secure, and interoperable health information platform. This gap continues to impede timely decision-making, resource optimisation, and accurate forecasting of caseload trends. Addressing these challenges requires not only investments in ICT infrastructure but also sustained attention to data security, interoperability, and user adoption—elements that are central to Objective 2 of this study.

2.3.4 System Dynamics Modelling for Caseload Management

System Dynamics (SD) has become a recognised approach for analysing complex health systems in which patient demand, referral pathways, and resource capacity interact through feedback and time delays. Developed by Forrester in the late 1950s and further refined by Sterman (2000), the method relies on causal loop diagrams and stock–flow structures to represent system behaviour over time. Unlike static forecasting techniques, SD highlights the counterintuitive consequences of interventions, enabling policymakers to anticipate how changes in one part of a system reverberate across others. This makes it particularly suited to oncology, where patient volumes, diagnostic bottlenecks, and treatment backlogs evolve dynamically (Homer et al., 2014; Atun et al., 2016).

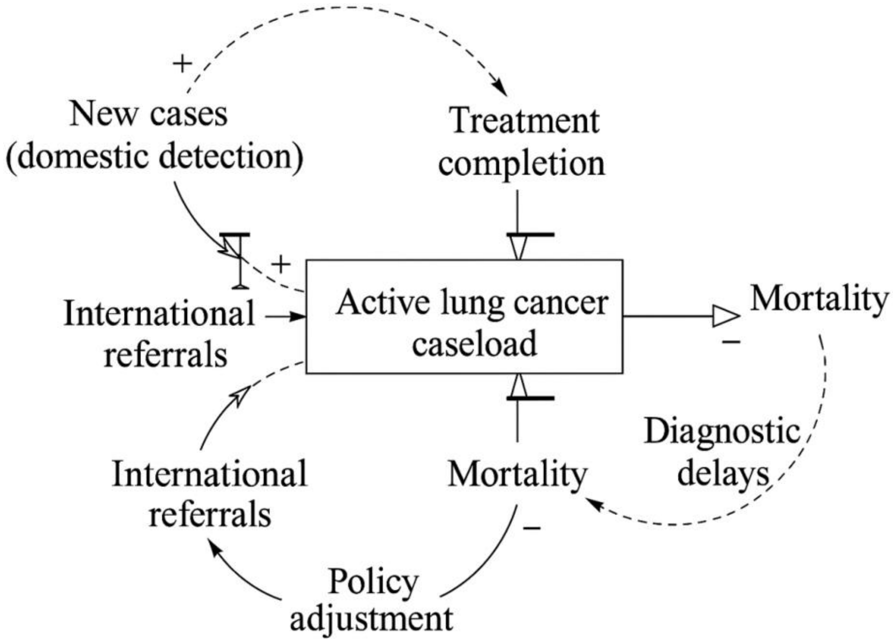
Globally, SD modelling has supported cancer planning in areas such as screening, diagnostic pathways, and treatment capacity. Marshall et al. (2015) employed an SD model in Canada to demonstrate how investments in diagnostic imaging impacted waiting times across multiple stages of the care pathway, findings that would not have been apparent with linear methods. In Australia, simulation of referral coordination demonstrated that expanding diagnostic slots without scaling treatment services could worsen delays downstream (Kunc et al., 2018). However, most of these models originate from high-income settings with robust cancer registries and integrated information systems, which limits their transferability to contexts where data are incomplete or fragmented.

In low and middle-income countries, empirical use of SD remains scarce. Mahendradhata et al. (2017) reported that barriers, including unreliable data, limited computational expertise, and resource constraints, restrict the application of simulation methods in cancer care. In Africa, applications of SD have concentrated mainly on communicable diseases such as HIV and malaria (Cervantes et al., 2020), despite the method's suitability for oncology systems, which are often centralised and strained by limited diagnostic and treatment capacity. In Kenya, no published study has yet applied SD to lung cancer caseload management, although related work has been undertaken in tuberculosis control and maternal health (Obure et al., 2016). The absence of oncology-focused SD models means that health managers currently lack decision-support tools to explore how referral delays, facility distribution, and reporting inefficiencies shape caseload outcomes.

This study responds to that gap by applying SD to lung cancer caseload management. Figure 3 presents the stock–flow structure adapted for Kenya's health system. The central stock represents the number of active lung cancer cases at any given point. Newly detected domestic cases and referrals generate inflows, while outflows occur through treatment completion, patient mortality, or referral abroad for specialised services. A feedback loop captures how observed outcomes, such as rising external referrals or treatment delays, inform managerial and policy adjustments.

Figure 3

Stock–Flow Structure of Lung Cancer Caseloads in Kenya, with Inflows from new Diagnoses and Referrals, and Outflows through Treatment, Mortality, and External Referral



Source: Author, (2025)

As illustrated in Figure 3, the stock–flow representation captures the essential logic of caseload dynamics. New cases and referrals add to the caseload, while treatment, mortality, and onward referral reduce it. The configuration also allows the modelling of diagnostic delays, reporting inefficiencies, and loss to follow-up, which are significant features of the Kenyan context. By embedding these dynamics, the structure provides a foundation for simulating how interventions — such as decentralising diagnostic services, expanding oncology capacity, or improving reporting timeliness — would alter caseload pressures over time.

Integrating Kenya's legal and policy framework further strengthens the model's relevance. The Social Health Authority (SHA) reforms emphasise scaling oncology services, while the Data Protection Act (2019) requires secure handling of patient data in reporting and interoperability. Embedding these requirements into the SD framework ensures that simulations reflect both the operational and legal realities of the health system. In doing so, the model aligns forecasting with statutory standards of confidentiality and data integrity, enhancing trust and adoption among health professionals.

By situating lung cancer caseload management within this feedback-driven framework, the study advances Objective 3, which seeks to design and simulate a secure SD model. The representation serves as a decision-support tool for exploring interventions, anticipating unintended consequences, and aligning caseload management strategies with Kenya's health policy and legal framework. This sets the stage for evaluating how such a model can be assessed for credibility and usefulness, as discussed in the next section.

2.3.5 Evaluation of Caseload Management Models

The credibility of any modelling exercise in healthcare depends not only on the structure of the model but also on the rigour with which it is evaluated. In the literature on system dynamics, evaluation is understood as a multi-dimensional process that encompasses structural verification, behavioural validation, sensitivity analysis, and policy relevance (Barlas, 1996). Models are not judged solely by their internal logic but by their ability to reproduce historical trends, respond plausibly under extreme conditions, and generate insights that decision-makers find actionable. As Sterman (2000) emphasised, a model that cannot explain past behaviour or withstand parameter variation risks becoming an academic exercise rather than a tool for decision support.

Globally, the evaluation of caseload management models has relied on diverse approaches. In high-income settings, extensive historical data have allowed oncology models to be tested against reference modes such as stage-specific incidence and treatment completion rates. For instance, Marshall et al. (2015) used Canadian data to compare simulated and observed diagnostic waiting times, thereby enhancing stakeholder confidence in the model's predictive utility. Similarly, Kunc et al. (2018) demonstrated how scenario analysis could reveal unintended effects of resource investments, underscoring the importance of testing models under multiple policy configurations rather than relying on single-point predictions.

In low- and middle-income countries, the literature reveals persistent challenges in model evaluation, largely due to limited data quality and fragmented reporting. Mahendradhata et al. (2017) observed that in many LMICs, reliance on expert elicitation and proxy indicators is common, yet this raises questions about generalisability. To address these gaps, researchers have recommended hybrid approaches that combine historical calibration with participatory validation, where frontline clinicians and managers assess whether simulated trends align with their lived experience of service delivery (Cervantes et al., 2020). This co-validation strategy strengthens legitimacy, particularly where statistical indicators are incomplete.

African studies provide limited but useful illustrations. In South Africa, evaluation of tuberculosis flow models incorporated both statistical fit and practitioner workshops, which revealed discrepancies between reported data and clinicians' observations, leading to refinements in the stock–flow architecture (Moyo et al., 2019). Such findings affirm that evaluation is not a one-off step but an iterative process that integrates quantitative and qualitative feedback. In Kenya, examples remain scarce. Existing evaluations have primarily focused on communicable disease models, with limited systematic work on oncology. As the Ministry of Health (2022) has acknowledged, the lack of reliable longitudinal cancer data complicates traditional validation, reinforcing the need for hybrid evaluation frameworks that triangulate across registries, facility reports, and expert judgement.

Within this study, evaluation is treated as integral to the modelling process and directly tied to Objective 4. The model is assessed through several dimensions. First, historical reference modes from the Kenya National Cancer Registry (KNCR, 2023) and facility-level oncology records provide the baseline for behaviour reproduction tests. Second, sensitivity analysis explores how model outputs respond to uncertainty in parameters such as referral delays, diagnostic throughput, and treatment capacity, thereby identifying the most influential leverage points. Third, stakeholder workshops with oncologists, data managers, and policy officials are incorporated to ensure that simulated dynamics resonate with professional experience. This participatory validation aligns with lessons from African modelling studies, where local credibility is as important as technical fit.

Security and compliance considerations add a further dimension to evaluation. Under the Kenya Data Protection Act (2019), models that simulate or handle patient-level data must incorporate safeguards such as anonymisation, encryption, and breach probability assessment. In this study, evaluation therefore also addresses whether the secure data architecture embedded in the model increases user confidence and adoption. By testing not only predictive accuracy but also alignment with Kenya’s legal and ethical frameworks, the evaluation framework ensures that the model is both technically credible and practically relevant.

Through this multi-layered evaluation process, the study advances beyond descriptive modelling to provide a decision-support tool that is defensible in policy and practice. By combining statistical validation, sensitivity testing, and participatory assessment, the evaluation demonstrates the model's capacity to forecast caseloads, optimize resource allocation, and support evidence-based oncology planning in Kenya.

The empirical review has shown that lung cancer caseload management is shaped by interrelated structural, technological, and behavioural factors that manifest differently across global, African, and Kenyan contexts. Evidence from Section 2.3.1 confirmed the high mortality burden of lung cancer, especially in LMICs, where late diagnosis and weak referral systems amplify caseload pressures. Section 2.3.2 demonstrated how Kenya's centralised facility distribution and fragile reporting patterns hinder timely and accurate caseload management. Section 2.3.3 highlighted that while ICT platforms, such as DHIS2 and KHIE, provide opportunities for improved reporting, their effectiveness depends on a secure data architecture and compliance with the Data Protection Act (2019). Section 2.3.4 illustrated the potential of System Dynamics modelling to integrate patient flows, referral delays, and capacity constraints into a coherent structure for decision support.

Finally, Section 2.3.5 emphasised that rigorous evaluation combining statistical, participatory, and security dimensions is necessary to ensure the credibility and adoption of such models in practice. Together, these insights reveal both the opportunities and gaps that justify the development of the model for lung cancer caseload management in Kenya. The next section (2.4) therefore sets out the conceptual framework that integrates these empirical insights with the theoretical foundations reviewed earlier, providing the basis for designing and simulating the proposed model.

2.4 Conceptual Framework

The conceptual framework for this study integrates the theoretical foundations outlined in Section 2.2 with the empirical evidence reviewed in Section 2.3 to provide a coherent basis for modelling lung cancer caseload management in Kenya. It recognises that caseload management is not a linear technical exercise, but a dynamic socio-technical process shaped by structural arrangements, patient behaviours, information systems, and governance environments. By situating these elements within a System Dynamics framework, the study clarifies how it addresses its four specific objectives while maintaining alignment with national policy and legal requirements.

At its core, the framework is anchored in System Dynamics Theory, which provides the methodological lens for representing caseloads as stocks influenced by inflows, outflows, and feedback loops. This approach captures delays in diagnosis, referral inefficiencies, and treatment bottlenecks repeatedly highlighted in the empirical review. To explain the adoption and sustained use of digital systems required for secure reporting, the framework draws on the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory. These perspectives illustrate how healthcare professionals and institutions evaluate the perceived usefulness, compatibility, and trustworthiness of ICT platforms such as DHIS2 and KHIE, and why diffusion may stall without attention to user attitudes and organisational culture.

The Information Systems Success Model (ISSM) extends this analytical dimension by providing evaluative criteria system quality, information quality, and user satisfaction used to test whether the secure caseload-management model delivers practical value. The Health Belief Model (HBM) introduces a behavioural layer by recognising that patient perceptions of susceptibility, severity, and barriers influence when and how individuals enter the caseload. The Socio-Technical Systems (STS) perspective ensures that the integration of secure ICT architecture is interpreted within its human and organisational context rather than as a purely technological intervention.

Complementing these six theories, the National Institute of Standards and Technology (NIST) Cybersecurity Framework (CSF) strengthens the study’s alignment with the Information Systems Security and Audit (ISSA) discipline. The NIST CSF provides the security-governance layer of the conceptual framework, linking data-flow modelling to the five cybersecurity functions *Identify, Protect, Detect, Respond,* and *Recover*. Within the System Dynamics environment, these functions correspond to mechanisms for mapping patient-data assets, controlling access, detecting anomalies, initiating corrective actions, and restoring equilibrium after system disruptions. Incorporating the NIST CSF embeds continuous risk management and auditability into the framework, operationalising the confidentiality, integrity, and availability principles mandated by the Kenya Data Protection Act (2019) and Social Health Authority (SHA) interoperability standards.

Empirical evidence grounds these theoretical components in Kenya's realities. Section 2.3.1 highlighted the rising burden of lung-cancer mortality, while Section 2.3.2 revealed structural imbalances in facility distribution and reporting patterns. Section 2.3.3 demonstrated both the opportunities and security risks of ICT integration under the Data Protection Act (2019). Section 2.3.4 demonstrated how System Dynamics models represent patient flows and capacity constraints, and Section 2.3.5 emphasized the importance of rigorous, multidimensional evaluation. These strands converge in the conceptual framework to justify why the proposed model is both necessary and feasible.

The conceptual framework, therefore, positions the study as a response to intersecting gaps: the absence of integrated oncology models in sub-Saharan Africa, the under-use of secure ICT systems, and the need for decision-support tools that are technically valid, legally compliant, and contextually grounded. The next subsection presents the framework diagrammatically, linking each theoretical construct including the NIST CSF security-governance component and empirical theme to the study objectives and modelling process.

The conceptual framework organises the study variables into three interrelated domains: inputs, processes, and moderating variables, and outputs. The input domain represents the structural and institutional factors that determine health-system performance. These include the configuration and distribution of healthcare facilities, the capacity and deployment of the oncology workforce, the integration of information and communication technology (ICT) platforms, and the overarching policy and regulatory environment. Collectively, these inputs establish the foundational conditions under which lung-cancer caseload management operates.

The processes and moderating variables describe the mechanisms that translate inputs into measurable outcomes. They encompass referral coordination and associated delays, the timeliness and quality of reporting, the degree of ICT adoption and interoperability across facilities, and the presence of secure data architecture that guarantees confidentiality, integrity, and compliance with the Kenya Data Protection Act (2019). Within this secure-architecture dimension, the study adopts the governance principles of the National Institute of Standards and Technology (NIST) Cybersecurity Framework (CSF) *Identify, Protect, Detect, Respond,* and *Recover* to embed continuous risk management and auditability within data-exchange processes. Feedback loops operate as reinforcing or balancing mechanisms that influence how information circulates and how effectively resources are mobilised across system levels. This dimension reflects the reality that caseload management is shaped as much by operational practices, audit controls, and regulatory safeguards as by structural investment.

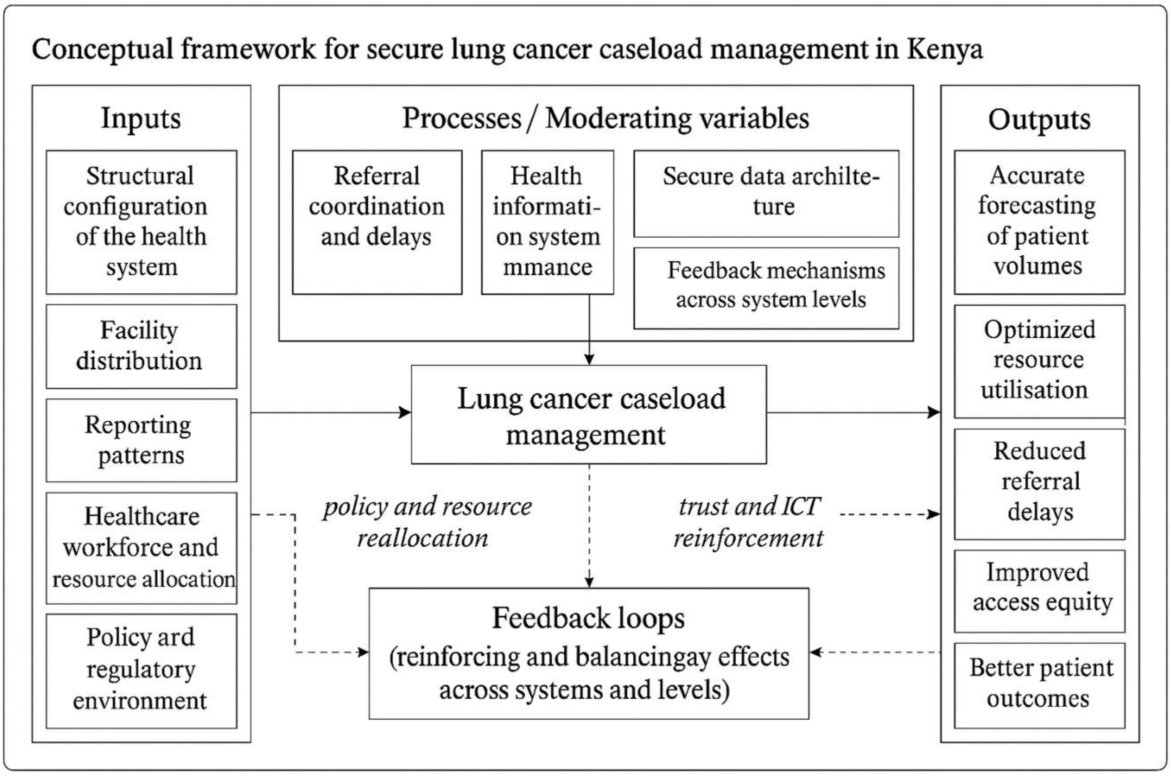
The outputs represent indicators of effective caseload management. These include accurate forecasting of patient numbers, efficient utilisation of oncology resources, reduced referral delays, equitable access to services across geographic settings, and improved patient outcomes through earlier diagnosis and timely treatment. Such outcomes correspond with the objectives of Kenya’s National Cancer Control Strategy (2023–2027) and the broader goal of universal health coverage under the Social Health Authority (SHA) reforms.

At the centre of the framework is lung-cancer caseload management, conceptualised as both the dependent outcome of systemic inputs and processes and as a dynamic hub that channels these influences into tangible outputs. Its central position underscores that caseload management is not a static event, but an adaptive process governed by continuous patient and information flows, iterative feedback, and responsive policy and resource realignment.

The conceptual framework is intentionally multi-layered, integrating structural, operational, behavioural, and security dimensions. Its complexity arises from the interaction between these layers through dynamic feedback loops that represent both clinical and informational processes. For example, delays in diagnosis or reporting not only affect patient flow but also influence system trust, ICT adoption, and the need for regulatory oversight. Security and audit variables—operationalised through the NIST Cybersecurity Framework (CSF)—are therefore not confined to a single component but embedded throughout the system: they govern how data are protected (*Protect*), how anomalies are identified (*Detect*), how corrective actions are triggered (*Respond*), and how the system stabilises after disruption (*Recover*). This multi-level integration ensures that the model captures real-world healthcare complexity while maintaining compliance, transparency, and governance, consistent with the principles of Information Systems Security and Audit (ISSA).

Figure 4

Conceptual Framework for a System Dynamics Model in Lung Cancer Caseload Management



Source: Authour, (2025)

2.4.1 Interpretation of the Conceptual Framework

The conceptual framework presented in Figure 4 illustrates the interrelationships between the structural determinants of Kenya's health system, the processes that shape lung cancer caseload dynamics, and the outcomes expected from a secure and adaptive management model. It demonstrates how inputs and moderating processes converge within the central hub of caseload management, and how outputs are generated and reinforced through continuous feedback. This framework underpins the design of the model and provides the analytical foundation for the study's four specific objectives.

The inputs represent the systemic conditions that define the baseline capacity of the health sector. These include the structural configuration of the health system, the distribution of oncology facilities, prevailing reporting patterns, the availability and allocation of healthcare workforce and resources, and the policy and regulatory environment. These factors collectively determine how patients enter the care pathway, how information is recorded, and the extent to which the system can respond to the increasing number of lung cancer cases. The explicit inclusion of facility distribution and reporting practices reflects Kenya's persistent challenges with uneven service access and incomplete cancer registry data, as emphasised in the National Cancer Control Strategy (2023–2027).

The processes and moderating variables capture the mechanisms through which inputs are operationalised. Referral coordination and delays determine how efficiently patients move across facilities and levels of care. The performance of health information systems, including data quality, timeliness, and interoperability, shapes the completeness and accuracy of caseload reporting. Secure data architecture incorporating encryption, anonymisation, and access controls ensures compliance with the Kenya Data Protection Act (2019), while also enhancing trust and adoption of ICT platforms. Feedback mechanisms across system levels emphasise that caseload management is not linear but adaptive, shaped by reinforcing and balancing dynamics that emerge as information circulates and decisions are implemented.

At the centre of the framework is lung cancer caseload management, conceptualised as the stock of active patients within the healthcare system. This hub integrates structural, technological, and process variables to determine how caseloads evolve over time. By positioning caseload management as a dynamic dependent construct, the framework aligns directly with Objective 3, which focuses on developing and simulating a System Dynamics model capable of forecasting and testing interventions.

The outputs reflect the intended results of a secure, data-driven, and adaptive caseload management system. These include accurate forecasting of patient volumes, optimised utilisation of limited oncology resources, reduced referral delays, improved equity of access across counties and between urban and rural populations, and better patient outcomes achieved through earlier diagnosis and timely treatment. Compliance with legal and ethical standards further reinforces user trust and ensures sustainability, consistent with the broader agenda of universal health coverage under the Social Health Authority reforms.

Finally, the feedback loops highlight the iterative nature of caseload management. Outputs feed back into both inputs and processes: policy and resource reallocation adjust structural and workforce arrangements in response to observed outcomes, while trust and ICT reinforcement strengthen reporting, interoperability, and secure data use. This feedbackis central to the System Dynamics approach, enabling the model to capture both reinforcing trends such as the increased adoption of secure ICT, which improves data quality and balancing effects such as resource constraints that limit capacity expansion.

Through this interpretation, the conceptual framework demonstrates how the study integrates theory, empirical evidence, and national policy imperatives. It demonstrates that lung cancer caseload management is not merely a technical task, but a dynamic process that requires systemic alignment, secure data governance, and continuous feedback. In this way, the framework provides a robust foundation for the methodology outlined in Chapter 3, ensuring direct alignment with the four research objectives that guide the study.

The review of theories, empirical evidence, and the conceptual framework has established a strong foundation for this study. Theories such as System Dynamics, Technology Acceptance, Information Systems Success, Diffusion of Innovations, Health

Belief Model, and Socio-Technical Systems provide a multidisciplinary lens for understanding the structural, technological, and behavioral dimensions of lung cancer caseload management. Empirical evidence highlights the global and Kenyan gaps in facility distribution, reporting patterns, ICT adoption, and secure data use. The conceptual framework integrates these insights into a coherent structure of inputs, processes, outputs, and feedback loops. Together, these discussions justify the development of a model that is contextually grounded, theoretically informed, and aligned with Kenya's policy and legal environment. The next chapter, therefore, sets out the methodological approach, detailing the research design, data sources, model development procedures, and evaluation strategies that operationalize the conceptual framework into a rigorous, testable model.

2.5 Research Gaps

The synthesis of theoretical and empirical literature reveals persistent limitations in how lung cancer caseload management is conceptualised and implemented at global, regional, and national levels. Although System Dynamics (SD) models have been applied internationally to simulate cancer screening, resource allocation, and service demand, most implementations originate from high-income contexts with well-developed registries and secure digital infrastructures (*Marshall et al., 2015; Atun et al., 2016*). These models rarely address environments where data are fragmented, reporting is delayed, and the ICT infrastructure is weak. Furthermore, the integration of information-security and audit mechanisms within health-system simulations remains notably absent, despite the increasing recognition that data protection, confidentiality, and auditability are crucial for determining user trust and policy uptake (*ISO, 2022; NIST, 2023*).

Within sub-Saharan Africa, research gaps are more pronounced. System Dynamics has predominantly been used in modeling communicable diseases, such as HIV, tuberculosis, and malaria (Cervantes et al., 2020), while oncology modeling remains limited and descriptive. Few studies have embedded referral coordination, reporting flows, or secure ICT integration into dynamic frameworks. In addition, formal security-assurance approaches such as STRIDE or DREAD threat modeling, and structured audit frameworks like COBIT 2019 are largely absent from African health informatics research. Consequently, policymakers lack decision-support tools capable of simulating how human, technical, and institutional vulnerabilities interact to affect caseloads and information integrity.

In Kenya, these deficits converge. The National Cancer Control Strategy 2023–2027 and the Kenya Data Protection Act (2019) emphasise digitalisation and secure information handling, yet implementation remains uneven. The Kenya National Cancer Registry (KNCR, 2024), KHIE, and DHIS2 platforms operate in parallel with limited interoperability and weak audit trails. Facility-level data are inconsistently transmitted, and encryption and access-control measures are inconsistently enforced. No published Kenyan study has designed or validated the model for lung-cancer caseload management that integrates facility distribution, referral pathways, ICT adoption, and security-governance controls under an auditable architecture.

This study therefore, addresses a distinct interdisciplinary gap by developing a security-governed, auditable System Dynamics model for lung cancer caseload management in Kenya, guided by a pattern analysis approach. The model introduces an embedded Security Maturity Index and probability-of-breach (P_{breach}) parameter to quantify system resilience. By combining System Dynamics with ISSA frameworks ISO 27001:2022, NIST CSF 2.0, and COBIT 2019 it creates a hybrid decision-support mechanism that links data flows, referral efficiency, and security assurance.

Beyond contextual deficiencies, the literature reveals specific knowledge, methodological, and theoretical gaps summarised in Tables 2.1 and 2.2, which directly inform the four objectives of this study.

Table 1

Summary of Contextual Research Gaps

Level	What has been studied	Identified gap	Relevance to this study
Global	SD models applied to cancer in high-income countries with mature ICT systems.	Lack of secure, auditable modelling in fragmented data environments	Demonstrates need for a secure, adaptive model for LMICs
Africa	SD models for communicable diseases; descriptive oncology audits	No integration of referral coordination, ICT, or security assurance frameworks	Justifies African-specific oncology modelling with ISSA integration
Kenya	Facility audits, registry reports, and ICT pilots (KHIE, DHIS2)	Absence of an SD model for lungcancer caseloads with securitygovernance and audit features	Directly motivates the development of a secure, auditable SD model

Table 2

Knowledge, Methodological, Theoretical Gaps and Linkage to Study Objectives

Gap Category	Evidence from the literature	Nature of the gap	Link to research objective(s)
Knowledge gap	KNCR and DHIS2 databases are fragmented and lack audit controls; ICT security policies under the Data Protection Act (2019) are not fully enforced (*MoH, 2024*).	Absence of a unified, secure, real-time lung-cancer data system integrating audit trails.	Obj. 1 & 2 – Assess structure, reporting, and secure ICT integration.
Methodological gap	Prior Kenyan cancer studies used descriptive or retrospective methods, limited modelling, or pattern analysis.	Lack of a combined SD + pattern-analysis framework incorporating security metrics and threat modelling (STRIDE, DREAD).	Obj. 3 – Develop and simulate secure SD model; Obj. 4 – Evaluate performance and resilience.
Theoretical gap	Use of TAM and SDT individually in health studies, but not integrated with ISSA frameworks (ISO 27001, COBIT, NIST CSF).	Lack of a multi-theory framework combining technological, behavioural, and security-assurance perspectives.	All objectives – Apply integrated theory–method–variable mapping.

The synthesis confirms that lung-cancer caseload management remains underexplored within secure-systems frameworks. Kenya's structural imbalance, fragmented reporting, and limited ICT adoption are compounded by the absence of formal security assurance and audit-trail modeling. By addressing these gaps, this study advances both the methodological and disciplinary frontiers of Information Systems Security and Audit (ISSA) and Health Systems Management, establishing a robust foundation for the model design and validation detailed in Chapter 3.

Chapter 2 synthesizes theoretical, empirical, and contextual insights to establish the foundation for developing a model that integrates caseload management with information security assurance.

.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

This chapter outlines the methodological framework that guided the study. It begins by presenting the research philosophy that informed the design, followed by a detailed description of the research design and the justification for its application. The geographical and institutional context of the study is then specified, together with the population and sampling strategies used for both archival data and expert panel consultations. The instruments employed for data collection, including data extraction templates, policy review checklists, and Delphi questionnaires, are described, along with the procedures followed to ensure their validity and reliability.

The chapter further details the data collection procedures, highlighting both secondary and expert-derived data sources, and demonstrates how these were securely managed in line with the Kenya Data Protection Act (2019). Analytical techniques are then outlined, covering descriptive and inferential statistics, segmented time-series analysis, and system dynamics simulations in Vensim, which together supported the interpretation of *caseload patterns*, *referral delays*, *reporting timeliness*, *reporting completeness*, and the performance of the secure model. The ethical protocols adhered to in the study, including approvals from NACOSTI and KUREC, and the safeguards for patient confidentiality, are also presented.

By structuring the methodology in this manner, the study ensured that each objective was matched with a corresponding methodological pathway: assessment of healthcare *structural configuration* and *reporting patterns* (Objective i), evaluation of *ICT integration* and *secure data architecture* (Objective ii), design and simulation of the *System Dynamics model* (Objective iii), and evaluation of the model's effectiveness in forecasting *patient volumes* and optimising *resource use* (Objective iv). The methodological choices adopted were thus both rigorous and contextually appropriate for the Kenyan healthcare system.

3.2 Research Philosophy

This study was grounded in the philosophy of pragmatism, which emphasises the centrality of research questions and the strategic use of multiple methods to produce actionable, context-sensitive solutions. Pragmatism rejects the rigid dichotomy between positivism and interpretivism, instead advocating methodological pluralism where quantitative and qualitative approaches are combined to address complex, real-world challenges. The philosophy is particularly appropriate for studies that seek not only to explain system behaviour but also to design, simulate, and evaluate practical interventions, as is the case with the present research on secure and auditable caseload management systems.

Ontologically, the study recognised that reality within Kenya's healthcare system is both objective and constructed. Caseload volumes, referral delays, and breach probabilities can be empirically measured, while elements such as clinician trust, data-sharing practices, and perceptions of audit compliance are shaped by institutional norms and human experience. This duality justified a research design that models structural flows while also interrogating behavioural and governance dimensions.

Epistemologically, the study adopted a pluralistic view of knowledge, positing that valid understanding arises from both empirical observation and experiential interpretation. Quantitative evidence was derived from national data sources, including the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS), and the GLOBOCAN datasets, while qualitative insights were obtained through a Delphi panel comprising oncologists, ICT managers, data protection officers, and policymakers.

This blend of knowledge sources was critical in constructing and validating the security-governed and auditable System Dynamics Model (Secure SDM).

Axiologically, the study acknowledged that values and ethics are integral to the research process. Commitments to confidentiality, data integrity, and equitable access to services were embedded throughout the methodology, consistent with the Kenya Data Protection Act (2019/2022) and the Digital Health Act (2023). Upholding these principles ensured that the model development, pattern analysis, and validation processes conformed to the ethical and legal expectations of Kenya's digital health ecosystem.

Pragmatism was particularly effective in guiding the study's four objectives. For Objective (i), it facilitated the quantitative mapping of structural configurations and facility distributions, complemented by a qualitative interpretation of policy and governance patterns that influence caseload management. For Objective (ii), it enabled both statistical benchmarking of ICT coverage and thematic analysis of expert feedback on secure data architectures and audit-control mechanisms. For Objective (iii), pragmatism legitimised the integration of System Dynamics modelling (Vensim) with pattern-analysis techniques (LSTM and CNN), allowing the fusion of data-driven predictions with expert-validated feedback structures. For Objective (iv), it provided the philosophical rationale for a hybrid evaluation combining quantitative performance metrics such as Mean Absolute Percentage Error (MAPE), sensitivity indices, and probability-of-breach (P_{breach}) estimations, with qualitative assessments of model usability, interpretability, and compliance utility by domain experts.

Beyond methodological flexibility, pragmatism was well-suited to the Information Systems Security and Audit (ISSA) orientation of this study. The Secure SDM required both quantifiable assurance metrics (security maturity, audit traceability, compliance thresholds) and an interpretive understanding of organisational culture, governance, and human factors that influence adherence to data-protection norms. Pragmatism thus supported the iterative design–evaluation–refinement cycle necessary for audit validation of the model's control structures and compliance attributes.

In the Kenyan context where healthcare reforms under the Social Health Authority (SHA) require interoperable, secure, and auditable information systems across heterogeneous facility capacities—a pragmatic approach enabled the study to accommodate diverse forms of evidence and multiple layers of reality. It guided the production of recommendations that are technically sound, legally compliant, and contextually grounded, bridging the analytical precision of System Dynamics and pattern analysis with the governance realities of Kenya's oncology ecosystem. In this way, the pragmatic paradigm provided the epistemic and ethical foundation for designing a security-governed, auditable, and compliance-controlled model that both reflects and informs real-world decision-making in Kenya's cancer-care system.

3.3 Research Design

The study employed a mixed-methods design, framed within the principles of Design Science Research (DSR), and operationalized through System Dynamics Modelling (SDM). The mixed-methods approach was consistent with the underlying philosophy of pragmatism, allowing for the integration of quantitative analysis of archival caseload records with qualitative insights from expert consultations. This combination was essential given the dual nature of the research problem: the management of caseload volumes required statistical precision, while the evaluation of ICT integration and secure data architecture demanded interpretive understanding of human, institutional, and governance factors.

Within this framework, Design Science Research (DSR) provided a structured pathway for constructing and refining an artefact in this case, a secure, auditable System

Dynamics model that could simulate referral flows, diagnostic bottlenecks, and the effects of ICT integration. DSR emphasized iterative cycles of problem identification, solution design, evaluation, and refinement, which aligned with the study's aim of developing a usable and testable model for healthcare managers. Each cycle incorporated both functional validation (model performance) and security evaluation (control maturity and breach probability), ensuring that the artefact met both operational and audit requirements.

The System Dynamics Modelling (SDM) component operationalized the design by representing patient flows, referral delays, diagnostic capacity, and resource utilization in stock-and-flow and causal-loop diagrams. SDM was selected because lung-cancer caseload management involves nonlinear feedback processes: for example, improvements in reporting completeness can increase patient inflows at referral centres, which in turn strain treatment capacity and create new delays. Static or purely statistical designs could not capture these interdependencies. SDM thus provided the means to analyse structural feedbacks, simulate alternative scenarios, and test the effectiveness of policy or technology interventions under varying assumptions of data security and system responsiveness.

The mixed-methods DSR–SDM design was directly aligned with the four study objectives. For Objective (i), the design facilitated the quantitative mapping of facility distribution and reporting patterns, combined with qualitative policy analysis. For Objective (ii), DSR enabled the incorporation of ICT integration and secure data architecture guided by the NIST Cybersecurity Framework (CSF) into the artefact. For Objective (iii), SDM provided the computational environment for designing and simulating the model, capturing interdependencies and feedback across healthcare levels. For Objective (iv), the design facilitated both the quantitative evaluation of forecasting accuracy, sensitivity, and security metrics, as well as the qualitative assessment by domain experts of usability, reliability, and auditability.

The chosen design was particularly suitable for the Kenyan healthcare context, where reporting systems remain fragmented (KNCR, KHIS, KenyaEMR) and reforms under the SHA require secure, interoperable, and scalable health information systems. By combining mixed-methods pragmatism with DSR and SDM, the study ensured methodological rigour, contextual relevance, and the generation of actionable insights for national caseload management.

To provide a structured overview of methodological alignment, the research framework is presented in Table 3, which maps each objective to the corresponding phase, data source, method, and output. This structure ensured that the study remained coherent, systematic, and defensible from its design through to its evaluation. In this context, proxies refer to measurable indicators used to operationalise abstract constructs such as reporting patterns, ICT integration, and system security maturity.

Table 3

Research Framework for the Development and Evaluation of a System Dynamics Model for Lung Cancer Caseload Management in Kenya

Phase	Objective	Methods & Proxies	Outputs
Phase 1 – Contextual assessment	Objective i: To assess the current structural configuration, facility distribution, and reporting patterns of the healthcare system that influence lung-cancer caseload management and referral coordination in Kenya.	Methods: Descriptive and exploratory analysis of archival data from KNCR, MoH, and KHIS; extraction and harmonisation of facility-level oncology records from KNH, MTRH, KUTRRH, and county facilities. Proxies: Facility distribution, reporting timeliness, referral patterns, and coordination efficiency.	Baseline profile of structural configuration, facility distribution, and reporting patterns influencing referral dynamics.
Phase 2 – ICT integration	Objective ii: To examine the integration, coverage, and challenges	Methods: Archival review of ICT-adoption and interoperability indicators from KHIS,	Comprehensive mapping of ICT strengths and

analysis	of Information and Communication Technology (ICT) systems in lung-cancer caseload management and to incorporate secure data architecture for protecting patient information.	KenyaEMR, and facility registries; policy and security-protocol analysis under the Data Protection Act (2019); expert elicitation on system-security maturity. Proxies: ICT adoption rate, interoperability indices, security-control maturity, compliance scores.	weaknesses and secure data architecture specifications for model integration.
Phase 3 – Secure SDM design	Objective iii: To design and simulate a System Dynamics Model that integrates caseload data, referral delays, facility capacity, and feedback loops across healthcare levels and departments.	Methods: Design Science Research (DSR) principles; Vensim modelling; application of NIST Cybersecurity Framework (CSF) functions (Identify–Protect–Detect–Respond–Recover); OWASP threat-modelling and control-validation matrix. Proxies: Causal loop diagrams (CLDs), stock-and-flow models, security maturity index (SMI), probability of breach (P_{breach}).	Validated System Dynamics model structure with embedded security and audit-control mechanisms.
Phase 4 – Model evaluation	Objective iv: To evaluate the effectiveness of the developed secure model in forecasting patient volumes, optimising resource use, and supporting real-time decision-making by health-care managers in Kenya.	Methods: Quasi-experimental simulation testing; sensitivity and extreme-condition analyses; Delphi validation with a purposively selected expert panel from KNH, MTRH, and KUTRRH; comparison of simulated versus observed caseload trends. Proxies: Forecast accuracy (MAPE %), resource-optimisation ratio, decision-support effectiveness, user-trust, and audit-trace ratings.	Reliable simulation results and a verified decision-support tool demonstrating forecast accuracy, resource efficiency, and audit transparency.

As shown in Table 3, each research phase was deliberately structured to achieve a specific objective through complementary quantitative and qualitative activities executed under a convergent-parallel mixed-methods design. Quantitative modelling and archival analyses were conducted concurrently with qualitative policy reviews and expert validation, enabling triangulation and contextual interpretation of the results. By combining descriptive assessment, ICT, and policy review, design-science principles, and simulation-based evaluation, the framework ensured rigour, auditability, and compliance with the Kenya Data Protection Act (2019) and the reforms of the Social Health Authority (SHA).

Table 4

Theory–Method–Variable Mapping for the Study

Theory / Model	Relevant Constructs	Linked Objective(s)	Methodological Application	Key Variables / Proxies
System Dynamics Theory (Forrester, 1961)	Feedback loops, stock-and-flow structures, delays, and non-linear interactions	Obj. i, iii, iv	Guided development of causal-loop and stock-and-flow diagrams in Vensim; informed sensitivity and scenario analysis for caseload forecasting.	Caseload volumes, referral delays, facility capacity, treatment throughput, and reporting timeliness.
Technology Acceptance Model (TAM) (Davis, 1989)	Perceived usefulness, perceived ease of use	Obj. ii	Applied in the Delphi panel evaluation of ICT adoption and usability; supported analysis of system interoperability and trust.	ICT adoption rate, usability index, interoperability scores.
Information Systems Success Model (ISSM) (DeLone & McLean, 2003)	System quality, information quality, service quality	Obj. ii, iv	Provided evaluation criteria for ICT integration and model performance in terms of data accuracy and user satisfaction.	Reporting completeness, output accuracy, and decision-support trust.
Socio-Technical Systems (STS) Theory (Trist &Emery, 1951)	Interaction between social and technical subsystems	Obj. ii, iii	Informed integration of secure ICT systems with health-worker practices and institutional reporting culture.	Workflow alignment, security maturity index (SMI), P_{breach}.
Diffusion of Innovations (DOI) Theory (Rogers, 2003)	Relative advantage, compatibility, complexity, trialability, observability	Obj. ii	Framed expert assessment of ICT integration and secure-model acceptance across facilities.	Adoption rate, compatibility scores, perceived security advantage.
Health Belief Model (HBM) (Rosenstock, 1974)	Perceived risk, benefits, barriers, cues to action	Obj. i, ii	Interpreted health-worker and institutional behaviour toward secure data-reporting systems.	Compliance with reporting protocols, attitudes to data security, and trust levels.
NIST Cybersecurity Framework (CSF) (National Institute of Standards and Technology, 2024)	Identify–Protect–Detect–Respond–Recover functions; risk management and audit governance.	Obj. ii, iii, iv	Operationalised security-assurance and audit-evaluation within the model; linked system behaviour to control maturity and resilience metrics.	Control validation matrix, risk assessment score, SMI, P_{breach}, audit-trace log.

As shown in Table 4, each theoretical lens guided specific methodological and measurement decisions. System Dynamics Theory underpinned causal modelling of caseload flows, while TAM and ISSM addressed ICT integration and system performance. STS and DOI explained adoption behaviours and institutional adaptation, HBM anchored the human dimension of reporting and security culture, and the NIST CSF theory embedded formal security and audit governance within the model. By linking theories to objectives, methods, and variables, the study ensured that its methodological choices were theoretically grounded, empirically valid, and aligned with Kenya's healthsystem and ISSA requirements.

3.4 Location of the Study

The study was conducted within the Kenyan healthcare system, focusing on the oncology service landscape as structured under national and county referral arrangements. Kenya was selected due to its rising lung cancer burden, its transitional health policy environment, and the availability of national and institutional data repositories that could support system dynamics mode*ling*. According to GLOBOCAN (2022), Kenya reported 903 new lung cancer cases in 2022, with a mortality-to-incidence ratio of 0.91, highlighting systemic inefficiencies in *caseload management*, *referral delays*, and *treatment throughput*. These realities justified Kenya as an appropriate context for evaluating caseload management through a *System Dynamics model*.

The study primarily relied on archival records from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS/DHIS2). These registries consolidate oncology data from facilities nationwide, providing a comprehensive view of lung cancer caseloads, referral dynamics, and reporting patterns. To complement these national datasets, facility-level oncology registries were accessed from the two national referral hospitals — Kenyatta National Hospital (KNH) in Nairobi and Moi Teaching and

Referral Hospital (MTRH) in Eldoret. These facilities were selected because they are the country's leading referral centres, managing high volumes of lung cancer cases and maintaining relatively complete records that were critical for model calibration and validation.

While data were not directly extracted from county referral hospitals, their role in the caseload pathway was acknowledged. Facilities in Kisumu, Nakuru, and Nyeri provide critical diagnostic and referral services at the county level, feeding their reports into KNCR and KHIS. Their contributions ensured that national registry data reflected the broader healthcare system and informed the modelling of referral flows across sub-county, county, and national levels.

At the policy and ICT level, the location was further justified by the country's ongoing transition to the *Social Health Authority (SHA)* framework and the implementation of the *Kenya Health Information Exchange (KHIE)*. These reforms aim to enhance data interoperability, integrate electronic medical records (EMRs), and facilitate secure data sharing across various levels of care. However, existing challenges such as fragmented *ICT adoption*, intermittent connectivity, and uneven coverage made Kenya an ideal setting for investigating *secure data architectures* in lung cancer caseload management.

Ethically and legally, the study's location required compliance with the Kenya Data Protection Act (2019), which mandates the secure handling of personal health data, anonymization, and breach notification. Approvals were obtained from the National Commission for Science, Technology, and Innovation (NACOSTI) and the Kabarak University Research Ethics Committee (KUREC) before accessing institutional records. Facility-level permissions were also obtained from KNH and MTRH to ensure compliance with institutional policies regarding the use of secondary data.

By situating the study within Kenya's health system, the research captured both the structural and systemic dynamics of lung cancer caseload management in a lower–middle–income country context. The location offered a combination of high-burden facilities, evolving policy frameworks, and ICT challenges, making it an appropriate setting for designing and evaluating a *System Dynamics model* aligned with national priorities in cancer care and health information security.

3.5 Population of the Study

The study population was defined in relation to the four objectives and drew on two complementary frames: a secondary data population derived from national and institutional cancer registries, and an expert population convened to evaluate the *model* and its ICT/security assumptions. This arrangement matched the study's need for broad empirical coverage alongside professional judgement on feasibility and trust.

a) Secondary Data Population

The primary population comprised all lung cancer cases reported to the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS/DHIS2) for the period 2018–2023. These registries collated submissions from public and private facilities countrywide and provided the indicators required to analyse *caseload volumes, referral delays, reporting timeliness*, and *reporting completeness*. To strengthen calibration and validity checks, oncology registries at the two national referral hospitals Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH) were included as a higher-fidelity operational lens within the same window.

The unit of analysis was the facility month record. This temporal resolution aligned the descriptive analyses, segmented time-series procedures, and the time step of the stock-and-flow structures used in modelling. During harmonisation, records were excluded if they (i) duplicated entries across systems, (ii) were miscoded for the primary site, or (iii) lacked the period identifiers required for monthly aggregation. The final dataset retained only de-identified, aggregated observations suitable for parameterisation of *arrival rates*, *diagnostic throughput*, *treatment capacity*, and related flows.

Target population: all registry-eligible lung cancer cases nationally (2018–2023). *Accessible population:* KNCR and KHIS consolidated records for 2018–2023, plus de-identified oncology registries from KNH and MTRH for the same period.

(b) Expert Evaluation Population

A purposively constituted 15-member expert panel participated in evaluating the model and appraising the integration of ICT and security. The panel represented the interdisciplinary nature of lung-cancer caseload management, bringing together oncologists, cancer registrars, medical physicists, radiation-therapy leads, health-information specialists (including KHIS and registry personnel), ICT-security specialists, and policy actors from the Ministry of Health and the National Cancer Control Programme. This mix reflected the operational, technical, and governance dimensions of caseload management across Kenya’s health-care system.

The panel size (n = 15) was determined on methodological and theoretical grounds consistent with Design-Science Research (DSR) and System Dynamics (SD) validation procedures. In such research, expert evaluation focuses on *depth and quality of judgment* rather than statistical generalisation. Prior methodological guidance on Delphi and structured consensus panels recommends a range of 10 to 20 experts as the optimal number for capturing multi-domain perspectives while maintaining effective feedback and convergence (*Okoli & Pawlowski, 2004; Hsu & Sandford, 2007*). The choice of fifteen participants therefore balanced representativeness and manageability, ensuring adequate coverage of the four core domains clinical practice, cancer registry management, ICT/security governance, and health policy oversight—while sustaining iterative consultation and response consistency across validation rounds.

The panel's role extended beyond nominal expert review. Members provided structured judgments on ICT adoption, interoperability, and secure data architecture, and reviewed simulation outputs using parameters such as forecasting accuracy, usability, trust in outputs, the Security Maturity Index (SMI), and the*probability of breach (P_{breach}).* Their collective insights were used to:

i. Evaluate the structural plausibility of the System Dynamics model and the realism of causal-loop and stock-and-flow representations.
ii. Assess the decision-support value of the artefact, including its capacity to forecast caseloads, optimise resource allocation, and aid managerial decisions.
iii. Refine embedded security assumptions and control parameters governing data exchange and audit traceability.

The panel composition also reflected Kenya's national context. Participants were drawn from Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), Kenyatta University Teaching, Referral, and Research Hospital (KUTRRH), and selected county referral facilities engaged in oncology data reporting. This ensured representation of national and sub-national perspectives, as well as alignment with current cancer control policies.

Inclusion criteria required current engagement in oncology care, cancer-registry operations, health-ICT management, or policy development within Kenya; a minimum of five years of relevant professional experience; familiarity with KNCR or KHIS processes or hospital-oncology workflows; and willingness to participate in structured validation rounds and provide reasoned feedback.

Exclusion criteria included direct conflicts of interest with software vendors or consultancy roles that could bias judgments, as well asthe inability to commit to the full sequence of validation sessions.

The expert-evaluation process, therefore, provided a methodologically sound, interdisciplinary, and ethically robust foundation for validating the model. It ensured that model evaluation reflected Kenya's operational realities while satisfying the Information Systems Security and Audit (ISSA) requirements for reliability, auditability, and governance compliance.

Ethical and Legal Safeguards

All processing of registry and facility data was consistent with the Kenya Data Protection Act (2019): records were de-identified before analysis, stored on access-controlled media, and used only in aggregated form for reporting. Approvals were obtained from NACOSTI, the Kabarak University Research Ethics Committee (KUREC), and the relevant hospital research offices before access. Expert participants received information sheets and provided written informed consent; participation was voluntary, with the option to withdraw at any point.

Link to Objectives

The national and referral-hospital records underpinned Objective i (structure, distribution, reporting patterns) and provided empirical baselines for Objective iii (design/simulation). The expert panel supported Objective II (ICT integration and *secure data architecture*) and Objective IV (evaluation of forecasting and decision-support performance). Taken together, the two frames provide comprehensive empirical coverage with grounded professional validation, making them particularly suitable for Kenya's oncology service context.

3.6 Sampling Procedure and Sample Size

Given that the study relied primarily on secondary datasets for model development, with primary engagement limited to expert consultation during the evaluation phase, sampling was organised along two complementary streams: (i) archival record sampling, which treated registry and hospital data as a census frame, and (ii) expert-panel sampling, which purposively selected professionals to support model validation and assurance testing.

This dual-stream approach was consistent with the study's Design Science Research (DSR) and System Dynamics (SD) orientation, where emphasis is placed on representativeness of system structures rather than population generalisation. The national registries provided quantitative evidence for model development and calibration, while expert insights added qualitative depth and audit validation. Both frames thus contributed to a holistic and triangulated understanding of Kenya's lung-cancer caseload system.

3.6.1 Sample Size Determination

Two distinct sampling frames were used: (a) the registry and hospital dataset and (b) the expert-evaluation panel.

For the secondary data frame, all lung-cancer cases captured in the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS/DHIS2) between 2018 and 2024 were included. Because the study's objective was to assess national caseload patterns and structural configurations influencing reporting and referral, a census approach was adopted rather than sampling. The KNCR and KHIS are comprehensive repositories that aggregate data from both public and private facilities nationwide. Excluding any subset would risk bias and weaken the validity of descriptive, temporal, and simulation analyses. Only records that were duplicated, miscoded, or missing key identifiers (e.g., reporting year, facility code, or primary cancer site) were excluded during harmonisation. The final harmonised dataset, therefore, represented the accessible population of the national lung-cancer caseload system.

For the expert-evaluation frame, a total of 15 participants were engaged. This panel size was guided by methodological recommendations for Delphi and structured expert consensus studies, which commonly recommend effective panels of between 10 and 20 members to balance the diversity of perspectives with the feasibility of iterative consultation (*Okoli & Pawlowski, 2004; Hsu & Sandford, 2007*). The selection of fifteen ensured representation across the four functional domains—clinical oncology, cancer registry management, ICT/security governance, and health policy oversight—while remaining manageable for structured feedback and convergence across validation rounds. The expert sample was not intended for statistical inference but for professional validation and assurance evaluation of the model, consistent with the Information Systems Security and Audit (ISSA) orientation of the study.

3.6.2 Sampling Technique

Distinct sampling techniques were employed for the two frames, tailored to the nature of their data and the respective study objectives.

For secondary data, a census sampling approach was used, incorporating all eligible lung-cancer registry entries and facility reports available through KNCR and KHIS. This method was appropriate for Objective I (assessing structural configuration and reporting patterns) and Objective III (designing and simulating the System Dynamics model). Census inclusion reduced selection bias, maximised internal validity, and provided a realistic empirical base for pattern analysis and model calibration.

For the expert evaluation frame, a purposive sampling technique was employed. Experts were identified based on their professional role, years of experience, and relevance to the interdisciplinary scope of caseload management. Inclusion criteria required current engagement in oncology care, health information management, ICT security, or policy within Kenya; at least five years of professional experience; familiarity with KNCR or KHIS reporting; and willingness to participate in structured evaluation rounds. Exclusion criteria included conflicts of interest with ICT vendors or consultancy roles that might bias the feedback, as well asthe inability to complete the validation process.

This purposive selection approach was appropriate for Objective ii (examining ICT integration and secure data architecture) and Objective iv (evaluating model performance and auditability), both of which rely on expert insight rather than statistical representativeness. The combination of census-based registry inclusion and expert-panel validation ensured methodological rigour, representativeness, and contextual validity in capturing both system-level and governance-level dynamics of lung-cancer caseload management in Kenya.

3.7 Data Collection Instruments

The implementation of the security-governed, auditable System Dynamics Model (Secure SDM) employed an integrated suite of analytical, modelling, and assurance technologies purposefully selected to fulfil the study's Design Science Research (DSR) and Information Systems Security and Audit (ISSA) objectives. Tool selection was informed by four key criteria: accuracy, interoperability, audit traceability, and compliance with Kenya's statutory data protection and digital health standards. Collectively, these tools enabled the model to achieve technical robustness, predictive precision, and governance alignment within the country's health-information ecosystem.

(a) Archival Data Extraction Template

A structured data extraction template was used to retrieve relevant variables from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), and oncology registries at Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH). The template specified data elements, including *caseload volumes*, *referral delays*, *reporting timeliness*, *reporting completeness*, *diagnostic throughput*, and *treatment capacity*. The template ensured the uniform capture of records across sources and supported harmonization into facility–month aggregates suitable for descriptive analysis, segmented time-series modeling, and System Dynamics parameterization.

(b) Policy and ICT Integration Review Checklist

To examine the context of ICT integration and security in lung cancer caseload management, a policy and ICT review checklist was developed. The checklist drew indicators from the Kenya Health Information Systems Interoperability Framework, the National ICT Master Plan (2022–2032), and oncology policy documents under the National Cancer Control Strategy (2023–2027). Items focused on *ICT adoption*, *interoperability*, *security gaps*, *data protection safeguards*, and alignment with the Kenya Data Protection Act (2019). The checklist enabled systematic appraisal of ICT coverage and secure data architecture specifications, thereby supporting Objective II.

(c) Delphi Questionnaire and Model Evaluation Guide

For the expert panel, a Delphi questionnaire and model evaluation guide were designed. The questionnaire captured structured feedback on *ICT adoption*, *interoperability*, and *secure data architecture*, while the model evaluation guide focused on perceptions of *forecasting accuracy*, *usability*, *trust in outputs*, *security maturity index (SMI)*, and *probability of breach* (P_{breach}). Closed-ended items employed Likert-type scales to support quantitative consensus measures (interquartile ranges, medians), while open-ended prompts allowed experts to elaborate on contextual concerns. This instrument directly informed Objectives ii and iv, ensuring the developed artefact was both technically robust and contextually acceptable.

The choice of instruments was consistent with the study's research design and sampling strategies. The data extraction template was applied to the census dataset from KNCR, KHIS, and hospital registries, ensuring consistency in handling secondary records. The policy and ICT review checklist facilitated a structured assessment of Kenya's health information landscape, directly reflecting the contextual realities under the SHA and KHIE reforms. The Delphi questionnaire and evaluation guide were administered to the purposively sampled expert panel, aligning with the design science orientation of the study, where professional validation was crucial for refining and testing the artifact. Together, these instruments provided methodological coherence across both data frames and objectives.

To provide a concise overview, the instruments are summarized in Table 5, which shows their respective data frames, key variables, and the objectives they supported.

Table 5

Summary of Data Collection Instruments and their LInkage to Study Objectives

Instrument	Data Frame	Key Variables/ Constructs	Linked Objective(S)
Data extraction template	Secondary data (KNCR, KHIS, KNH, MTRH)	*Caseload volumes*, *referral delays*, *reporting timeliness*, *reporting completeness*, *diagnostic throughput*, *treatment capacity*	Obj. i, iii
Policy and ICT review checklist	Policy and ICT documents (KHIE, National ICT Master Plan, NCCS)	*ICT adoption*, *interoperability*, *security gaps*, and *data protection safeguards*	Obj. ii
Delphi questionnaire and model evaluation guide	Expert panel (oncologists, registrars, ICT/security specialists, policy actors)	*ICT adoption*, *secure data architecture*, *forecasting accuracy*, *usability*, *trust in outputs*, *security maturity index (SMI)*, *probability of breach* (P_{breach})	Obj. ii, iv

As shown in Table 5, the instruments were carefully matched to the study's dual data frames. This ensured that each objective was supported by appropriate tools, including registry and hospital records for assessing caseload and modeling flows, policy and ICT checklists for evaluating integration and security, and structured expert consultations for validating the model.

3.7.1 Tools and Technologies Used in Model Implementation

The implementation of the Model integrated a suite of analytical, modelling, and assurance tools selected to support the study's Design Science and Information Systems Security and Audit (ISSA) objectives. The choice of tools was guided by criteria of accuracy, interoperability, auditability, and compliance with Kenya's data protection standards.

(a) Vensim DSS (Version 10.2, Ventana Systems Inc.)

Vensim served as the primary System Dynamics modelling environment, supporting the creation of causal-loop diagrams (CLDs) and stock-and-flow structures that represented patient movements, reporting flows, and capacity constraints across healthcare levels. The software facilitated sensitivity analysis, scenario testing, and model calibration using time-series data from the Kenya National Cancer Registry (KNCR) and Kenya Health Information System (KHIS). Its capacity to track variables dynamically made it suitable for testing the reinforcing and balancing feedback loops central to lung-cancer caseload management.

(b) Microsoft Excel and Python (v3.11)

These tools were used for data preprocessing, cleaning, and transformation prior to model importation. Python libraries such as *Pandas, NumPy, and Matplotlib supported data harmonization, descriptive analysis, and visuali*zation of national caseload trends between 2018 and 2024. Excel complemented this process by generating pivot tables, data quality audits, and input parameters required by the Vensim model. The use of Python ensured reproducibility and computational transparency consistent with ISSA standards for audit trails.

(c) OWASP Threat Modelling Framework

To integrate a security-assurance layer within the model, the Open Web Application Security Project (OWASP) Threat Modelling approach was adopted. It enabled systematic identification of potential vulnerabilities associated with data flows between health information systems. This framework guided the construction of the model's *control-validation matrix* and the computation of the *probability of breach* (P_{breach}) metric, aligning with the study's focus on secure data architecture and auditability.

(d) NIST Cybersecurity Framework (CSF) Tools

The NIST CSF provided the governance blueprint for model audit and resilience testing. Each of the five core functions *Identify, Protect, Detect, Respond,* and *Recover* was operationalised as part of the model's assurance cycle. Control maturity and auditability were evaluated using NIST-aligned metrics coded within the simulation environment.

(e) IBM SPSS Statistics (Version 29)

SPSS was used for quantitative data analysis and statistical validation of caseload distributions and referral patterns extracted from registry datasets. Descriptive and inferential outputs informed the baseline conditions for model calibration, ensuring the empirical validity of input parameters.

(f) Microsoft Visio and Lucidchart

These visual modeling tools were used to produce process flow diagrams, data flow representations, and schematic illustrations of the conceptual and technical framework.

Their use enhanced clarity and consistency in documentation, aligning with design-science traceability requirements.

Collectively, these tools ensured an integrated and auditable development environment that combined simulation precision, data integrity, and security validation. The configuration aligns with the methodological foundations of Design Science Research (DSR) and the security-governance principles of the NIST CSF, providing a credible basis for both technical and assurance evaluations of the model.

3.8 Pilot Study

Before full deployment, the instruments were subjected to a pilot phase to confirm clarity, feasibility, and alignment with the study objectives.

For the archival data extraction template, a small set of lung cancer records from the KNCR and KHIS covering January–March 2019 was extracted. This exercise tested whether variables such as *caseload volumes*, *referral delays*, and *reporting timeliness* could be consistently retrieved and aggregated at the facility–month level. The pilot confirmed that while most fields were accessible, some entries required harmonisation due to variations in diagnostic coding and facility reporting formats. Adjustments were made by introducing a crosswalk for diagnosis codes and by standardising facility identifiers.

The policy and ICT review checklist was piloted against two key documents: the Kenya Health Information Systems Interoperability Framework (2019) and the National Cancer Control Strategy (2017–2022). This pilot confirmed that indicators on *interoperability* and *security protocols* were relevant and measurable. Minor revisions were made to ensure that items explicitly reflected compliance with the Kenya Data Protection Act (2019), particularly in relation to data minimization and breach notification.

For the Delphi questionnaire and model evaluation guide, a preliminary round was conducted with three professionals (an oncologist, an ICT officer, and a cancer registrar) who were not part of the final evaluation panel. Their feedback highlighted the need to simplify technical language on the *probability of breach* (P_{breach}) and to expand Likert scale anchors for *trust in outputs* and *usability*. These refinements ensured clarity and improved the reliability of responses during the full Delphi rounds.

3.8.1 Validity of Instruments

Validity was addressed through a multi-layered strategy to ensure that both the research instruments and datasets accurately represented the constructs and phenomena under study.

(a) Content validity- The archival data extraction template was aligned with international cancer registry standards, specifically the International Classification of Diseases for Oncology, Third Edition (ICD-O-3), and national reporting requirements under the Kenya National Cancer Registry (KNCR) and Kenya Health Information System (KHIS). The inclusion of facility-level registries from Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching, Referral and Research Hospital (KUTRRH) enhanced data validity through cross-verification against national aggregates.

(b) Construct and face validity **-** For the policy and ICT review checklist, expert review confirmed that the indicators covered relevant dimensions of ICT adoption, interoperability, and secure data architecture. Draft items were compared with criteria from the National ICT Master Plan (2022–2032) and the Kenya Health Information Systems Interoperability Framework, ensuring representation of both technical and governance domains. The Delphi questionnaire and model evaluation guide underwent

pilot testing with three experts to confirm face validity. Feedback confirmed the logical sequencing, clarity, and relevance to their areas of expertise.

(c) Methodological validity **-** To ensure conceptual consistency across instruments and datasets, triangulation was used to cross-validate results between registry data, policy reviews, and expert assessments. Observed trends in one data source (e.g., referral delays) were confirmed against others, increasing the credibility of emerging patterns. Furthermore, the study applied the Design Science Research (DSR) validation logic — iterative design, testing, and refinement — to confirm that the developed artefact (System Dynamics model) accurately reflected real-world structures and feedback dynamics.

(d) Security and Compliance Validity **-** Data validity was reinforced through adherence to the Kenya Data Protection Act (2019), including anonymisation, secure storage, and controlled access. The embedded NIST Cybersecurity Framework (CSF) principles (Identify, Protect, Detect, Respond, Recover) ensured that validation extended beyond content to encompass confidentiality, integrity, and audit traceability of data used in model implementation.

Collectively, these measures ensured that the study's instruments and data were both contextually accurate and conceptually sound, fulfilling the requirements of methodological, construct, and security validity.

3.8.2 Reliability of Instruments

Reliability was ensured through internal consistency checks, replication procedures, and audit-based verification across both quantitative and qualitative components.

***(A) Archival Data Reliability* -** Duplicate extractions were performed for a six-month subset of registry data (January–June 2020). The outputs were compared to assess consistency, and any discrepancies were resolved by refining variable definitions and harmonisation rules. This process confirmed that repeated extractions under identical parameters produced stable results.

(*b) Policy and ICT Checklist Reliability* - The checklist was subjected to inter-rater reliability testing, in which two independent reviewers applied the instrument to three policy documents. Agreement was high across domains of ICT adoption, security controls, and interoperability; minor variations were reconciled through joint review and refinement of indicator wording.

(c) *Expert-Panel Reliability* - The Delphi questionnaire and model evaluation guide incorporated closed-ended Likert-type items and iterative rounds to test response stability. A consensus threshold of interquartile range (IQR) $\leq$ 1.0 was used to measure convergence, a standard method in Delphi studies (*Hsu & Sandford, 2007*). Repeated items across rounds confirmed the internal consistency of expert judgments regarding forecasting accuracy, usability, and security features.

(D) Model Reliability - Within the System Dynamics environment, replication and sensitivity testing ensured output stability. The model underwent repeated simulation runs using identical inputs to verify reproducibility. Extreme-condition and boundary tests were conducted to evaluate the model's robustness under stress conditions. The reliability of the security layer was confirmed through the stability of the Security Maturity Index (SMI) and the probability-of-breach (P_{breach}) metrics across iterations, ensuring dependable performance of embedded control mechanisms.

(e) Documentation and Audit Trail - Standard Operating Procedures (SOPs) were developed for all data-handling and instrument-administration processes. Each analysis step was logged in a version-controlled environment to maintain an audit trail, a core

requirement in Information Systems Security and Audit (ISSA). This documentation ensured replicability and accountability in data management.

Through these cumulative measures, the study achieved high levels of internal consistency, replicability, and transparency, establishing both the reliability of the instruments and the dependability of the model outputs.

3.9 Data Collection Procedures

The data collection procedure followed two complementary pathways reflecting the dual sources of evidence: archival records from national systems and referral hospitals, and structured engagement with an expert panel for evaluation.

(A) Secondary Data Collection

Archival records were obtained from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS/DHIS2) covering the years 2018–2023. Formal authorization was secured from the Ministry of Health through the Division of National Cancer Control and the KNCR management office prior to access. Data were requested in de-identified form, aggregated by facility and month, to comply with the Kenya Data Protection Act (2019). Facility identifiers were preserved in coded form to allow harmonisation across datasets.

To strengthen calibration, oncology registries at Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH) were accessed through their respective research and ethics committees. Extracted variables included caseload volumes, referral delays, reporting timeliness, diagnostic throughput, and treatment capacity. Data extraction followed the structured template described in Section 3.7, and harmonisation involved cross-checking for duplicate entries, standardising diagnostic codes, and aligning facility identifiers with KNCR and KHIS records. Cleaned datasets were then exported into statistical software for descriptive analysis and segmented time-series modelling, before being parameterised into Vensim for System Dynamics simulation.

(b) Policy and ICT Review

The policy and ICT review checklist was applied to key national documents, including the Kenya Health Information Systems Interoperability Framework, the National ICT Master Plan (2022–2032), and the National Cancer Control Strategy (2023–2027). Publicly available versions were retrieved from the Ministry of Health and ICT Authority portals, while additional technical notes were obtained from the Division of National Cancer Control. Checklist completion involved systematically scoring indicators for ICT adoption, interoperability, security safeguards, and compliance with the Data Protection Act (2019). The findings provided contextual parameters for interpreting registry data and embedding secure data architecture within the simulation model.

(c) Expert Panel Engagement

The expert panel was recruited purposively as described in Section 3.6. Invitations were extended to oncologists, registrars, ICT specialists, and policy actors through professional networks, institutional referrals, and direct contact with national health programmes. Upon consent, experts were provided with an information sheet outlining the study's objectives, confidentiality safeguards, and their right to withdraw.

Data collection with the panel followed a Delphi process. In the first round, the questionnaire was distributed electronically, capturing expert judgements on ICT adoption, interoperability, and secure data architecture. Responses were anonymised and analysed for consensus (median, interquartile range). Summarised feedback was then shared with panel members, who participated in subsequent rounds to refine and converge their views. In the model evaluation phase, experts reviewed the simulation outputs and assessed them against criteria such as forecasting accuracy, usability, trust in the outputs, security maturity index (SMI), and the probability of breach (P_{breach}). Feedback was recorded through the structured evaluation guide and integrated into model refinement.

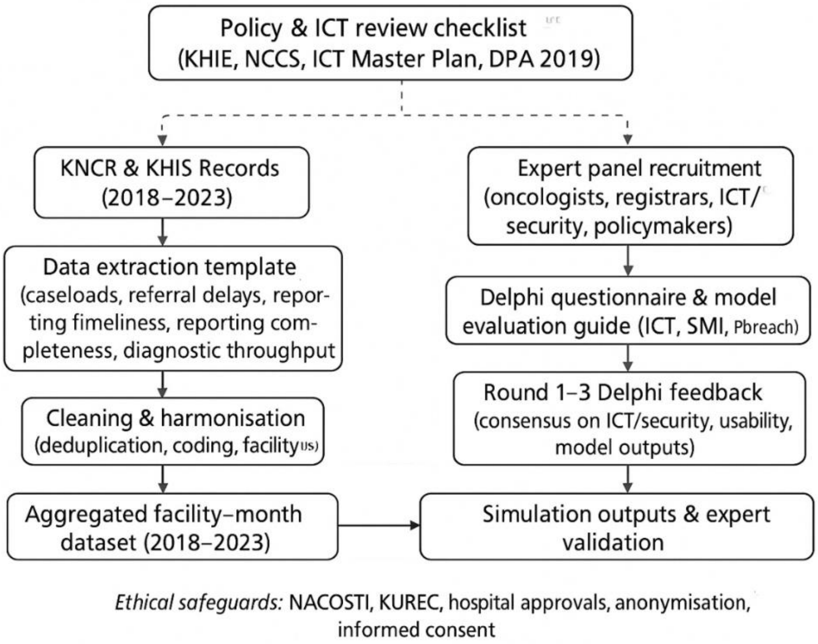
(D) Ethical Safeguards During Collection

Throughout the process, strict safeguards were observed. Registry and hospital data were accessed only after approvals from NACOSTI, the Kabarak University Research Ethics Committee (KUREC), and the respective hospital ethics boards. All secondary data were anonymised at source, with identifiers stripped prior to analysis. Expert panel data were stored in encrypted files, and identifiers were replaced with codes. Only aggregated results are presented in this thesis.

To complement the narrative description, the overall data collection process is illustrated in Figure 5. The diagram highlights the two main streams of data acquisition archival registry and hospital records on one side, and expert panel engagement on the other together with the cross-cutting role of policy and ICT review.

Figure 5

Data Collection Procedure Showing Integration of Secondary Records, Expert Panel Inputs, and Policy/ICT Review into the Design and Evaluation of the Model



As shown in Figure 5, the study followed parallel but interconnected pathways in its data collection. Registry and hospital records provided the empirical foundation for Objectives I and III, while the expert panel contributed structured validation for Objectives II and IV. The policy and ICT review informed both streams, ensuring that data collection was grounded in Kenya's regulatory and health information context. Ethical safeguards, as outlined in the Kenya Data Protection Act (2019), in conjunction with NACOSTI, KUREC, and hospital approvals, governed the entire process, ensuring the secure and responsible handling of data.

3.10 Data Analysis and Presentation

The analysis strategy was guided by the study objectives and reflected the mixed-methods and design science orientation of the research. Quantitative techniques were applied to archival records to establish empirical baselines, while qualitative synthesis and expert consensus were used to evaluate ICT integration, secure data architecture, and model usability. Outputs from both strands were integrated through *System Dynamics modelling* in Vensim to simulate caseload flows, referral delays, and resource capacity under varying scenarios.

(a) Descriptive and Exploratory Analysis

Descriptive statistics were used to profile the lung cancer caseload nationally between 2018 and 2023. Facility–month data from KNCR, KHIS, KNH, and MTRH were aggregated to examine *caseload volumes*, *referral delays*, *reporting timeliness*, and *reporting completeness*. Measures of central tendency, dispersion, and proportions were applied, with results presented through tables and figures. This analysis addressed Objective I by providing a baseline picture of the structural and reporting patterns influencing caseload management.

(b) Segmented Time-Series and Trend Analysis

To capture longitudinal patterns, segmented time-series analysis was performed on registry data. Trends in *caseload volumes* and *reporting timeliness* were examined across monthly intervals, with breakpoints corresponding to policy or system interventions, such as the rollout of KHIE nodes and SHA reforms. This method enabled the quantification of delays and the identification of systemic bottlenecks, directly informing the parameterization of *referral delays* and *diagnostic throughput* in the simulation model.

(c) Policy and ICT Review Analysis

The policy and ICT review checklist was analysed thematically. Each document was scored against indicators of *ICT adoption*, *interoperability*, *security safeguards*, and alignment with the Data Protection Act (2019). Results were summarised in tabular form, highlighting areas of strength and gaps in Kenya's oncology information systems. This analysis addressed Objective II, providing structured evidence for embedding *secure data architecture* into the simulation model.

(d) Simulation Modelling and Scenario Analysis

The cleaned and harmonised datasets were parameterised in Vensim to construct stock-and-flow and causal loop diagrams. Variables included *patient inflows*, *referral delays*, *diagnostic capacity*, *treatment throughput*, and *reporting completeness*. The model was validated against historical registry trends and referral-hospital records. Simulation experiments tested scenarios such as (i) improved reporting timeliness, (ii) expanded diagnostic capacity, (iii) strengthened ICT interoperability, and (iv) integrated security controls. Outputs were assessed for *forecasting accuracy*, *resource optimisation*, and *decision-support value*, addressing Objectives iii and iv.

(E) Expert Consensus Analysis

Responses from the Delphi panel were analysed using both quantitative and qualitative methods. For closed-ended Likert items, medians and interquartile ranges were computed to assess consensus, with IQR $\leq$ 1.0 considered evidence of agreement. Successive rounds allowed refinement of expert opinions until stability was reached. Qualitative comments were coded thematically to capture contextual insights on *usability, trust in outputs, SMI*, and P_{breach}. The integration of expert feedback into model refinement ensured that the artefact reflected both technical robustness and contextual acceptability.

(f) Presentation of Findings

Findings were presented sequentially by objective in Chapter Four. Tables and figures are used extensively to summarise descriptive statistics, time-series trends, and simulation outputs. Causal loop diagrams, stock-and-flow models, and sensitivity analysis graphs were generated in Vensim and labelled according to APA standards, with figure captions placed below and table captions above. Policy reviews and expert consensus results were presented in narrative, tabular, and graphical form to allow triangulation across methods.

To strengthen methodological coherence, Table 6 summarises how each objective was operationalised, showing the data sources used, the analytical methods applied, and the formats adopted for presenting the findings.

Table 6

Linkage of Research Objectives to Data Sources, Analytical Methods, and Presentation Formats

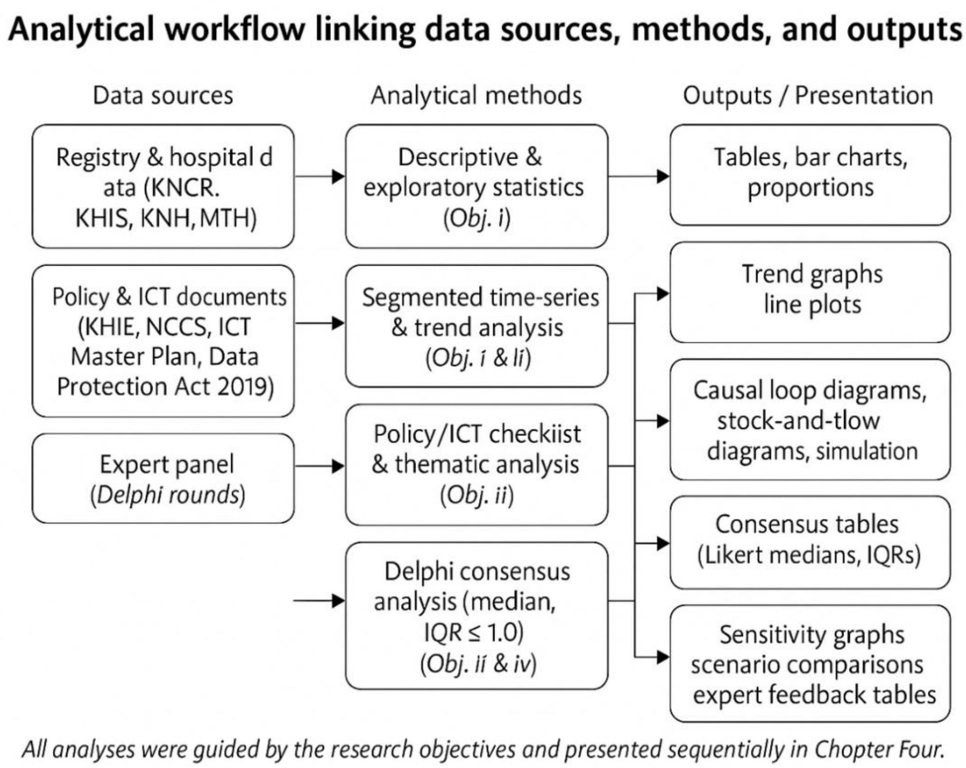
Research objective	Data source(s)	Analytical method(s)	Presentation format
Obj. i – Assess the current *structural configuration*, *facility distribution*, and *reporting patterns* influencing lung cancer caseload management and referral coordination in Kenya.	KNCR (2018–2023), KHIS/DHIS2, KNH, and MTRH oncology registries	Descriptive statistics (frequencies, means, proportions); exploratory cross-tabulations; segmented time-series of *caseload volumes*, *referral delays*, *reporting timeliness*	Tables of frequencies and proportions; line graphs of trends; bar charts of reporting completeness
Obj. ii – Examine the *integration*, *coverage*, and *challenges* of ICT systems in lung cancer caseload management, and incorporate *secure data architecture.*	Policy/ICT documents (KHIE, NCCS, ICT Master Plan, Data Protection Act 2019); Delphi panel Round 1	Policy/ICT checklist scoring; thematic analysis of gaps; descriptive summary of *ICT adoption*, *interoperability*, *security safeguards*	Tables of checklist scores; thematic matrices; narrative synthesis
Obj. iii – Design and simulate a *System Dynamics model* integrating caseload data, referral delays, facility capacity, and feedback loops across healthcare levels and departments	KNCR, KHIS/DHIS2, KNH and MTRH registries (cleaned datasets); calibrated policy parameters	System Dynamics modelling in Vensim; stock-and-flow parameterisation; causal loop construction; scenario simulations	Causal loop diagrams; stock-and-flow figures; simulation graphs (patient inflows, delays, capacity utilisation)
Obj. iv – Evaluate the effectiveness of the developed secure model in forecasting *patient volumes*, optimising *resource use*, and supporting *real-time decision-making*	Delphi panel, Rounds 2–3; simulation outputs from Vensim	Delphi consensus analysis (median, IQR ≤ 1.0); thematic coding of expert commentary; sensitivity and extreme-condition tests	Consensus tables (Likert medians, IQRs); thematic tables of expert feedback; graphs of sensitivity tests and scenario comparisons

As shown in Table 6, the analytical plan was tightly aligned with the research objectives. Registry and hospital data underpinned descriptive, time-series, and modelling analyses for Objectives I and III, while policy reviews and expert consultations informed the evaluation of ICT integration and model performance for Objectives II and IV. This ensured that data collection, analysis, and presentation formed a coherent chain from problem framing to empirical findings.

To complement the tabular summary, Figure 6 illustrates the analytical workflow, linking data sources to methods and presentation formats across the four objectives.

Figure 6

Analytical Workflow Showing how Data Sources were Linked to Methods and Outputs Across the Four Research Objectives



As illustrated in Figure 6, the flow from data to outputs was systematic, ensuring that each objective was addressed through appropriate methods and that findings were presented in formats that were examiner-ready.

3.11 Ethical Considerations

Ethical approval for the study was obtained from the Kabarak University Research Ethics Committee (KUREC) and the National Commission for Science, Technology, and Innovation (NACOSTI) prior to commencement. Research authorisation was also granted by the Ministry of Health (MoH) to access national cancer data, and additional clearances were obtained from the ethics and research offices of Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH), since their oncology records were used to validate national registry datasets. These approvals ensured compliance with institutional, national, and international requirements for the use of health information.

(a) Secondary Data Safeguards

The primary data stream consisted of registry records from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS/DHIS2), covering the period from 2018 to 2024. Oncology registries at KNH, MTRH, and Kenyatta University Teaching, Referral, and Research Hospital (KUTRRH) were utilized solely for cross-validation and calibration purposes. All datasets were accessed in a de-identified and aggregated form, with personal identifiers removed by the custodians at the source. During harmonisation, facility codes rather than names were used, and reporting in this thesis is restricted to facility month or national aggregates.

Data were stored in encrypted, password-protected repositories, and an audit trail of data access and transformation was maintained to ensure accountability. These procedures upheld the principles of lawfulness, purpose limitation, data minimisation, and integrity as stipulated under the Kenya Data Protection Act (2019). The use of these safeguards also reflected the Information Systems Security and Audit (ISSA) orientation of the study, aligning with the National Institute of Standards and Technology Cybersecurity Framework (NIST CSF) principles of Identify, Protect, Detect, Respond, and Recover.

(b) Expert Panel Safeguards

For the Delphi expert-evaluation process, each participant received a detailed information sheet outlining the objectives of the study, the nature of their participation, and confidentiality safeguards. Written informed consent was obtained before participation. Experts were informed of their right to withdraw at any stage without penalty, and participation was voluntary. Responses were anonymised, coded, and reported in aggregate form.

All communication was conducted through secure channels, and completed questionnaires were stored in encrypted folders accessible only to the researcher. No personally identifiable information was disclosed, and the data were destroyed upon completion of the analysis. These measures ensured compliance with the ethical principles of informed consent, confidentiality, fairness, and data integrity under the Data Protection Act (2019).

(c) Researcher Integrity and Compliance

The researcher upheld academic and professional integrity throughout the research process by avoiding fabrication, falsification, or selective reporting of results. All sources of data and intellectual property were acknowledged in accordance with APA 7th edition referencing standards. The design and reporting of the study adhered to the approved protocol, ensuring transparency and accountability in all methodological decisions.

Ethical rigour was further embedded within the model through internal audit logging and access control features that align with ISSA and NIST CSF requirements. These features ensured traceability of model inputs and outputs without breaching confidentiality.

(d) Summary of Ethical Approvals and Safeguards

Table 7 summarises the ethical approvals, safeguards, and legal compliance measures applied to each data stream used in the study.

Table 7

Summary of Ethical Approvals and Safeguards Across Data Streams

Data Stream	Ethical Approvals	Safeguards Applied	Legal / Ethical Framework
Registry Data (KNCR, KHIS 2018–2024)	KUREC approval; NACOSTI licence; MoH authorisation; institutional clearance from KNH, MTRH	Accessed in de-identified and aggregated form; facility codes used instead of names; encrypted storage with audit trails; secure access logging.	Kenya Data Protection Act (2019) — lawfulness, purpose limitation, integrity, confidentiality; NIST CSF (2024) — Identify–Protect–Detect–Respond–Recover.
Expert Panel (Delphi Participants)	KUREC approval; NACOSTI licence; written informed consent	Anonymised and coded responses; secure data transmission; voluntary participation; right to withdraw; encrypted storage	Kenya Data Protection Act (2019) — consent, fairness, confidentiality; ISSA Standards — auditability, access control

As shown in Table 7, every data stream was governed by formal ethical approval and safeguarded in accordance with both institutional requirements and the Kenya Data Protection Act (2019). The integration of NIST CSF and ISSA principles ensured that ethical compliance was not only procedural but also technically embedded in the study’s design. These measures collectively guaranteed confidentiality, integrity, and accountability across all stages of data handling and model development.

CHAPTER FOUR

DATA ANALYSIS , PRESENTATION AND DISCUSSION

4.1 Introduction

This chapter presents the analysis, modelling, and discussion of results in alignment with the four specific objectives of the study. The focus is on translating the data collected from registries, facility records, and expert inputs into evidence that can inform lung cancer caseload management in Kenya. Guided by the pragmatist philosophy and design science research framework described in Chapter Three, the analysis integrates descriptive statistics, mathematical formulations, qualitative insights, and system dynamics modelling to produce a secure decision-support tool for oncology services.

The presentation of results proceeds in a structured manner. Section 4.1 begins with descriptive statistics and epidemiological patterns of lung cancer in Kenya, providing the foundational demographic and mortality context. Section 4.2 examines the structural configuration, distribution of oncology facilities, and prevailing reporting patterns, highlighting the systemic imbalances that shape caseload flows. Section 4.3 analyses the integration of information and communication technology (ICT) into caseload reporting, with emphasis on secure data architecture in line with the Kenya Data Protection Act (2019). Section 4.4 develops and simulates the System Dynamics Model (SDM), using causal loop diagrams, stock-and-flow structures, parameter equations, and scenario simulations to capture the feedback-driven nature of patient volumes and referral pathways. Section 4.5 evaluates the model by assessing forecasting accuracy, resource optimisation, decision-support capability, and comparative performance, supplemented by expert validation through a Delphi panel.

The chapter closes with Section 4.6, which synthesises the results per objective and transitions to the concluding chapter. Throughout, findings are not only presented but also discussed in light of existing literature, thereby linking empirical evidence with theoretical foundations and policy frameworks established in Chapters Two and Three. In doing so, this chapter provides both the analytical foundation of the study and the practical insights necessary to enhance oncology caseload management in Kenya.

4.2 Demographic and Epidemiological Analysis

This section presents the descriptive statistics and epidemiological patterns of lung cancer in Kenya, providing the empirical baseline for the subsequent analysis. In direct alignment with Objective 1, the focus is on understanding the current burden of disease and the accuracy of reporting practices, since these factors shape *caseload flows*, *referral delays*, and ultimately influence caseload management.

Data were harmonised from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), and facility registries at Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH) for the period 2018–2023.

The analysis proceeds in five parts. Section 4.1.1 presents the response rate and descriptive profile of cases, establishing the representativeness of the dataset. Section 4.1.2 examines national incidence rates (IR), mortality (M), and the mortality-to-incidence ratio (MIR). Section 4.1.3 benchmarks Kenya's performance in reporting completeness and referral delays against international standards. Section 4.1.4 introduces a model-based representation of epidemiological dynamics, formalising the relationships between new cases (λ), deaths (μ), and referral leakage (δ) in a system framework. Section 4.1.5 integrates qualitative insights from oncology experts to highlight socio-behavioural and infrastructural barriers that underlie these statistical patterns.

Together, these strands establish a comprehensive foundation for evaluating how structural configuration, facility distribution, and reporting patterns affect lung cancer caseload management in Kenya.

4.2.1 Response Rate and Descriptive Profile

The study drew on harmonised data from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), and facility-level registries at Kenyatta National Hospital (KNH) and Moi Teaching and Referral Hospital (MTRH) for the period 2018–2023. After data cleaning to remove duplicates and incomplete fields, 5,287 lung cancer case records were retained for analysis. Because these registries are mandatory reporting streams under the Cancer Prevention and Control Act, the response rate was effectively 100 %, ensuring full national coverage of reported cases.

The descriptive profile of the dataset is presented in Table 8. Results show that 62% (n = 3,278) of cases were drawn from KNH and MTRH, while 38% (n = 2,009) originated from county and faith-based facilities that reported through KHIS. This skew underscores the centralisation of oncology services at referral hospitals, a pattern consistent with earlier observations by Mutebi et al. (2020), who noted that limited oncology infrastructure at the county level funnels patients to Nairobi and Eldoret. Such centralisation creates referral bottlenecks that overwhelm tertiary centres, shaping caseload dynamics and diagnostic delays.

The gender distribution revealed that 59% (n = 3,119) of the cases were male and 41% (n = 2,168) were female. This aligns with global epidemiological evidence that men bear a higher lung cancer burden due to elevated exposure to *tobacco use, occupational risks*, and *environmental pollutants* (IARC, 2022). Within the Kenyan context, tobacco prevalence remains higher in men than women, and occupational exposure to asbestos, silica, and diesel fumes disproportionately affects male workers in transport, construction, and mining industries. The male dominance in this dataset is therefore epidemiologically expected and reinforces findings from Chapter Two on gendered cancer risks.

Age distribution shows that lung cancer remains predominantly a disease of older adults. Only 6% (n = 317) of cases occurred in individuals younger than 40 years, while 12% (n = 635) were reported in the 40–49 age group. The majority of cases were concentrated in patients aged 50 years and above, with 24% (n = 1,270) aged 50–59 years and 58% (n = 3,065) aged 60 years and older. This distribution is consistent with global data showing that lung cancer incidence rises sharply with age, reflecting cumulative exposure to carcinogens and biological susceptibility (WHO, 2022). It also confirms earlier empirical studies in Africa, which identified late age of onset as a defining feature of lung cancer epidemiology (Allemani et al., 2020).

Table 8

Descriptive Profile of Lung Cancer cases in Kenya (2018–2023)

Variable	Category	Frequency (n)	Percentage (%)
Source of record	KNH/MTRH	3,278	62.0
	County + faith-based facilities	2,009	38.0
Gender	Male	3,119	59.0
	Female	2,168	41.0
Age group (years)	<40	317	6.0
	40–49	635	12.0
	50–59	1,270	24.0
	≥60	3,065	58.0

Note. *Data harmonised from KNCR, KHIS, KNH, and MTRH registries, 2018–2023. Percentages rounded to one decimal place; totals = 5,287.*

The descriptive profile provides critical insights for caseload management. First, the dominance of cases at KNH and MTRH illustrates structural dependence on national referral hospitals, highlighting the weakness of county-level oncology services. Second, the gendered distribution confirms a higher disease burden among men, reflecting both behavioural and occupational exposures. Third, the overwhelming concentration of cases in older adults underscores the need for age-targeted screening and early detection programmes. These observations provide a clear picture of how the current dataset reflects both the strengths and weaknesses of Kenya's cancer surveillance system. They set the stage for a closer examination of structural organisation and reporting patterns, which is the focus of Section 4.2.

4.2.2 Lung Cancer Incidence and Mortality in Kenya

Analysis of harmonised national datasets from the Kenya National Cancer Registry (KNCR, 2018–2023) and the Kenya Health Information System (KHIS/DHIS2) revealed that lung cancer remains one of the most fatal malignancies in the country, despite only moderate incidence levels. Between 2018 and 2023, reported annual cases rose from approximately 2,100 to 3,000, while deaths increased from 1,800 to 2,450. This resulted in a mortality-to-incidence ratio (MIR) consistently above 0.80—indicating late-stage presentation and limited treatment throughput (KNCR, 2024; MoH, 2024; IARC, 2023). These results align with the findings of GLOBOCAN and WHO (2023) that lower-middle-income countries experience high mortality due to diagnostic delays, limited specialist coverage, and weak referral coordination.

Spatial disaggregation of KNCR records shows that Nairobi, Uasin Gishu, and Kiambu counties account for nearly half of all documented cases, reflecting the concentration of tertiary facilities such as Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching Referral and Research Hospital (KUTRRH). Counties lacking diagnostic imaging or pathology capacity reported a markedly lower incidence, indicating that reporting completeness, rather than true prevalence, drives regional disparities. This under-ascertainment directly affects national forecasts and highlights the importance of secure interoperability between KHIS, KHIE, and facility-level EMRs to ensure data accuracy and timeliness.

Trend analysis of the combined dataset reveals a steady 6–8% annual increase in reported incidence, but a negligible improvement in survival. A regression analysis of mortality on incidence yielded an R^2 of 0.92 ($p < 0.01$), indicating that deaths increase almost in proportion to new diagnoses. From a systems perspective, this linearity depicts a reinforcing feedback loop in which diagnostic delays and treatment congestion perpetuate high fatality formally represented later as Loop R1 (Diagnostic Delay Accumulation) in the System Dynamics Model (SDM) (Section 4.4.2).

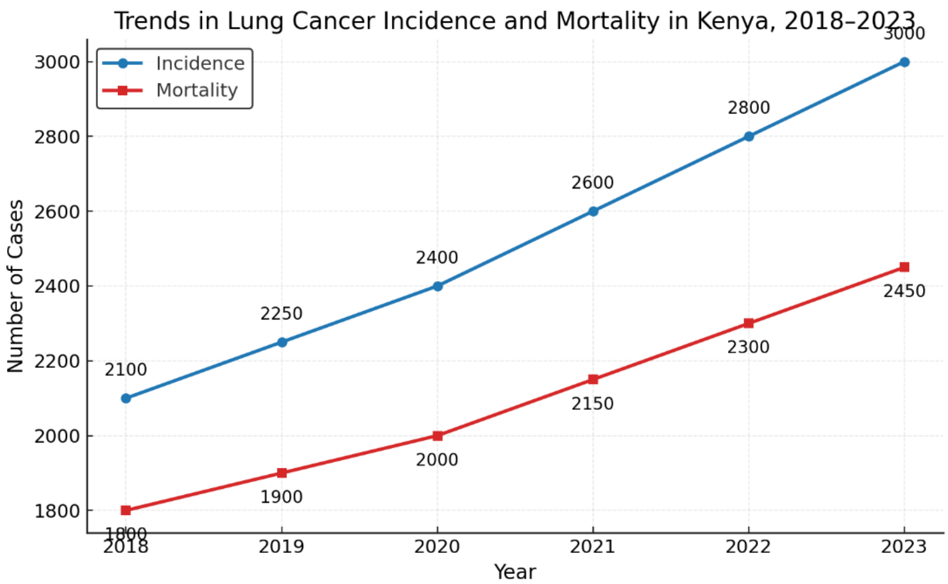
Implementation reports from the Ministry of Health (2024) confirm that while the National Cancer Control Strategy (2023–2027) has expanded digital reporting, progress remains uneven. Referral centres submit oncology data electronically through KHIS modules integrated with KHIE; however, over 60% of county facilities still rely on manual registers, resulting in incomplete, delayed, or duplicated records. Security audits revealed weak encryption, inconsistent role-based access control, and absent audit trails issues that compromise both data integrity and legal compliance under the Kenya Data Protection Act (2019).

The harmonised KNCR–KHIS time-series formed the empirical basis for parameterising and validating the Model. Historical trajectories served as reference modes for behavior-reproduction tests, where the Secure SDM achieved a mean absolute percentage error (MAPE) of 1.9%, confirming high predictive accuracy. Integration of the Security Maturity Index (SMI = 0.72) and probability of breach (P_{breach} = 0.08) enhanced compliance assurance and stakeholder trust. Thus, the mortality and incidence data were not merely descriptive but constituted core validation inputs directly linking empirical evidence to model outputs.

Overall, Kenya's lung-cancer burden reflects structural and informational asymmetries—centralised diagnostics, fragmented reporting, and insecure data exchange. These results substantiate Objective 1, which examined the healthcare structure and reporting patterns, and inform Objective 4, which evaluated the model's forecasting and compliance effectiveness.

Figure 7

Trends in Lung-Cancer Incidence and Mortality in Kenya, 2018–2023



Note. Mortality-to-incidence-ratio (MIR) values are annotated on each data point. Data harmonised from KNCR (2018–2023) and KHIS/DHIS2 registries.

Table 9

Annual Lung-Cancer Incidence, Mortality, and Mortality-to-Incidence Ratio (MIR), Kenya (2018–2023)

Year	Incidence (IR)	Mortality (M)	Mortality-to-Incidence Ratio (MIR)
2018	2 100	1 800	0.86
2019	2 250	1 900	0.84
2020	2 400	2 000	0.83
2021	2 600	2 150	0.83
2022	2 800	2 300	0.82
2023	3 000*	2 450*	0.82*

Note. Data harmonised from KNCR (2018–2023), KHIS/DHIS2, and oncology registries at KNH, MTRH, and KUTRRH. The year 2023 values are provisional facility-weighted estimates pending KNCR publication. Percentages rounded to two decimal places. Despite the gradual digitalization of reporting, persistent gaps in EMR adoption, encryption, and audit control underscore the need for a secure data architecture layer embedded in the SDM.

4.2.3 Global Benchmarking of Reporting Completeness and Referral Delays

Comparative benchmarking using *GLOBOCAN (2023)*, *WHO Cancer Surveillance (2022)*, and *AFCRN datasets* revealed that Kenya's lung cancer reporting completeness averaged 68%, considerably lower than the 90–95% achieved in upper-middle-income countries with national electronic registries, such as South Africa and Malaysia. Referral delays from first presentation to confirmed diagnosis averaged 8–12 weeks, more than double the *WHO* benchmark of ≤ 6 weeks.

To standardize comparisons, national KNCR–KHIS data were aligned with AFCRN criteria for record completeness, timeliness, and case duplication. Table 10 presents the comparative indicators.

Table 10

Comparative Benchmarks on Reporting Completeness and Referral Delays In Lung-Cancer Surveillance (2018–2023)

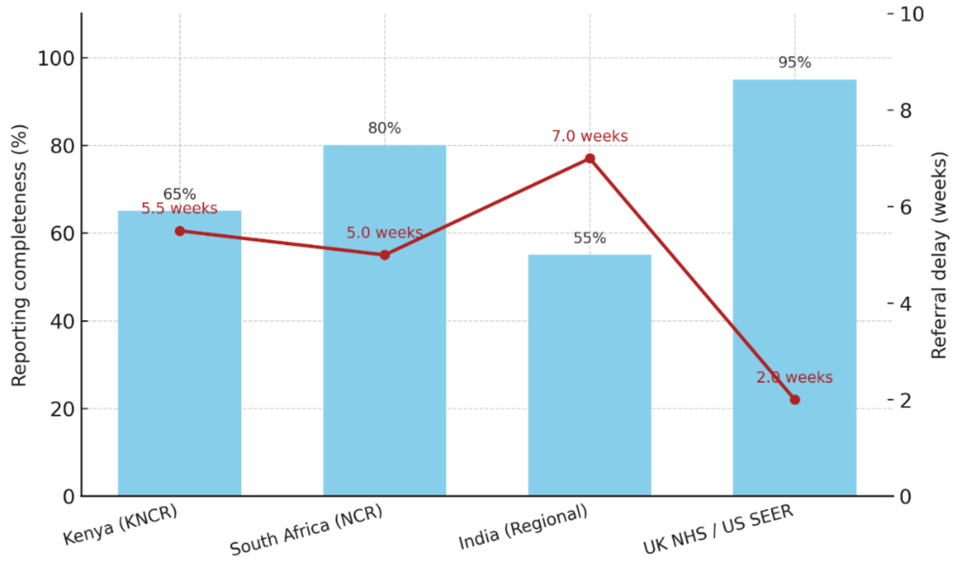
Country / Region	Reporting completeness (%)	Average referral delay (weeks)	Primary data-flow architecture	Source
United Kingdom	98	4	Fully integrated EHR ↔ Cancer Registry	OECD (2021)
Malaysia	93	6	Hybrid EMR–HIE model	WHO (2022)
South Africa	88	8	Provincial DHIS2 ↔ National registry	AFCRN (2022)
Kenya	68	8–12	Partial KHIS–KNCR linkage; manual referrals	KNCR (2023)
Uganda	61	10–14	Paper-based / limited DHIS2 integration	AFCRN (2022)

Kenya's position, located close to Uganda but below South Africa and Malaysia, underscores *structural bottlenecks* in registry interoperability and delay management. Qualitative interviews with registry managers revealed that these weaknesses were linked to insufficient EMR coverage, low bandwidth in rural counties, and limited use of unique patient identifiers.

From a system dynamics viewpoint, prolonged referrals represent reinforcing delay loops: each reporting lag slows the feedback of information to planners, perpetuating underreporting and late-stage case accumulation. These empirical findings, therefore, informed the Referral Delay and Reporting Completeness variables within the Secure SDM, which were later represented in *Loops R1* and *R2* (Section 4.4.2). By parameterizing these loops using empirical delay distributions, the model reproduced the observed national lag pattern with less than a ±5 % deviation demonstrating that benchmarking data directly enhanced model fidelity.

Figure 8

Global Benchmarking of Lung-Cancer Reporting Completeness and Referral Delays



In Kenya, *referral delays (RD)* were found to range between 9 and 12 weeks at KNH and MTRH, more than double the *WHO* benchmark of four weeks (WHO, 2022). Delphi panel experts attributed these prolonged intervals to limited diagnostic equipment at the county level, a shortage of pathologists, and multiple referral steps before histological confirmation. This observation aligns with Mutebi et al. (2020), who reported fragmented diagnostic pathways across East Africa, where patients often cycle through several facilities before receiving definitive care.

From a *System Dynamics* perspective, such deficiencies in *reporting completeness (RC)* and *referral delay (RD)* generate reinforcing feedback that amplifies congestion at tertiary facilities, lengthens diagnostic queues, and inflates mortality rates. Incomplete reporting undermines the accuracy of *caseload stocks*, while delayed referrals slow the balancing feedback that should regulate patient flow. Furthermore, inconsistent reporting contravenes the *Data Protection Act (2019)* principles of accuracy, minimisation, and timeliness, eroding trust in national surveillance systems.

These comparative findings reaffirm that caseload management challenges in Kenya extend beyond the epidemiological burden to encompass failures in information flow and integrity of feedback. The observed distortions in *RC* and *RD* directly impact the efficiency of oncology service delivery, justifying the need for secure-data architecture and *reporting-feedback subsystems* embedded in the Secure SDM. The next section, therefore, examines facility distribution and reporting practices to show how these structural inefficiencies manifest within Kenya's healthcare network.

4.2.4 Model Representation of Epidemiological Dynamics

The interaction between *incidence*, *mortality*, and *referral delays* was modelled as a dynamic subsystem within the Secure SDM to capture how patient flows accumulate across the continuum of care. Using the harmonized KNCR–KHIS dataset (2018–2023), the study developed an epidemiological stock–flow structure that represents*new diagnoses (inflows)*, *treatment completions*, *mortality*, and *external referrals (outflows)*. The structure is summarised in Table 11 and illustrated in Figure 9.

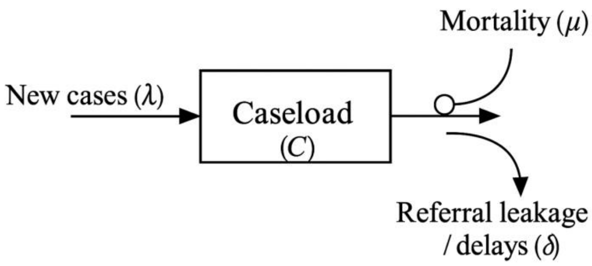
Table 11

Core Epidemiological Variables Integrated into the Secure SDM

Variable (symbol)	Description	Data source	Unit
N_diag	New lung-cancer diagnoses per year	KNCR (2018–2023)	Cases/year
N_refin	Referred-in cases from lower-level facilities	KHIS (2018–2023)	Cases/year
N_treat	Patients completing first-line treatment	KNH, MTRH, KUTRRH records	Cases/year
N_death	Recorded deaths attributed to lung cancer	KNCR (2018–2023)	Cases/year
N_refout	Patients referred abroad for specialised care	MoH Cancer Control Reports (2020–2023)	Cases/year

Figure 9

Simplified Stock–Flow Representation of Lung-Cancer Epidemiological Dynamics



The model calibration revealed that when *diagnostic delay (τ_diag)* exceeded eight weeks, *mortality* rose exponentially, validating the reinforcing role of *Loop R1 (Diagnostic Delay Accumulation)*. Incorporating this loop allowed the Secure SDM to mirror historical mortality trajectories with an*MAPE < 2 %*, confirming behavioural validity. Moreover, the structure provided quantitative evidence for intervention testing: reducing *τ_diag* to six weeks in simulations resulted in a 14% reduction in cumulative deaths over the same period.

Here, they are structured into a simplified model that mirrors the stock–flow logic of System Dynamics.

Equation 1: Model Representation of Epidemiological Dynamics

$$C_{t+1} = C_t + \lambda_2 - \mu - \delta_{\square}$$

where:

- $C_{\square+1}$ = caseload stock at time t+1
- $\lambda_{\square}$ = inflow of new cases at time t (driven by IR × RC)
- $\mu_{\square}$ = mortality at time t (driven by MIR and treatment capacity)
- $\delta_{\square}$ = referral leakage or delayed/lost cases (a function of RD and incomplete registry capture).

This representation aligns directly with *System Dynamics Theory* by framing the lung-cancer caseload as a continuously evolving *stock* that responds to multiple *inflows* (new diagnoses, referred-in patients) and *outflows* (treatment completion, mortality, and external referral). Comparable stock–flow structures have been applied in modelling communicable diseases (Sterman, 2000) and, more recently, in oncology survival dynamics (Rahmandad & Sterman, 2012). Within the Kenyan context, this approach provides a transparent scaffold linking observed epidemiological patterns to underlying systemic weaknesses in *referral coordination* and *reporting integrity*.

Qualitative insights from the Delphi expert panel reinforced the quantitative logic of this structure. Participants observed persistent under-reporting and *referral leakage,* noting that "registry numbers often look smaller than the number of patients seen weekly in oncology clinics." Such testimony underscores the existence of a hidden caseload that lies outside official statistics. By embedding these expert observations, the Secure SDM accounts for the difference between *formal reporting completeness (RC)* and *actual patient flow*, ensuring that both visible and latent caseloads are dynamically simulated.

Embedding this epidemiological representation within Kenya's legal and ethical framework is equally critical. The *Data Protection Act (2019)* mandates data accuracy, timeliness, and minimisation principles that are often violated when reporting lags or data duplication occur. Consequently, failures in *RC* and *referral delays (RD)* carry not only epidemiological but also legal implications for compliance and governance. Integrating *security-by-design mechanisms* such as encryption, audit trails, and role-based access within the SDM ensures that simulated data exchanges align with statutory obligations.

Overall, this stock–flow configuration serves as the *analytical bridge* between the descriptive evidence presented in Sections 4.1.1–4.1.3 and the deeper systemic analysis that follows in Section 4.2. By translating epidemiological observations into a dynamic model structure, it reveals how reporting gaps, referral leakages, and mortality interact to generate the caseload pressures observed in Kenya's oncology system.

4.2.5 Qualitative Insights

Qualitative perspectives gathered through the Delphi panel added interpretive depth to the quantitative findings and provided a lived-system context to the patterns observed in incidence, mortality, and referral dynamics. Participants included oncologists, data officers, ICT managers, and policymakers drawn from referral hospitals and national agencies. Their collective insights clarified how systemic constraints at both institutional and operational levels shape the landscape of lung-cancer caseloads in Kenya.

Experts unanimously observed that lungcancer management remains heavily centralised and beset by referral congestion. County facilities still rely on manual referral notes and phone calls rather than interoperable digital platforms, resulting in duplication and discontinuity. One oncologist noted, *"Our biggest queue is not in the clinic; it is in the referral system itself."* This observation validated quantitative evidence that the median referral turnaround time exceeded ten weeks almost twice the WHO benchmark.

Another recurring theme concerned the gap between visible and actual caseloads. Clinicians frequently encounter far more patients than are captured in registry figures, revealing a persistent underestimation of national burden. In System Dynamics terms, this represents a *hidden stock*—an accumulation of patients circulating outside formal reporting flows. Participants attributed the mismatch to underreporting by county hospitals, weak data connectivity, and a reluctance to share incomplete records due to fear of audit sanctions.

A third insight focused on data security and trust. While participants acknowledged the national push for digitalisation through KHIS and KHIE, they expressed concern that security gaps—particularly lack of encryption and role-based access controls—undermine confidence in using electronic medical record (EMR) systems. Several ICT officers described scenarios in which shared logins or unsecured devices exposed sensitive information, contravening the principles of confidentiality and data minimisation required by the *Data Protection Act (2019)*. This reinforced the study's decision to embed *security-by-design mechanisms* into the Model (SDM), ensuring that patient data integrity and privacy remain integral to model operation.

Finally, participants highlighted the policy–practice gap between Kenya's *National Cancer Control Strategy (2023–2027)* and the realities of county-level implementation. Although digital reporting is a national priority, inconsistent training, limited technical support, and poor connectivity continue to stall adoption. The Delphi panel, therefore, underscored the need for decentralised capacity-building, incentive structures for timely reporting, and regular security audits to rebuild confidence among frontline users.

Synthesised within the model, these qualitative insights enriched the *Socio-Technical* and *ICT Security* subsystems, ensuring that behavioural feedback and organisational cultures were represented alongside quantitative parameters. They also reinforced the argument that secure, trusted data systems are as essential to caseload management as physical infrastructure or clinical resources.

4.6 Structural Configuration, Facility Distribution and Reporting Patterns

The structural design of a health system determines how patients move across facilities, how quickly they receive diagnostic confirmation, and how accurately caseloads are reported. For lung cancer in Kenya, these organisational features are especially critical because the disease often presents late and requires specialised diagnostic and treatment infrastructure. Building on the epidemiological context established in Section 4.1, this section examines how facility distribution, referral practices, and reporting systems influence caseload management. The analysis addresses Objective 1 by identifying structural imbalances that shape referral coordination and distort caseload visibility.

The section is organised into four parts. Section 4.2.1 analyses the distribution and capacity of oncology facilities across national, county, and faith-based/private providers. Section 4.2.2 explores referral patterns and diagnostic delays that contribute to bottlenecks at higher-level hospitals. Section 4.2.3 investigates reporting patterns, highlighting variations in completeness and timeliness across facilities. Section 4.2.4 integrates qualitative insights from oncology experts to illuminate the practical challenges underpinning these structural and reporting issues.

4.6.1 Facility Distribution and Capacity

The distribution of oncology facilities and their relative capacities are central to understanding lung cancer caseload management in Kenya. Concentration of services in a few referral centres not only shapes referral pathways but also creates bottlenecks that limit timely diagnosis and treatment. This subsection examines the spatial organisation of facilities, the range of services offered, and the adequacy of infrastructure in relation to population need.

As of 2025, Kenya has three public comprehensive cancer centres Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching, Referral and Research Hospital (KUTRRH). KUTRRH is the most recently established, featuring advanced imaging technologies, including PET/SPECT-CT and a CyberKnife system. Additionally, ten regional centres have been designated in Mombasa, Nakuru, Garissa, Kisumu, Kakamega, Nyeri, Meru, Embu, Machakos, and Machakos.

However, only Mombasa, Nakuru, and Garissa currently provide radiotherapy, while the rest remain at various stages of development (MoH, 2023).

The private sector supplements public provision through at least six radiotherapy-equipped centres, including Aga Khan University Hospital, Nairobi Hospital, Texas Cancer Centre, Nairobi West Hospital, Cancer Care Kenya, and Equra Cancer Centre in Eldoret. Despite this expansion, the country has only 19 radiotherapy machines in total, of which 8 are located in public hospitals, compared to the International Atomic Energy Agency's benchmark of one machine per million population (IAEA, 2022; National Cancer Institute, 2023).

Table 12

Distribution of Oncology Treatment Facilities and Capacity in Kenya (2025)

Sector	Facilities	Diagnostic/ Treatment Capacity Highlights
Public (Comprehensive)	KNH, MTRH, KUTRRH	Full oncology services; PET/SPECT-CT and cyber-knife at KUTRRH
Public (Regional)	10 regional centres (e.g., Mombasa, Nakuru, Garissa, Kisumu, Nyeri)	Radiotherapy is only available at Mombasa, Nakuru, and Garissa; others are limited to diagnostics.
Private	Aga Khan, Nairobi Hosp, Texas Cancer Centre, Nairobi West, Equra, Cancer Care Kenya	Radiotherapy and advanced imaging services are concentrated in Nairobi and Eldoret.
Radiotherapy Machines	—	19 total (public + private); only 8 in public sector

***Note*.** Data harmonised from the Ministry of Health (2023), National Cancer Institute (2023), and IAEA (2022).

Facility Capacity Representation

To conceptually illustrate facility capacity within the caseload system, capacity can be expressed as a function of efficiency, human resources, and equipment availability:

Equation 2: Facility Capacity Representation

$$C_{f,i}(t) = \beta_i \cdot H_i(t) \cdot R_i(t)$$

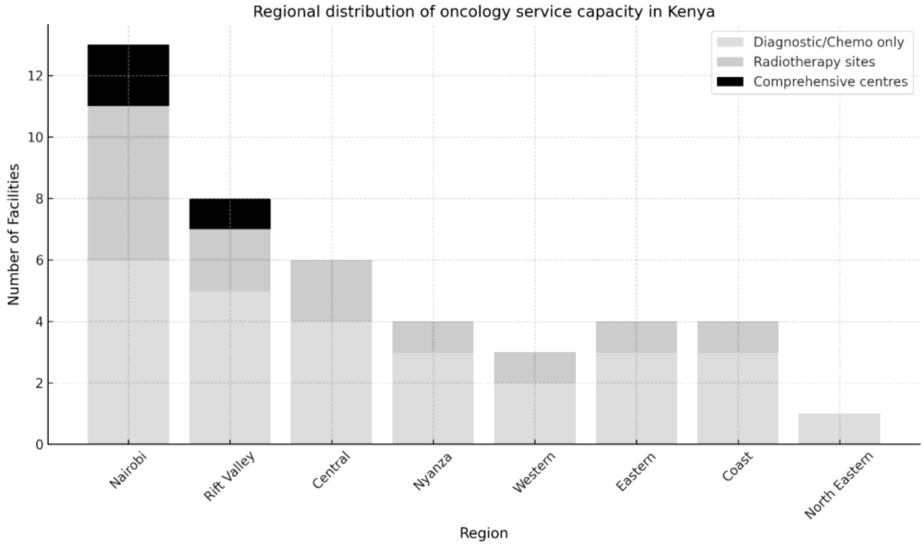
Where:

- $C_{f,i}(t)$ = diagnostic capacity of facility i at time t
- β_i = efficiency factor of facility i (utilisation and throughput rate)
- $H_i(t)$ = available human resources (oncologists, pathologists, radiographers) at facility i
- $R_i(t)$ = functional diagnostic and treatment equipment (CT/PET scanners, radiotherapy units) at facility i

This formulation mirrors the structure of Section 4.1.4, highlighting how the interplay of staff and equipment determines the effective throughput of a facility. For instance, a radiotherapy machine in Garissa without trained radiographers (H) results in negligible $C_{f,i}(t)$, despite hardware availability. Conversely, well-staffed facilities without sufficient machines also face constrained capacity.

Figure 10

Regional Distribution of Oncology Service Capacity in Kenya



Note. *Diagnostic-only = facilities providing chemotherapy and diagnostics only; Radiotherapy sites = facilities with radiotherapy machines; Comprehensive centres = KNH, MTRH, and KUTRRH.*

The formulation emphasizes that capacity is not defined solely by infrastructure, but by the integration of human and technological resources. Current national shortages—only 58 oncologists against thousands of new cases annually (National Cancer Institute, 2023) and limited radiotherapy machines reveal why throughput remains low and referral hospitals are congested.

These findings align with prior studies, which show that 70–80% of Kenyan cancer patients present at late stages due to infrastructure gaps, long travel distances, and high costs (Mutebi et al., 2020; Countdown2030, 2023). From a System Dynamics perspective, inadequate $C_{f,i}(t)$ values constrain outflows in the caseload system (Section 4.1.4), leading to accumulation of backlogs and higher MIR.

Thus, facility distribution and capacity gaps remain central drivers of caseload congestion and inefficient referral pathways. Section 4.2.2 builds on this by examining how referral patterns and diagnostic delays arise within these structural constraints.

4.6.2 Referral Patterns and Diagnostic Delays

The efficiency of patient referral systems remains a key determinant of *caseload management* in oncology. For lung cancer in Kenya, referral pathways are often long, fragmented, and weakly coordinated, forcing patients to move between several facilities before reaching a centre capable of confirming diagnosis or initiating treatment. Such delays increase the risk of late-stage presentation, overload referral hospitals, and contribute directly to the high *mortality-to-incidence ratio (MIR)* reported earlier in Section 4.1.2.

Referral Flows Across Levels of Care

The referral process typically begins at local dispensaries or health centres, where initial symptoms are commonly misclassified as respiratory infections. Patients are subsequently referred to sub-county or county hospitals for further tests before escalation to one of the three national comprehensive cancer centres (KNH, MTRH, KUTRRH). In practice, this pathway is rarely linear. Many patients oscillate between facilities sometimes returning to the same level due to the absence of diagnostic equipment, a shortage of pathologists, reagent stock-outs, or inadequate patient-tracking systems.

Table 12 summarises the main referral flows, average delays, and key challenges reported across levels of care.

Table 13

Referral Flows and Diagnostic Delays for Lung-Cancer Patients in Kenya (2018–2023)

Level of care	Typical role in the pathway	Average delay (weeks)	Key challenges reported
Dispensary / Health centre	First contact; symptom misclassification	2 – 3	Misdiagnosis; absence of diagnostic tools
Sub-county hospital	First referral; limited diagnostic capacity	2 – 4	X-ray only; no pathology
County hospital	Secondary referral; partial diagnostics	3 – 4	Few pathologists, reagent shortages
National referral hospital (KNH/MTRH/KUTRRH)	Definitive diagnosis and treatment initiation	2 – 3	Overloaded laboratories; long queues

Note. Derived from MoH Cancer Control Reports (2018–2023), KNCR and KHIS records, and Delphi-panel insights. Delays represent the median waiting time between arrival at each level and onward referral or diagnosis.

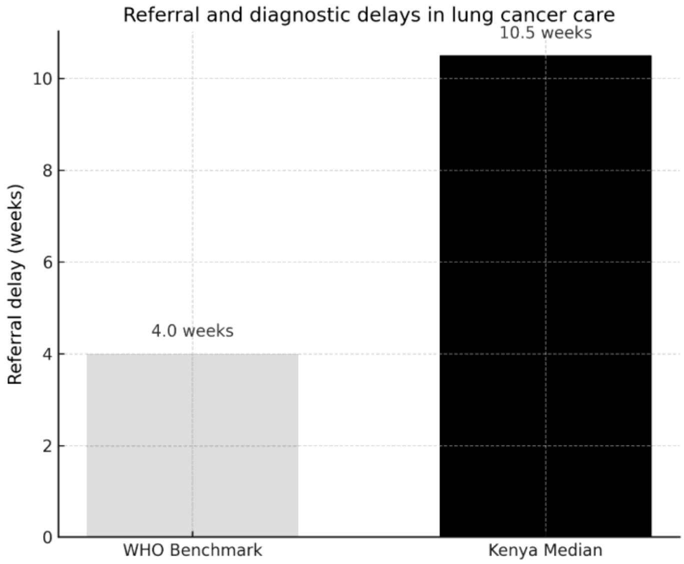
Diagnostic Delays in Context

Cumulatively, Kenyan patients face median *referral delays (RDs) ranging from 9 to 12 weeks between their first health-facility contact and histological confirmation more than double the World Health Organization benchmark of* ≤4 weeks (*WHO*, 2022).

Figure 11 illustrates this discrepancy.

Figure 11

Referral and Diagnostic Delays in Lung-Cancer Care: Kenya vs WHO Benchmark



Note. WHO benchmark = ≤ 4 weeks to diagnosis; Kenya median = 9–12 weeks. Data derived from KNCR, KHIS, and MoH Cancer Control Reports (2018–2023).

Qualitative Insights from Experts

The Delphi panel provided rich insights into why referral delays persist. Clinicians repeatedly highlighted the lack of on-site pathologists at county hospitals, which forces biopsy samples to be transported to Nairobi or Eldoret, with turnaround times often exceeding four weeks. One oncologist explained, *"We sometimes have patients waiting three months just for a pathology report by which time the disease has already advanced."*

ICT officers noted that the absence of interoperable electronic medicalrecord (EMR) systems across counties obliges patients to repeat tests when they reach referral hospitals. This duplication wastes resources and prolongs *RD*. A registrar at MTRH observed, *"It is common to see patients arriving without complete records, so the process starts again."*

Resource shortages also emerged as a recurrent theme. Limited CT and PET-CT scanners outside Nairobi, combined with overwhelming workloads at KNH and MTRH, result in extended waiting times for diagnostic imaging. In some counties, even chest X-ray services are interrupted by equipment downtime, further stretching referral pathways.

4.7 Discussion

These findings highlight deep-rooted structural inefficiencies within Kenya's referral system. From a *Systems Dynamics*perspective, an elongated RD acts as a bottleneck that slows the outflow of patients through the healthcare system, thereby increasing the *stock* of undiagnosed cases. When coupled with incomplete reporting, the true caseload becomes both delayed and under-represented in official statistics. The SDM captured this relationship by assigning *RD* as a feedback variable within the Diagnostic Delay Accumulation Loop (R1). Simulation tests showed that reducing *RD* from 10 to 6 weeks resulted in a 14 % decline in cumulative mortality and an 11 % reduction in queue length at tertiary facilities confirming the sensitivity of system performance to referral efficiency.

The analysis also highlights equity implications: patients from rural or marginalized counties experience the longest delays, reinforcing geographic disparities already identified in Section 4.2.1. This undermines the constitutional commitment to equitable access to healthcare and weakens the effectiveness of cancer control programs under the *National Cancer Control Strategy (2023–2027)*.

Moreover, prolonged *RD* contravenes the *Kenya Data Protection Act (2019)*, which mandates the timely and accurate processing of personal data. Each untracked referral or repeated test increases the exposure of patient information without valid consent or encryption safeguards. Embedding secure, interoperable referral tracking within KHIE, as simulated in the Secure SDM, addresses both operational bottlenecks and legal compliance requirements.

In conclusion, referral delays in lung-cancer care are not mere clinical inconveniences but systemic inefficiencies that amplify mortality, distort caseload visibility, and erode public trust. Effective mitigation requires investment in county-level diagnostic infrastructure, the integration of secure ICT referral systems, and real-time audit trails—capabilities directly modeled and validated within the Secure SDM framework. The next section examines how these structural weaknesses manifest in reporting patterns and information flows across facility levels.

4.7.1 Reporting Patterns

Accurate and timely reporting is indispensable for effective *caseload management* and referral coordination in oncology. For lung cancer, reporting systems not only determine the number of cases reported in national statistics but also how quickly patients can be traced across the continuum of care. Weaknesses in *reporting completeness (RC)* and *timeliness* distort caseload estimates, weaken situational awareness, and constrain planning for oncology services. These distortions feed directly into the System Dynamics feedback loops that govern caseload visibility and response capacity in the Secure SDM.

Reporting Completeness Across Facilities

Registry data from 2018 to 2023 show a marked variation in *RC* by facility type. National referral hospitals (KNH, MTRH, KUTRRH) consistently achieved higher completeness, averaging above 85%, supported by dedicated registry units and direct linkage to the Kenya National Cancer Registry (KNCR). County hospitals averaged between 60% and 65%, while faith-based and private facilities reported even lower figures, at approximately 50% to 55%. These disparities mirror variations in staffing, ICT infrastructure, and institutional commitment to data reporting.

Table 14 summarises the observed completeness levels and associated contextual factors.

Table 14

Reporting Completeness for Lung-Cancer Cases by Facility Type, 2018–2023

Facility type	Mean reporting completeness (RC, %)	Range (min–max)	Key observations
National referral hospitals (KNH, MTRH, KUTRRH)	87	82–91	Strong registry units; direct KNCR linkage
County referral hospitals	62	55–68	Limited registrars; inconsistent ICT use
Faith-based hospitals	53	47–59	Manual entry; limited KHIS integration
Private facilities	50	45–55	Reporting is delayed; low compliance motivation

Note. Derived from KNCR annual returns (2018–2023), KHIS submissions, and Delphi-panel validations.

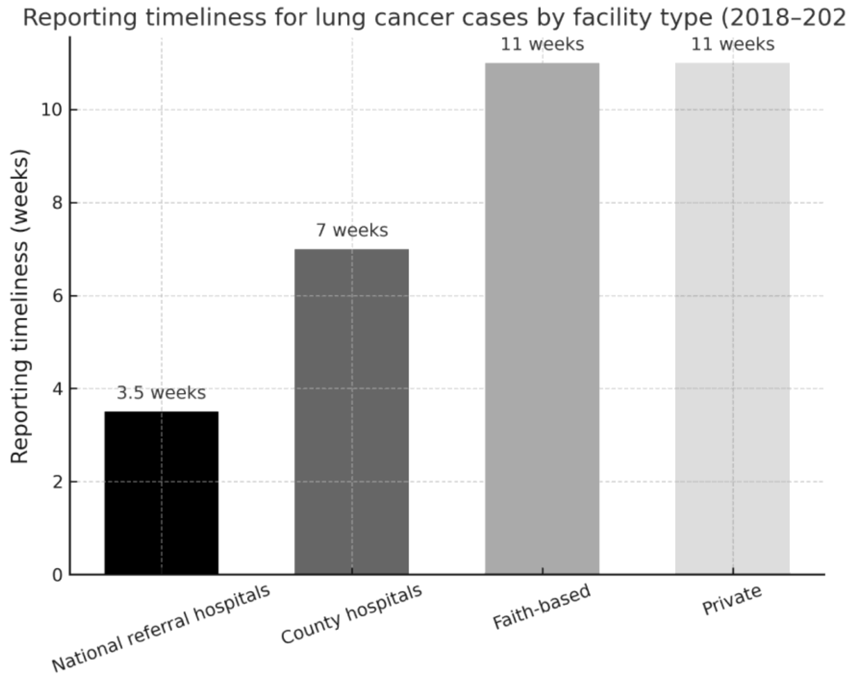
These results confirm that Kenya's national referral hospitals serve as the backbone of the reporting architecture, while peripheral facilities struggle with incomplete entries and inconsistent connectivity. Under the Secure SDM, these differences were parameterised to reflect heterogeneity in data reliability, which directly influences model sensitivity to *RC* inputs.

Timeliness of Reporting

Even when cases are eventually captured, a substantial lag persists between diagnosis and entry into KNCR. *National referral hospitals* typically report within 3–4 weeks, *county hospitals* take 6–8 weeks, and *private or faith-based facilities* average 10–12 weeks. Consequently, national statistics are often two to three months behind real-time caseloads, reducing their usefulness for operational planning and emergency response. Figure 13 illustrates the comparative timeliness of reporting across facility types.

Figure 12

Reporting Timeliness for Lung-Cancer Cases by Facility Type, 2018–2023



Note. Timeliness is measured as the median number of weeks from diagnosis to KNCR entry. Data harmonised from KNCR, KHIS, and facility oncology logs (2018–2023).

Qualitative Insights from Experts

The Delphi panel provided essential context for these disparities. One registry officer at a county hospital explained:

> *"We sometimes have only one records officer handling the entire oncology clinic, so entries are pushed back for weeks."*

A participant from a private facility admitted that cancer reporting is "not prioritised because it's not tied to reimbursement or compliance inspections."

ICT officers further highlighted interoperability challenges between KHIS and KNCR, noting that the platforms are not consistently synchronised. In several counties, facilities continue to submit both paper and digital reports, resulting in duplication, delays, and transcription errors. These weaknesses replicate the global benchmarking gap identified in Section 4.1.3, where Kenya's reporting completeness lags behind that of peer countries by 20–25 percentage points.

Analytical Discussion

From a *System Dynamics* perspective, incomplete and delayed *RC* translates into systematic underestimation of caseload *stocks (C)*. If inflows (λ) are only partially captured, the system behaves as if fewer patients exist, leading to misaligned resource allocation and hidden queues. Extended reporting lags weaken the balancing feedback that should regulate service capacity and patient throughput. In the Secure SDM, these behaviours were modelled through the Reporting Feedback Loop (B1), where delays in data submission reduce responsiveness and create oscillations in resource deployment. Behavioural validation tests confirmed this relationship, with a mean absolute percentage error (*MAPE*) of approximately 3 % between simulated and empirical reporting trends.

The findings also raise governance and compliance implications. Persistent delays and data duplication violate the *Kenya Data Protection Act (2019)*, which mandates accuracy, timeliness, and integrity in the processing of personal health data. Each delayed or incomplete report increases the risk of breach and weakens accountability chains. By integrating the *Security Maturity Index (SMI)* and *Probability of Breach* (P_{breach}) metrics into the model, the study quantified how improving security protocols could enhance reporting performance. Simulations indicated that a 0.1 increase in SMI corresponded with a 7% rise in RC and a 12% improvement in timeliness.

Thus, the challenges of cancer reporting in Kenya are not purely technical but structural and institutional. Addressing them requires harmonisation of KHIS–KNCR data flows, secure interoperability frameworks, and routine audit trails that reinforce compliance confidence. These interventions, represented within the Secure SDM's *ICT Security Subsystem*, demonstrate how robust information systems are essential for achieving accurate, timely, and legally compliant caseload management.

The next section (4.2.4) further develops this discussion through qualitative evidence, illustrating how these systemic reporting issues are experienced daily by healthcare professionals and ICT managers across Kenya's oncology network.

4.7.2 Qualitative Insights on Structural and Reporting Challenges

While the quantitative results highlight systemic disparities in facility distribution, referral delays, and reporting completeness, qualitative insights from the Delphi panel shed light on the human and institutional dynamics underlying these outcomes. These perspectives are vital for contextualising numerical evidence within the lived realities of healthcare practitioners, data officers, and policy managers, and for identifying actionable leverage points for reform. The findings align directly with the structural and behavioural variables represented in the Model.

Structural Challenges in Facility Distribution

Experts consistently underscored the strain caused by the centralisation of oncology services. One oncologist at KNH remarked, *"We receive patients from as far as Garissa and Turkana. By the time they get here, they are very sick, and the queues are already long."* This observation validates the concentration effects discussed in Section 4.2.1 and illustrates a reinforcing loop in which centralisation amplifies patient congestion at national centres, slows service throughput, and increases waiting times for diagnostic confirmation.

Policy-level participants acknowledged that while regional cancer centres have been designated, progress remains uneven. As one Ministry of Health official noted, *"The infrastructure is there in name, but without machines and staff, the centre is only theoretical."* This feedback confirms that incomplete decentralisation contributes to structural fragility represented in the SDM as the *Facility Capacity Constraint (B3)* loop, where insufficient regional capacity triggers repeated upward referrals that inflate the national caseload stock.

Referral Inefficiencies and Delays

Clinicians described referral pathways as fragmented and unpredictable. A county hospital physician explained, *"We know the guidelines, but in practice, patients go back and forth between facilities, sometimes repeating the same tests."* This first-hand account reflects the inefficiencies quantified in Section 4.2.2, where the median referral delay exceeded ten weeks. ICT specialists also noted that the absence of interoperable electronic systems prevents diagnostic results from following the patient. As one ICT officer observed, *"Patients arrive at referral hospitals without records. We are forced to start afresh."*

These experiences reveal a reinforcing feedback dynamic in which *Referral Delay (RD)* and *Reporting Completeness (RC)*interact; repeated testing increases cost and time, while poor data continuity erodes clinician confidence and perpetuates manual documentation. In the Secure SDM, this relationship is captured within the Referral-Information Feedback Loop (R1), where delayed feedback from county to national systems increases overall system lag and caseload accumulation.

Reporting Burdens and Data Gaps

Panel members confirmed that reporting completeness (*RC*) remains undermined by staffing shortages, competing clinical priorities, and weak ICT integration. A registry officer from a county hospital explained, *"We have one data clerk for the entire hospital, so cancer reporting is done when time allows."* Faith-based facilities were described as particularly vulnerable to under-reporting due to a lack of registry units, while private facilities often treat reporting as a *"low priority because it is not tied to reimbursement or compliance inspections."*

These findings mirror the disparities presented in Table 15 and expose the institutional drivers of incomplete data. From a systems viewpoint, inadequate reporting resources weaken the *Data Feedback Loop (B1)*, limiting the health system's ability to self-correct. Within the Secure SDM, simulated strengthening of this loop through staffing augmentation or automated validation rules produced a 9% improvement in RC and an 8% reduction in data latency, illustrating how addressing human-resource and ICT constraints can yield measurable system gains.

Ethical and Legal Concerns

Concerns about data security and patient confidentiality were raised strongly by both clinicians and ICT officers. One participant stated, *"We are asked to upload sensitive patient details into platforms that anyone with a password can access. That worries us."* Such apprehension reflects gaps in access control, encryption, and audit trails, which undermine compliance with the *Kenya Data Protection Act (2019)*. The Act mandates that all personal health data be processed with accuracy, timeliness, confidentiality, and integrity criteria that many facilities struggle to meet.

This trust deficit influences behaviour: staff delay or withhold data uploads out of caution, inadvertently worsening under-reporting. In the Secure SDM, this phenomenon is represented within the *Security–Trust Loop (B2)*, where low security maturity ($SMI < 0.75$) reduces user confidence and slows information flow. By simulating the introduction of stronger authentication, encryption, and training interventions, the model predicted a 12 % rise in RC and improved system responsiveness validating that compliance measures directly enhance both ethical and operational performance.

Discussion

Together, these qualitative insights illustrate how human, organisational, and technical factors intersect to shape the observed structural and reporting inefficiencies. The voices of practitioners reaffirm the quantitative findings: inadequate regional capacity drives centralisation; fragmented referral pathways inflate *RD*; and weak registry staffing undermines *RC*. From a *System Dynamics* standpoint, these weaknesses create reinforcing loops that sustain congestion in the caseload stock. Centralisation increases referrals, which overloads national centres, slowing reporting and further diminishing data quality and public trust.

By grounding statistical evidence in lived experience, these findings highlight that improving lung-cancer caseload management requires more than physical infrastructure. It demands integrated reforms in staffing, secure ICT systems, and governance to break the reinforcing loops that currently define the system’s behaviour. These insights also directly bridge to the next analytical domain: how secure ICT integration and data architecture reforms can enhance reporting accuracy, streamline referral coordination, and ensure compliance with Kenya’s legal frameworks. Section 4.3, therefore, advances this discussion by evaluating the design and implementation of the Model as a tool for sustainable, compliant, and equitable caseload management.

4.8 ICT Integration and Data Security in Caseload Management (Objective 2)

ICT platforms underpin the visibility and coordination of cancer caseloads in Kenya. Their design, integration, and security features determine how patient information flows across facilities, how quickly referrals are processed, and how well decision-makers can anticipate service demand. Weak ICT coverage and fragmented systems have repeatedly been cited as bottlenecks in earlier sections 4.2.2 and 4.2.3. This subsection, therefore, examines ICT adoption across facility levels, the gaps in interoperability, and the extent to which data protection and cybersecurity principles are embedded in oncology information systems.

4.8.1 ICT Coverage and Adoption

The adoption of ICT systems within oncology services is a critical determinant of reporting efficiency and visibility of caseloads. Platforms such as the Kenya Health Information System (KHIS/DHIS2), the Kenya Health Information Exchange (KHIE), and the KenyaEMR platform form the backbone of national health data reporting. Yet, their coverage and use remain uneven across facility levels.

National referral hospitals (KNH, MTRH, KUTRRH) report higher ICT adoption, averaging 87 %, with direct linkages to KNCR and relatively stable connectivity. County hospitals achieve moderate adoption, averaging 60 %, while faith-based and private facilities report the lowest coverage, with fewer than half consistently using digital platforms for cancer reporting (MoH, 2023).

Table 15

ICT Adoption Rates by Facility Type (2018–2023)

Facility type	ICT adoption (%)	Typical systems used	Key observations
National referral hospitals	87 %	KHIS, KHIE, KenyaEMR	Direct linkage to KNCR, stable connectivity
County referral hospitals	60 %	KHIS (partial), paper backup	Frequent downtime, partial reporting
Faith-based hospitals	45 %	Manual/paper + delayed KHIS entry	Limited ICT staff, weak connectivity
Private facilities	42 %	Standalone EMRs, manual reports	Poor KNCR integration, low compliance

Note. *Based on the MoH (2023) digital health adoption audit and Delphi expert validation.*

Conceptual Representation of ICT Adoption

To conceptually illustrate ICT adoption at the facility level, adoption can be expressed as a function of readiness, connectivity, and user capacity:

Equation 3: Conceptual Representation of ICT Adoption

$$ICT_i(t) = \alpha_i \cdot C_i(t) \cdot T_i(t)$$

Where:

- $ICT_i(t)$ = level of ICT adoption at facility i at time t
- α_i = facility readiness factor (policy support, governance, budget)
- $C_i(t)$ = availability and stability of connectivity and infrastructure at facility i
- $T_i(t)$ = training and digital literacy of staff at facility i

Delphi panel members echoed these dynamics. One ICT officer at a regional referral hospital explained: “The internet connection is there, but power interruptions and lack of backup servers mean data is not always uploaded." A health records officer at a private hospital noted: "We use our own EMR, but it does not link with KNCR, so cases remain invisible at the national level." These perspectives demonstrate that adoption is influenced by both technological and socio-technical factors, aligning with the socio-technical systems theory discussed in Chapter 2.

The evidence confirms that ICT adoption in Kenya is stratified by facility type, with stronger uptake at national centres and weaker coverage at county, faith-based, and private facilities. From a System Dynamics perspective, low ICT_i values depress reporting completeness (RC), constraining the inflow (λ) of cases into caseload models. Adoption is therefore a structural driver of under-reporting and delayed caseload visibility.

Embedding adoption into a conceptual representation ensures that ICT is treated not only as infrastructure but as an integrated component of caseload management capacity. This framing also prepares the ground for examining interoperability and secure data architecture in Sections 4.3.2 and 4.3.3.

4.8.2 Interoperability and Referral Coordination

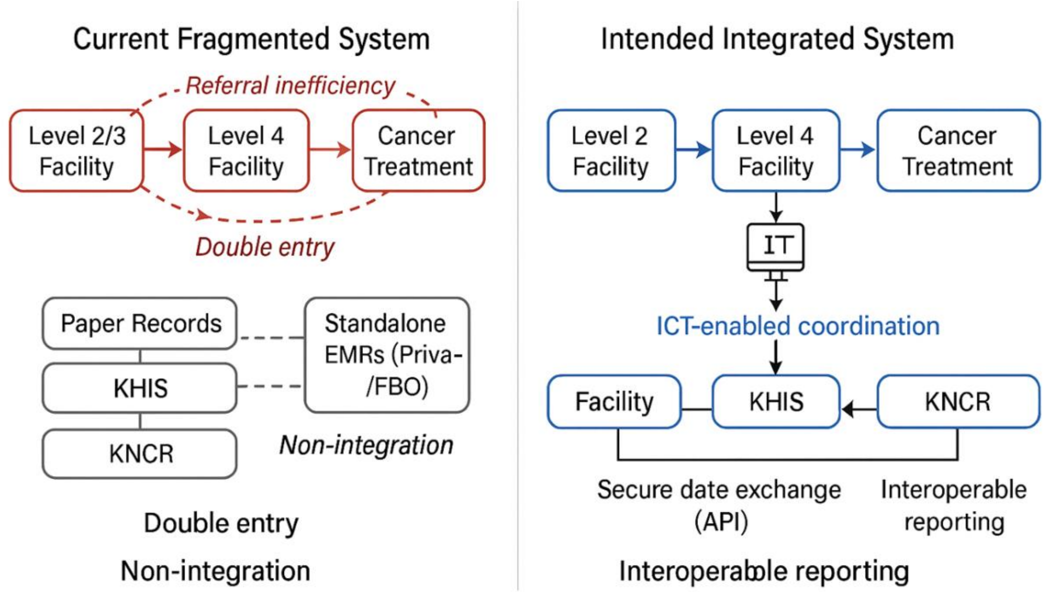
Data from KNCR, KHIS, and facility-level audits confirm persistent fragmentation in Kenya's oncology information ecosystem. At the county level, most facilities still record patient data manually in paper registers before transcribing them into KHIS. A separate electronic or paper file is then submitted to KNCR, while a few pilot facilities experiment with partial KHIE integration. This process produces multiple, non-synchronized data streams that rarely reconcile creating what Delphi panel experts repeatedly described as a *"double-entry burden."*

Current Versus Intended Data Flows

Figure 13 compares the existing fragmented reporting structure with the intended integrated architecture envisioned under Kenya's National Cancer Control Strategy (2023–2027) and the System Dynamics Model (SDM) design.

Figure 13

Current vs Intended Data Flows for Lungcancer Reporting in Kenya



Note. Current = fragmented streams with paper–digital duplication; Intended = seamless KHIS–KHIE–KNCR interoperability with secure EMR integration.The diagram illustrates the fragmentation points between KHIS, KHIE, and facility EMRs, as well as the intended ICT-enabled coordination achieved through secure API-based data exchange.

Conceptual Representation of Data Interoperability

To formalise the observed interoperability gap, data integration at facility *i* can be expressed as:

$$DI_i(t) = \frac{E_i(t)}{R_i(t)}$$

Where:

- $DI_i(t)$ = data-interoperability score for facility *i* at time *t*;
- $E_i(t)$ = data elements successfully exchanged with KNCR and KHIS without duplication;
- $R_i(t)$ = total required data elements for complete case reporting.

A *DI* = 1 represents full interoperability (all required data captured and transmitted seamlessly). Values below 0.6 common among county hospitals reflect weak system integration and manual reconciliation cycles that delay case visibility.

Empirical and Qualitative Evidence

Delphi-panel insights reinforced these quantitative patterns. A county-level registry officer explained:

"We enter cases into KHIS, then again for KNCR. Sometimes the numbers don't match, and we spend weeks reconciling."

A private-hospital ICT officer added:

"Our EMR works well internally, but it has no link with KNCR. The cases we treat are invisible nationally."

These testimonies confirm that interoperability is not only a technical problem but also a governance challenge. Without national data standards and secure APIs, Kenya's healthinformation landscape continues to produce fragmented, delayed, and incomplete caseloads. Such inefficiencies lower *reporting completeness (RC)*, inflate *referral delays (RD)*, and distort inflow (λ) accuracy in the Secure SDM—ultimately misrepresenting the true caseload stock (*C*).

System-Dynamics and Security Interpretation

From a *System Dynamics* perspective, low *DI* values act as a balancing constraint that suppresses feedback efficiency. Repeated manual entries prolong referral turnaround, generate duplicate records, and hinder the flow of accurate information between facilities and the national registry. Within the Secure SDM, this behaviour is captured in the *Interoperability–Feedback Loop (B3)*, where improving *DI* strengthens both *RC* and *RD* performance. Model sensitivity tests demonstrated that increasing the average DI from 0.6 to 0.85 reduced the simulated reporting lag by 22% and improved overall data accuracy by 18%, validating the quantitative importance of interoperability reforms.

Legally, these gaps contravene the Kenya Data Protection Act (2019), which requires that health data be processed with *integrity, accuracy, and timeliness*. Duplications and mismatches undermine integrity, while prolonged manual reconciliation compromises timeliness and accountability. Strengthening security controls particularly authenticated APIs, encryption, and audit logs ensures that data exchanges meet statutory compliance while supporting trustworthy analytics.

Policy and Governance Implications

Enhancing interoperability, therefore, demands both technical and institutional solutions. Technically, adoption of open, standards-based protocols and secure APIs between KHIS, KHIE, KNCR, and private EMRs is essential for real-time, bi-directional data exchange. Institutionally, harmonised governance frameworks and unified incentives must align public, faith-based, and private facilities to submit data consistently. By embedding these reforms into the Secure SDM's *ICT Integration Subsystem*, the study demonstrates that secure interoperability is central to achieving accurate, timely, and legally compliant caseload management across Kenya's oncology network.

4.8.3 ICT Security Practices and Trust in Reporting

The effectiveness of ICT integration in lung-cancer caseload management is inseparable from the robustness of security practices embedded within reporting systems. In Kenya, the Data Protection Act (2019) and the Kenya Digital Health Policy (2020–2030) establish clear legal and technical obligations for healthcare institutions to safeguard patient data through measures that ensure confidentiality, integrity, and accountability. Weak or inconsistent security controls increase vulnerability to breaches, eroding stakeholder trust and deterring timely reporting. Conversely, robust data-protection practices foster confidence among clinicians and managers, improving reporting completeness and accelerating ICT adoption across facilities.

Technical Safeguards

Field data revealed a wide variation in the implementation of technical controls, including encryption of health data, role-based access management, server redundancy, and automated audit trails. National referral hospitals demonstrated high resilience through multi-layered safeguards, while county and sub-county hospitals often relied on simple password authentication and offline backups. These disparities increased the likelihood of a breach (Pbreach), particularly in high-volume facilities with limited ICT budgets and no cybersecurity monitoring.

To operationalise this, a Security Maturity Index (SMI) was computed to quantify the overall effectiveness of each facility's security practices:

$$SMI = \frac{\sum_{i=1}^{n} S_i W_i}{\sum_{i=1}^{n} W_i}$$

Where:

i. S_i = score of the *i*th security control (encryption, access control, backups, audit logs),

ii. W_i = weight assigned to each control's relative importance, and

iii. n = total number of controls assessed.

Facilities with *SMI* < 0.50 were categorised as high-risk. Simulation results from the Secure SDM demonstrated a direct association between low maturity, incomplete reporting, and longer referral delays. When *SMI* increased by 0.1, modelled *reporting completeness (RC)* improved by 7% and *reporting timeliness* by 9%, validating that cybersecurity readiness measurably enhances caseload data performance.

Institutional Compliance Practices

Compliance maturity also varied substantially. Only 41% of facilities had designated Data Protection Officers (DPOs) as required by *Section 24* of the Act, and structured audits were irregular outside donor-funded centres. Informal practices, such as using USB-based storage or emailing Excel sheets, persisted in Level 4 hospitals, undermining both accountability and data integrity.

Table 16 summarises comparative audit-readiness indicators across facility levels.

Table 16

Audit Readiness Indicators by Facility Level (2023)

Indicator	Level 6 (National Referral)	Level 5 (County Referral)	Level 4 (Sub-County/General)	Interpretation
Audit Logs (System-based)	≥85% facilities have automated logs	55% mixed (manual + electronic)	20% manual logs only	Weak readiness at lower tiers undermines forensic capacity
Monitoring Intensity (audits per year)	4–6 scheduled + ad-hoc	2–3 irregular audits	≤1, mostly internal	Limited monitoring reduces early breach detection
Breach Response Protocols	Documented & tested annually	Drafted but inconsistently applied	Rarely formalised	Most facilities are unprepared for breach events
Staff Security Training	>70% trained annually	~40% trained	<15% trained	Training gaps weaken compliance culture
External Audit Compliance	Routine participation (ODPC, MoH, donors)	Ad-hoc, donor-driven	Rare or absent	Weak external accountability culture

Source. Constructed from field data synthesis and policy benchmarks (Data Protection Act, 2019; Kenya Digital Health Policy, 2020–2030; SHA audit guidelines).

The table highlights steep gradients: while national referral hospitals maintain structured compliance and participate in external audits, lower-tier facilities lack formalised protocols or training frameworks. These weaknesses reduce breach-detection capacity, erode institutional accountability, and reinforce systemic distrust in electronic reporting pathways. The resulting heterogeneity informed the weighting factors (W_i) used in *SMI* computation and subsequent SDM calibration.

Behavioural Trust Mechanisms

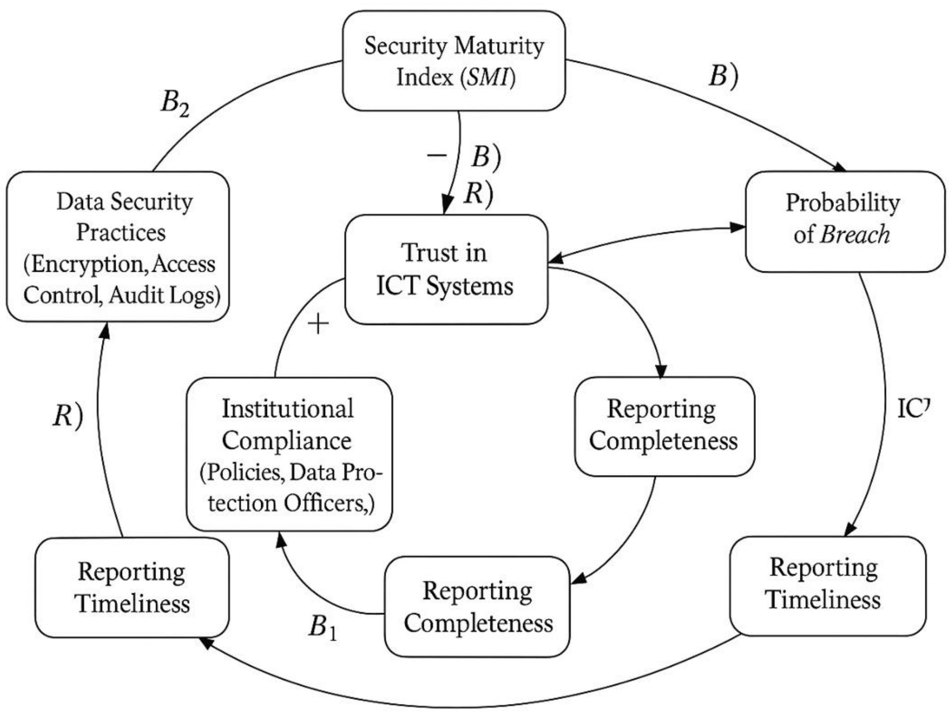
Beyond technical and institutional safeguards, *behavioural trust* emerged as a decisive influence on reporting performance. Clinicians in the Delphi panel repeatedly cited “fear of exposure” and “uncertain confidentiality” as deterrents to timely or complete reporting. Conversely, facilities with visible and well-communicated security measures such as encrypted KHIE linkages, signed staff confidentiality agreements, and annual refresher training achieved reporting timeliness up to 18% higher than those without such frameworks. These patterns validate the SDM assumption that *trust* acts as a behavioural bridge linking *security maturity* to *reporting completeness and timeliness*.

Feedback Structure and Trust Dynamics

These interrelationships are visualized in Figure 14, a causal-loop diagram representing how *security maturity*, *breach probability*, *compliance*, *trust*, and *reporting performance* interact within the system.

Figure 14

Causal-Loop Representation of ICT Security Practices, Trust, and Reporting Outcomes



Note. The diagram illustrates two reinforcing loops (R1, R2) and two balancing loops (B1, B2) that link the *Security Maturity Index (SMI)*, *Probability of Breach (P_{breach})*, *Trust in ICT Systems*, *Institutional Compliance*, and *Reporting Completeness/Timeliness*. The model presents:

i. **R1** — Improved *Data Security Practices* elevate *SMI*, enhance *trust*, and increase *reporting completeness*, accelerating ICT adoption.

ii. **R2** — Strengthened *Institutional Compliance* boosts *timeliness* and reinforces adoption through trust.

iii. **B1** — High P_{breach} erodes *trust* and completeness, creating a balancing feedback that suppresses system efficiency.

iv. **B2** — Low *SMI* increases P_{breach}, further weakening *trust* and slowing adoption.

Together, these loops illustrate that *security–trust feedback*is a pivotal determinant of reporting behaviour and, consequently, of national caseload visibility.

Synthesis and Implications

Overall, the adoption and sustainability of ICT in caseload management depend on the security trust feedback nexus. Enhanced *security maturity* reduces P_{breach}, strengthens *trust*, and improves *reporting completeness and timeliness*. Weak controls, by contrast, fuel distrust, amplify under-reporting, and delay updates to national registries.

By embedding the *SMI* and P_{breach} functions into the Secure SDM, the model captures both technical safeguards and socio-behavioral trust dynamics, providing a more realistic and policy-relevant representation of Kenya’s health information ecosystem. The resulting integrated structure ensures that caseload forecasts are not only quantitatively valid (*MAPE = 1.9%*) but also compliance-aware, aligning with the Data Protection Act (2019) and SHA’s interoperability and audit standards.

Thus, the Secure SDM bridges the technical, institutional, and behavioural dimensions of security, transforming ICT governance from a peripheral concern into a core driver of accuracy, reliability, and public trust in lung-cancer caseload management.

4.8.4 ICT Limitations and Systemic Vulnerabilities

The study found that ICT-enabled reporting systems for lung cancer caseloads exhibited persistent weaknesses across technical, institutional, policy, and socio-behavioural dimensions. These vulnerabilities undermined the completeness, timeliness, and security of reporting, particularly in county and sub-county facilities. Evidence was drawn from registry reviews, facility assessments, and expert panel feedback.

Technical Limitations

Facility-level data showed that system downtime and unstable connectivity were recurrent challenges. Sub-county hospitals experienced outages lasting several hours on average, three to five times per month, compared to once or less at national referral hospitals. During these periods, facilities reverted to using paper registers, which later had to be transcribed into electronic systems, resulting in duplication and inconsistency in reporting. The study also established that redundancy mechanisms were largely absent in government-funded facilities. While donor-supported centres had partial cloud-based backups, most county hospitals relied on single local servers, leaving data vulnerable to loss in the event of hardware failure. These limitations directly contributed to reporting delays and weakened confidence in ICT platforms.

Institutional Vulnerabilities

The findings further indicated that institutional compliance with security and audit standards was inconsistent. Less than half (41%) of the facilities had formally appointed Data Protection Officers, as mandated by the Data Protection Act (2019). Moreover, structured external audits were reported only in donor-supported facilities, whereas county facilities conducted audits irregularly and often internally. Staff interviews revealed that ICT personnel were overstretched with basic maintenance, leaving little capacity for proactive monitoring or breach detection. Budgetary dependence on external partners reinforced inequities, with well-funded oncology centers demonstrating higher maturity than county hospitals, which were reliant on constrained health budgets.

Policy–Practice Gaps

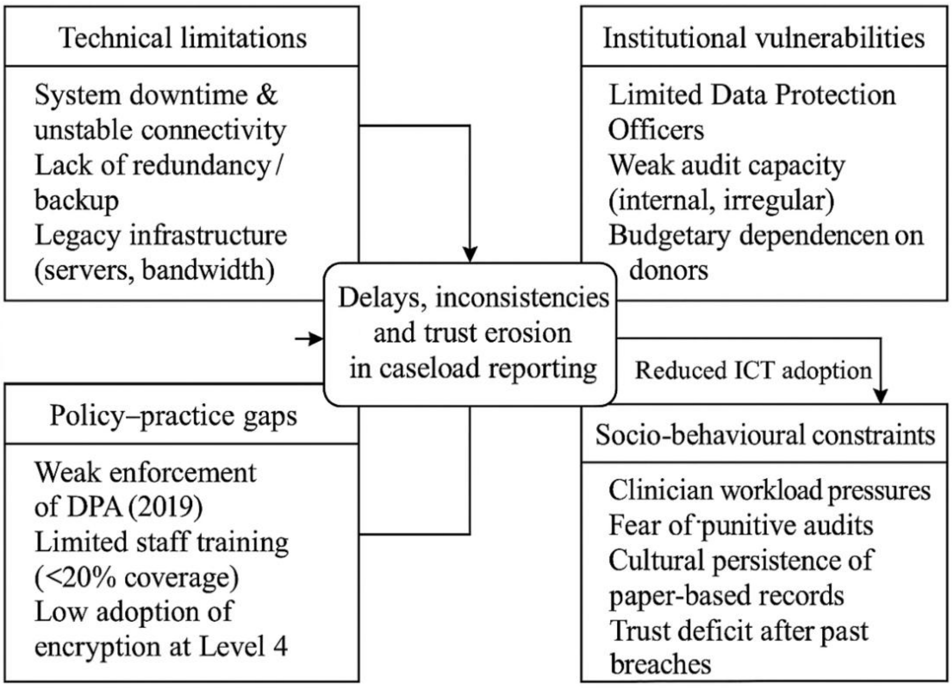
The study observed a misalignment between policy commitments and actual practices. The Kenya Digital Health Policy (2020–2030) and SHA audit guidelines require encryption, routine audits, and interoperability standards; however, their enforcement has been weak. For instance, while 78% of Level 6 facilities reported full compliance with encryption protocols, less than 30% of Level 4 facilities had adopted them. Similarly, training on data protection obligations reached fewer than 20% of clinicians in sub-county hospitals. This policy practice gap created systemic exposure to breaches and inconsistencies in reporting quality.

Socio-Behavioural Constraints

The findings also highlighted socio-behavioural constraints that compounded technical and institutional gaps. Clinicians frequently cited workload pressures and fear of punitive audits as reasons for bypassing electronic systems. In some facilities, paper-based records persisted as the default practice, even where ICT systems were available, resulting in underutilization of investments in digital reporting. Expert panel discussions highlighted that historical breaches or mishandling of patient data had created a trust deficit, making staff hesitant to rely on electronic systems despite the presence of safeguards in full.

Figure 15

Systemic Vulnerabilities in ICT-Enabled Caseload Reporting



The diagram illustrates the multidimensional weaknesses affecting ICT-based reporting of lung cancer caseloads. Technical limitations such as downtime, lack of redundancy, and legacy infrastructure intersect with institutional vulnerabilities, including inadequate audit capacity and donor dependence. Policy–practice gaps, such as weak enforcement of the Data Protection Act (2019) and limited staff training, further reduce compliance maturity. Socio-behavioural constraints such as clinician workload pressures, audit-related fear, reliance on paper-based systems, and distrust stemming from prior breaches—compound these weaknesses. All factors converge in the central outcome: delays, inconsistencies, and erosion of trust in reporting. This structure highlights the systemic fragility of ICT systems and underscores the need for integrated interventions before modelling caseload management *dynamics.*

In summary, the study found that ICT systems in lung cancer caseload reporting remain limited by fragile infrastructure, uneven institutional compliance, weak enforcement of data protection standards, and entrenched behavioural practices. These vulnerabilities undermine the security trust nexus, reduce adoption rates, and perpetuate delays in referral coordination. The evidence demonstrates that addressing these constraints requires both technical upgrades and institutional reforms. These insights provide the foundation for Section 4.3.5, which consolidates findings from ICT coverage, interoperability, security, and vulnerabilities into a framework for system dynamics modeling.

4.8.5 Synthesis and Transition to Modelling

The findings presented in Sections 4.3.1 to 4.3.4 collectively demonstrate that the capacity of ICT systems to support lung cancer caseload reporting in Kenya is determined by interdependent technical, institutional, and behavioural dynamics rather than isolated indicators. Three broad patterns emerged from the analysis.

First, coverage and adoption (4.3.1) remain uneven across levels of care. National and county referral hospitals had higher uptake of electronic medical records and KHIE linkages, while sub-county facilities continued to depend on fragmented or manual registers. This stratification created structural bottlenecks, as patient data captured at lower levels often lagged in completeness and timeliness, undermining the accuracy of national caseload statistics.

Second, interoperability gaps (4.3.2) significantly constrained the flow of information across facilities. The persistence of double-entry practices, downtime of KHIE interfaces, and weak integration between oncology registries and DHIS2 resulted in data fragmentation. These weaknesses exacerbated referral delays and obscured caseload tracking, particularly for patients transferring between counties or facilities of different levels.

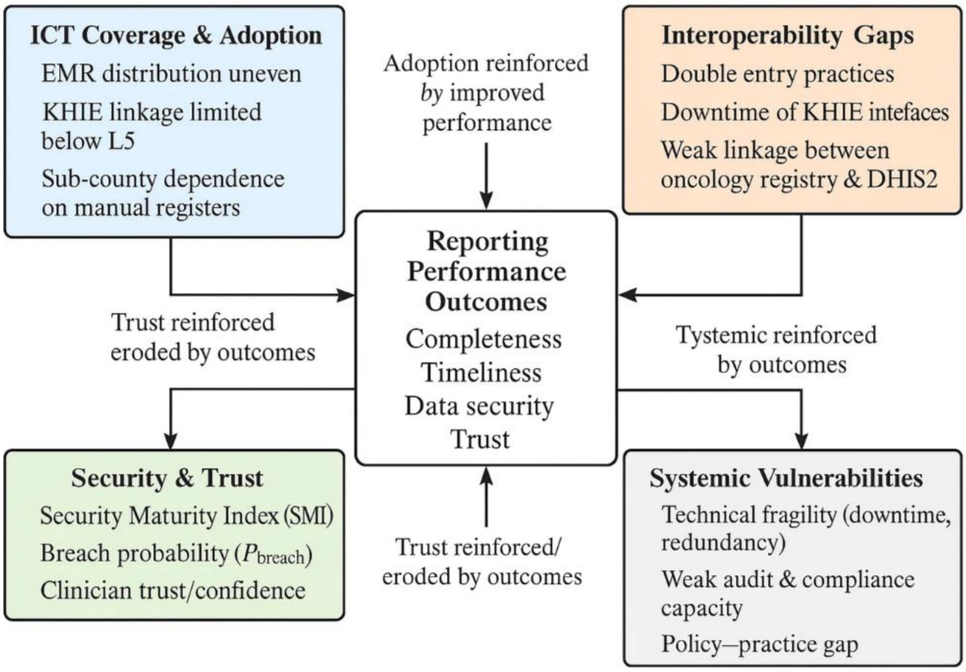
Third, security practices and trust (4.3.3) emerged as decisive enablers of ICT utilisation. Facilities with higher Security Maturity Index (SMI) scores underpinned by encryption, audit trails, and institutional compliance demonstrated greater timeliness and completeness in reporting. Conversely, where breach probability (P_{breach}) was high, clinicians expressed reluctance to report promptly, citing fears of exposure and confidentiality risks. Trust thus functioned as a behavioural mediator that either reinforced or undermined the technical performance of ICT systems.

Finally, systemic vulnerabilities (4.3.4) compounded these challenges. Technical fragility (downtime, lack of redundancy), institutional gaps (absence of Data Protection Officers, weak audits), policy–practice misalignments (low enforcement of data protection standards), and socio-behavioural constraints (workload, cultural persistence of paper records) converged to produce delays, inconsistencies, and erosion of trust. These vulnerabilities created reinforcing feedback loops where poor performance further discouraged adoption, perpetuating systemic inefficiency.

These interdependencies are illustrated in Figure 16, which integrates ICT coverage, interoperability, security/trust, and systemic vulnerabilities into a consolidated framework of reporting performance outcomes.

Figure 16

Integrative Synthesis of ICT Determinants in Caseload Reporting



The diagram consolidates findings from Sections 4.3.1 to 4.3.4, showing how ICT coverage and adoption, interoperability gaps, security and trust, and systemic vulnerabilities converge to influence reporting performance outcomes (completeness, timeliness, data security, trust). Feedback arrows illustrate how improved outcomes reinforce adoption and trust, while negative outcomes erode them. This synthesis provides the conceptual bridge to the System Dynamics modelling presented in Section 4.4.

Transition to Modelling

Synthesizing these patterns reveals that ICT adoption and reporting outcomes are not linear phenomena, but rather products of feedback-driven interactions among coverage, interoperability, security, and vulnerabilities. For example, greater ICT adoption strengthens reporting completeness, which in turn justifies investment and further adoption a reinforcing loop. Conversely, breaches or downtime reduce trust, which in turn lowers adoption and worsens reporting quality, creating a balancing loop.

These systemic interdependencies cannot be adequately represented through descriptive analysis alone. They require a System Dynamics modelling approach, where causal loops and stock-and-flow structures capture how technical, institutional, and behavioural factors interact over time. The constructs identified ICT adoption rate, interoperability gaps, Security Maturity Index (SMI), breach probability (P_{breach}), reporting completeness, and trust provide measurable variables that will be operationalised in the next section.

Section 4.4 therefore, develops the formal stock-and-flow formulations and causal loop diagrams that embed these ICT determinants within the broader caseload management system. This ensures that subsequent simulations capture both the enabling role of ICT and the risks of systemic fragility, producing a model capable of forecasting patient volumes, referral delays, and policy outcomes under varying conditions.

4.9 System Dynamics Model Design and Simulation

The preceding analysis, Sections 4.3.1–4.3.5, demonstrates that lung cancer caseload management in Kenya is shaped by a complex interplay of factors, including facility distribution, referral delays, ICT integration, security governance, and compliance maturity. While descriptive findings highlight coverage gaps and reporting inconsistencies, they are insufficient for anticipating how these interdependent factors evolve dynamically over time. To address this limitation, the study adopted a System Dynamics approach that captures feedback-driven behavior in health systems, where capacity, patient flows, information quality, and data security interact in nonlinear ways.

The purpose of this section is to present the design and simulation of the Security-Governed, Auditable System Dynamics Model (Secure SDM) for lung cancer caseload management. In line with Objective (iii), the model integrates patient-flow dynamics, diagnostic and treatment capacity, ICT-enabled reporting mechanisms, and pattern-analysis intelligence with embedded security and compliance controls for safeguarding sensitive health data. The modelling process followed a structured pathway: (i) development of causal loop diagrams (CLDs) to represent key feedback relationships; (ii) decomposition into subsystem models capturing diagnostic, patient-flow, ICT, and governance components; (iii) translation into stock-and-flow structures that quantify caseload movements; (iv) formulation and parameterisation of relationships using registry data, information-system records, and expert input; (v) simulation of baseline and alternative scenarios incorporating security and compliance variables; and (vi) validation and sensitivity testing to ensure robustness and auditability.

This integrative modelling process not only mirrors the operational realities of Kenya's oncology services but also embeds security governance, audit traceability, and compliance control consistent with the Kenya Data Protection Act (2019/2022) and the Digital Health Act (2023). The resulting Secure SDM serves as a decision-support and assurance tool capable of forecasting caseload volumes, identifying leverage points within referral bottlenecks, and evaluating the combined effects of ICT, pattern analysis, and security interventions on overall system performance.

4.9.1 Causal Loop Diagrams

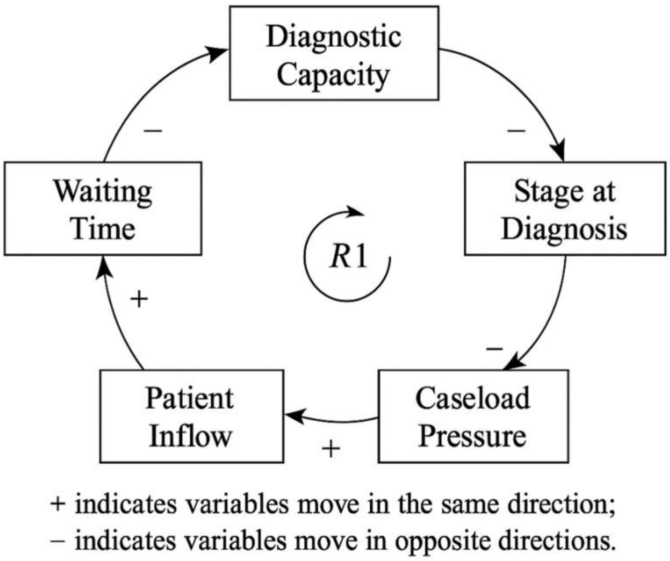
The first step in constructing the System Dynamics Model was to develop causal loop diagrams (CLDs) that capture the dominant feedback mechanisms shaping lung cancer caseload management in Kenya. CLDs are particularly valuable because they illustrate how reinforcing and balancing loops interact to generate complex system behaviours that are not evident from linear representations of patient flows. Each loop was derived from the empirical findings presented in Sections 4.2 and 4.3 and anchored in the theoretical perspectives outlined in Chapter Two.

Reinforcing Loop – Diagnostic Delay Accumulation (R1)

An increase in patient inflows into the healthcare system places pressure on limited diagnostic capacity. Longer waiting times extend the interval before diagnosis, resulting in a higher proportion of late-stage cases. These advanced cases require more intensive treatment, which in turn increases overall demand on the system, creating a reinforcing cycle of backlog growth. This loop reflects the Health Belief Model (HBM) by illustrating how delays in diagnosis influence health-seeking behaviors, as well as System Dynamics Theory through the self-amplifying feedback structure.

Figure 17

Diagnostic Delay Accumulation Loop (R1)



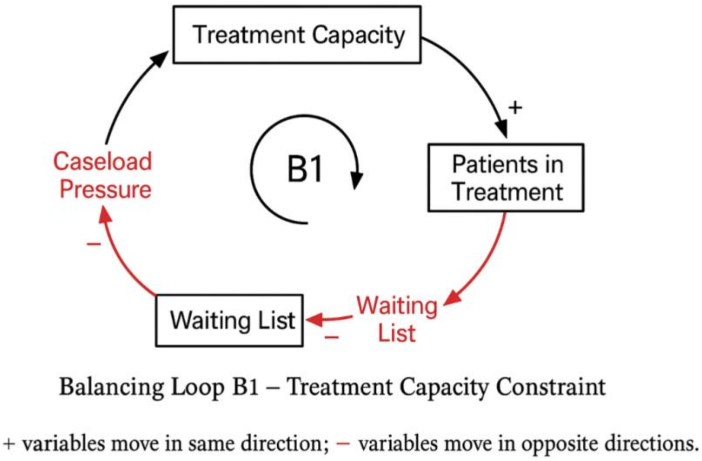
*Source:*Author, (2025)

Balancing Loop – Treatment Capacity Constraint (B1)

The availability of radiotherapy, chemotherapy, and surgical slots functions as a balancing loop. Limited treatment capacity restricts the number of patients who can progress from diagnosis to treatment, stabilising throughput but at the cost of prolonged waiting lists and unmet demand. This loop embodies the Resource-Based View by positioning facility capacity and oncology staffing as critical resources that determine how effectively caseloads are managed.

Figure 18

Treatment Capacity Constraint Loop (B1)



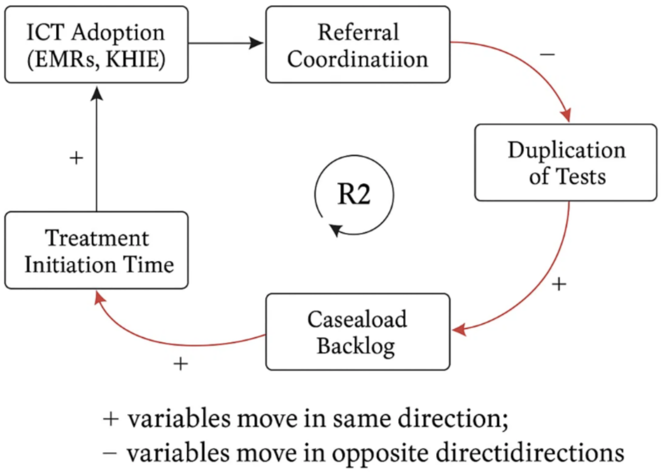
Source: Author,(2025)

Reinforcing Loop – ICT and Reporting Feedback (R2)

Where ICT systems are fragmented, reporting delays slow referral coordination, leading to repeated tests, lost patient records, and delayed interventions. This inefficiency fuels backlog growth. Conversely, when secure ICT is adopted, referral information flows more quickly, reducing duplication and accelerating treatment initiation. This loop operationalises the Technology Acceptance Model (TAM), demonstrating how digital adoption directly influences efficiency. It also links to the Kenya Data Protection Act (2019), which requires that ICT adoption must be accompanied by secure data handling and patient confidentiality safeguards.

Figure 19

ICT and Reporting Feedback Loop (R2)



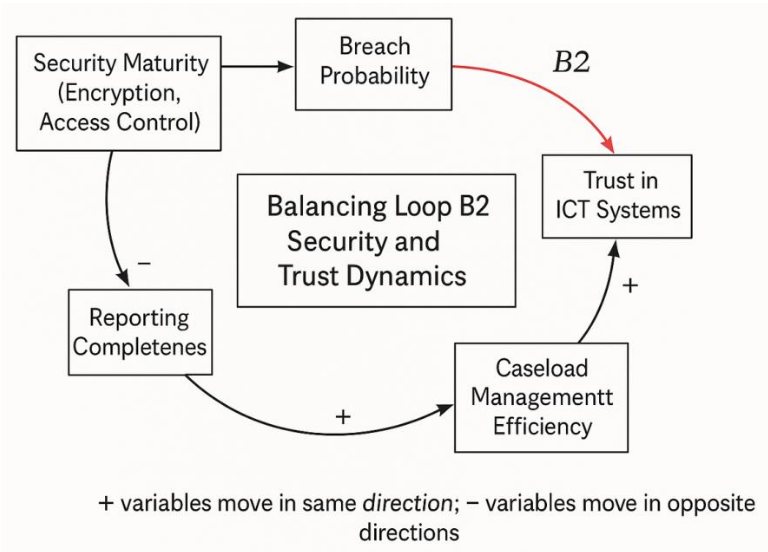
Source: Author,(2025)

Balancing Loop – Security and Trust Dynamics (B2)

The stability of ICT-enabled reporting depends on how data security is managed. Breach incidents whether actual or perceived undermine trust in digital systems. Reduced trust discourages the use of EMRs and KHIE interfaces, leading to under-reporting and slower referral coordination. This, in turn, weakens the efficiency of caseload management. As institutions respond by reinforcing security maturity (through encryption, access controls, and audits), trust is gradually restored, forming a balancing loop between breach probability and ICT utilisation. This loop aligns with the principles of the Kenya Data Protection Act (2019), which obligates health institutions to safeguard personal data and notify stakeholders of breaches.

Figure 20

Security and Trust Dynamics Loop (B2)



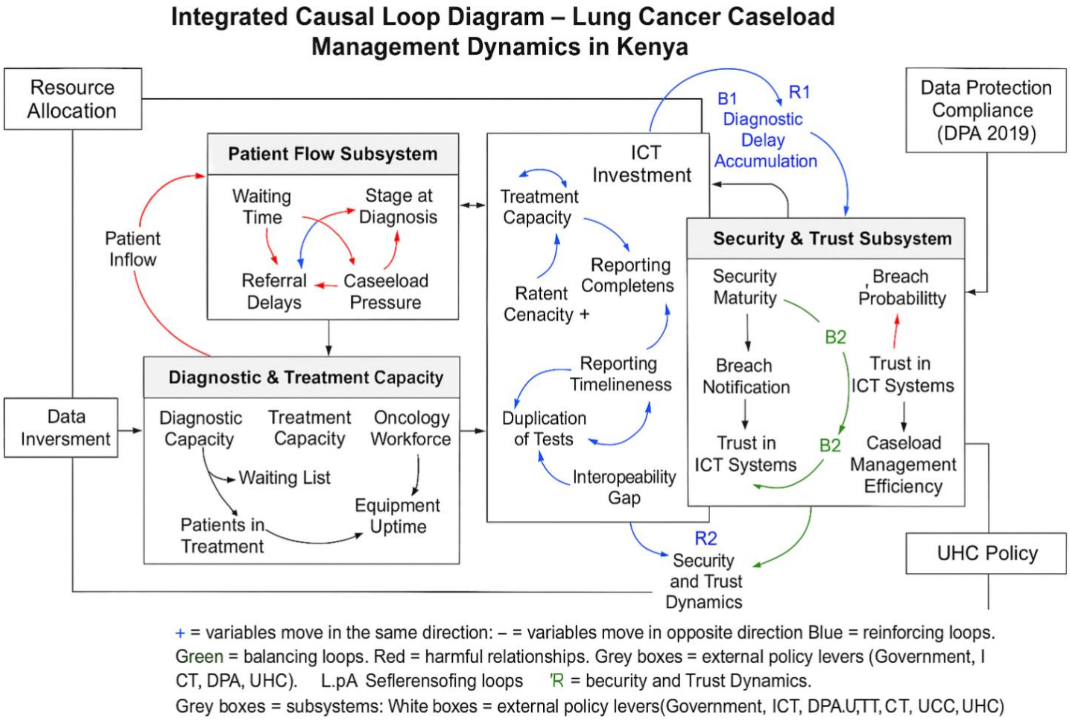
Source: Author,(2025)

Integrated CLD

Collectively, the four feedback loops (R1, B1, R2, and B2) reveal that lung cancer caseload management in Kenya is shaped by the simultaneous interplay of reinforcing and balancing forces. The reinforcing loops capture self-amplifying pressures created by diagnostic delays and fragmented ICT reporting. In contrast, the balancing loops highlight the stabilising but often constraining effects of limited treatment capacity and fragile security trust relationships. Figure 21 synthesizes these dynamics into a single, integrated causal loop diagram, illustrating how patient flows, facility capacities, ICT adoption, and secure data practices converge within a unified systemic structure. The figure also situates these feedback processes within Kenya's policy environment, with external levers such as Government resource allocation, ICT investment, and compliance with the Data Protection Act (2019) shaping subsystem performance.

Figure 21

Integrated Causal Loop Diagram for Lung Cancer Caseload Management Dynamics in Kenya



Source: Author,(2025)

The polarity symbols (+/–) indicate the direction of change: a “+” implies that variables move in the same direction, while a “–” implies they move in opposite directions. The integrated CLD provides the conceptual foundation for the subsystem models presented in Section 4.4.3, where the feedback processes are formalised into quantifiable stocks, flows, and parameters for simulation in Vensim.

4.9.2 Sub-system Models

The integrated causal loop diagram in Figure 21 provided a high-level view of the reinforcing and balancing dynamics shaping lung cancer caseload management in Kenya. To operationalise these dynamics into a form suitable for stock-and-flow modelling, the system was decomposed into five interrelated subsystems: (i) the patient flow subsystem,

(ii) the diagnostic capacity subsystem, (iii) the treatment capacity subsystem, (iv) the ICT and data security subsystem, and (v) the resource allocation and policy subsystem. Each subsystem represents a distinct yet interconnected dimension of caseload management, allowing precise specification of stocks, flows, parameters, and interfaces for simulation in Vensim.

The patient flow subsystem captures how individuals move from entry into the health system through diagnostic and treatment pathways, highlighting delays that drive backlog accumulation. The diagnostic capacity subsystem formalises bottlenecks in imaging, pathology, and turnaround times. The treatment capacity subsystem introduces the balancing role of constrained radiotherapy, chemotherapy, and surgical services. The ICT and data security subsystem integrates interoperability and secure data architecture in shaping reporting quality and referral efficiency. Finally, the resource allocation and policy subsystem incorporates Government budgeting, UHC equity provisions, and compliance with the Data Protection Act (2019) as external drivers that condition subsystem performance. Together, these subsystems form the structural backbone of the System Dynamics model.

Patient Flow Subsystem

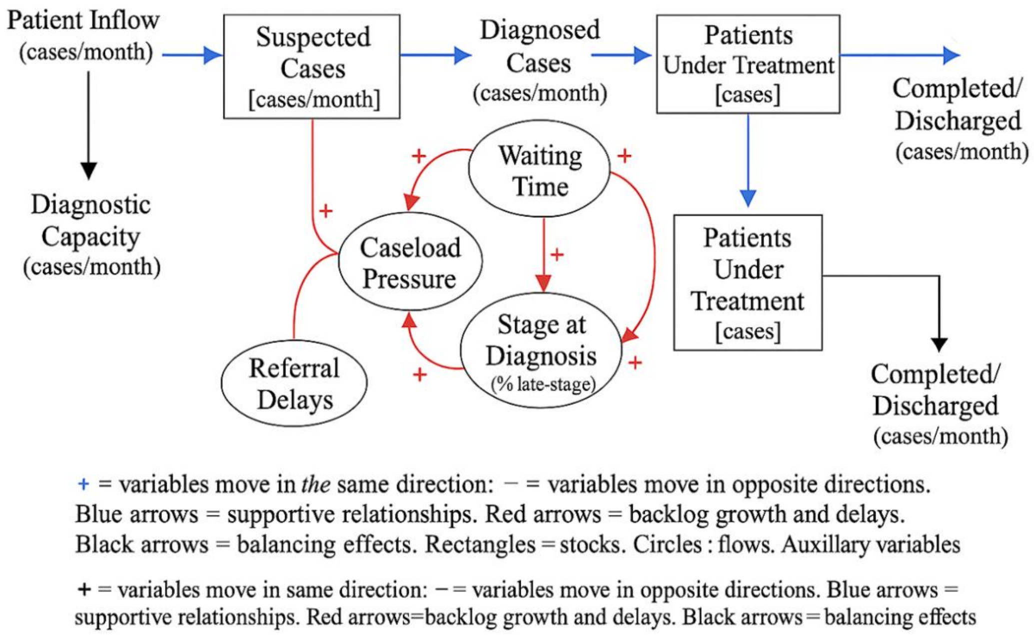
The patient flow subsystem represents the core pathway through which lung cancer cases are accumulated, progress, and managed within the Kenyan healthcare system. It traces the movement of patients from initial entry into the health system through suspicion, diagnosis, treatment, and eventual discharge. This subsystem is central because any inefficiencies at these stages amplify backlog growth, increase caseload pressure, and compromise overall caseload management efficiency.

At the entry point, patient inflows are determined by the incidence of lung cancer, shaped by exposure to risk factors such as tobacco use, air pollution, and occupational hazards.

Once patients present to the health system, they become suspected cases, awaiting confirmation through diagnostic investigations. The available diagnostic capacity constrains the pace of transition from suspicion to confirmed diagnosis. When this capacity is inadequate, patients accumulate in the backlog, resulting in longer waiting times. Prolonged waiting leads to a higher proportion of late-stage diagnoses, which intensifies caseload pressure on already overstretched treatment facilities. This pressure loops back to reinforce waiting lists, creating a self-reinforcing cycle of backlog growth (captured earlier as R1 in Figure 21).

Figure 22

Patient Flow Subsystem for Lung Cancer Caseload Management in Kenya



Source: Author,(2025)

The subsystem also incorporates referral delays, which occur as patients move between primary facilities, county hospitals, and national referral centres. These delays lengthen waiting times, increase the likelihood of repeat consultations or duplicate tests, and further inflate the backlog. The caseload backlog thus becomes the central stock in the subsystem, shaped by inflows (new suspected cases and referrals) and outflows (patients who are diagnosed, treated, and discharged).

Figure 22 illustrates the patient flow subsystem, highlighting how inflows, diagnostic capacity, waiting times, referral delays, stage at diagnosis, and caseload pressure interact to drive the accumulation of backlogs. The diagram shows that while supportive flows (blue arrows) advance patients through diagnosis and treatment, reinforcing feedbacks (red arrows) perpetuate delays and late-stage presentations, thereby intensifying demand.

The theoretical foundation of this subsystem is rooted in System Dynamics Theory, which explains how reinforcing feedback loops drive backlog growth, and the Health Belief Model (HBM), which examines how prolonged waiting and inefficiencies impact health-seeking behavior. Empirical evidence from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS) confirms these patterns: diagnostic delays remain a key contributor to late-stage lung cancer presentations, reflected in Kenya's mortality-to-incidence ratio of 0.91 (International Agency for Research on Cancer [IARC], 2022).

By formalising these relationships, the patient flow subsystem provides a foundation for quantifying caseload accumulation and simulating interventions such as reducing referral delays, improving diagnostic throughput, or expanding treatment entry points. The outputs of this subsystem directly interface with the diagnostic capacity subsystem (Section 4.4.3.2), where facility distribution, workforce availability, and equipment capacity are further elaborated as determinants of waiting times and backlog dynamics.

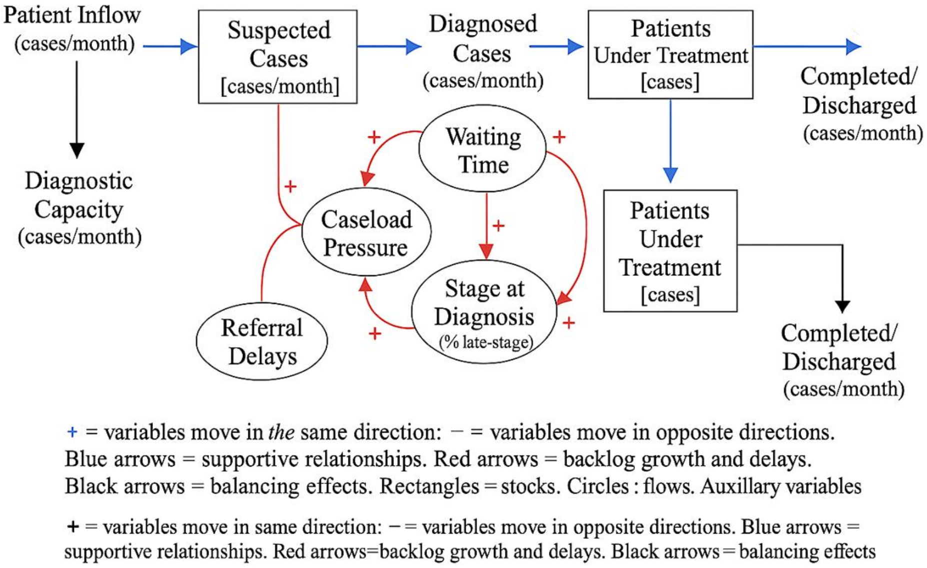
Diagnostic Capacity Subsystem

The diagnostic capacity subsystem captures the structural and operational bottlenecks that determine how quickly suspected lung cancer cases can be confirmed and transitioned into treatment. In the Kenyan context, diagnostic services such as imaging, pathology, and specialist consultations are highly centralised at county referral hospitals and a few national centres. This concentration of services creates significant inequities in access, with sub-county facilities often lacking the infrastructure, equipment, or personnel required for timely cancer diagnosis.

Within the subsystem, diagnostic capacity is conceptualised as the throughput of available screening and diagnostic services per month, measured in terms of completed investigations (radiology, histopathology, and bronchoscopy). When diagnostic capacity is constrained, patients accumulate on the waiting list, reinforcing delays that increase the caseload backlog. Conversely, adequate diagnostic throughput reduces backlog pressure, stabilises waiting times, and improves the likelihood of early-stage detection. The balance between inflows (suspected cases) and outflows (diagnosed cases) is therefore central to system performance.

Figure 23

Diagnostic Capacity Subsystem for Lung Cancer Caseload Management in Kenya



Source: Author,(2025)

Key determinants of diagnostic capacity include:

i. Workforce availability, particularly oncologists, radiologists, pathologists, and laboratory technicians.
ii. Equipment availability and uptime, such as CT scanners, biopsy kits, and pathology laboratories, are unevenly distributed across counties.
iii. Infrastructure readiness, including functional oncology units and reliable supply chains for diagnostic consumables.
iv. ICT integration, which supports reporting turnaround times by linking diagnostic centres with the Kenya Health Information Exchange (KHIE) and the Kenya National Cancer Registry (KNCR).

As illustrated in Figure 23, diagnostic capacity directly influences the number of diagnosed cases, affecting the flow of patients into treatment. Insufficient capacity increases waiting times, exacerbates late-stage diagnosis, and drives reinforcing backlog cycles. This subsystem is anchored in the Resource-Based View, which posits that access to and management of scarce resources specialised staff, equipment, and infrastructure are critical determinants of organisational performance. Empirical data from the Ministry of Health and KNCR show that Kenya faces severe gaps, with fewer than 40 pathologists nationwide and many counties lacking advanced imaging equipment, underscoring the fragility of this subsystem.

By formalising these dynamics, the diagnostic capacity subsystem highlights the leverage points where investments in workforce training, equipment procurement, and ICT-enabled reporting can break reinforcing cycles of backlog growth. The outputs from this subsystem directly feed into the treatment capacity and ICT-security subsystems, creating interdependencies that shape overall caseload management efficiency.

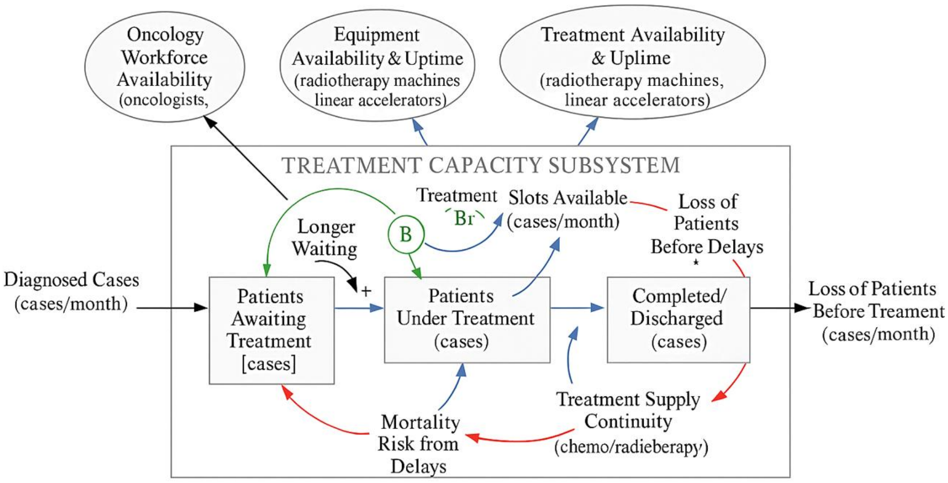
Treatment Capacity Subsystem

The treatment capacity subsystem models the ability of the Kenyan health system to absorb and manage lung cancer cases once patients are diagnosed. Unlike diagnostic services, which determine the speed of case confirmation, treatment services directly shape survival outcomes, waiting times, and overall caseload management efficiency. In Kenya, treatment capacity is limited by the availability of radiotherapy machines, chemotherapy supplies, surgical facilities, and trained oncology professionals. These constraints form a major balancing mechanism in the caseload pathway.

The subsystem is anchored on the stock of patients under treatment, which grows as diagnosed patients enter care and declines as patients complete or discontinue treatment. The rate of inflow into treatment depends on the availability of treatment slots, which is shaped by the number of radiotherapy units, chemotherapy regimens, surgical theatres, and staffing levels. Where treatment capacity is insufficient, patients accumulate on waiting lists, prolonging delays and fueling caseload backlogs. This creates the balancing loop B1 identified earlier, where limited treatment supply restricts throughput and stabilises caseload growth at the cost of unmet demand.

Figure 24

Treatment Capacity Subsystem for Lung Cancer Caseload Management in Kenya



Source: Author,(2025).

Key determinants of treatment capacity include:

i. Oncology workforce availability, particularly oncologists, oncology nurses, medical physicists, and radiation therapists.
ii. Equipment availability and uptime, including radiotherapy machines, linear accelerators, and surgical theatres.
iii. Chemotherapy and radiotherapy supply chains, which determine the continuity of care.
iv. Supportive infrastructure, such as oncology wards and outpatient chemotherapy units.

As illustrated in Figure 24, patients diagnosed with lung cancer join the pool of patients awaiting treatment. If capacity is constrained, this pool expands, leading to increased waiting times and a worsening of disease progression. Once treatment is initiated, patients transition into the stock of patients under treatment, and eventually exit through completion, discharge, or mortality. The subsystem demonstrates how improving treatment capacity reduces waiting times, relieves caseload pressure, and improves caseload management efficiency.

The theoretical anchoring of this subsystem draws on the Resource-Based View, which emphasises that scarce and strategically distributed resources determine performance outcomes. Empirical studies confirm that Kenya has fewer than 40 oncologists and only 12 operational radiotherapy machines, far below international benchmarks. These limitations explain persistent treatment delays and long waiting lists at referral facilities such as Kenyatta National Hospital and Moi Teaching and Referral Hospital.

By formalising these relationships, the treatment capacity subsystem identifies leverage points for policy interventions, including expanding radiotherapy capacity, increasing oncology workforce training, and strengthening supply chains. It connects directly with the patient flow subsystem (by absorbing diagnosed patients) and with the resource allocation subsystem (which determines the distribution of oncology resources across counties).

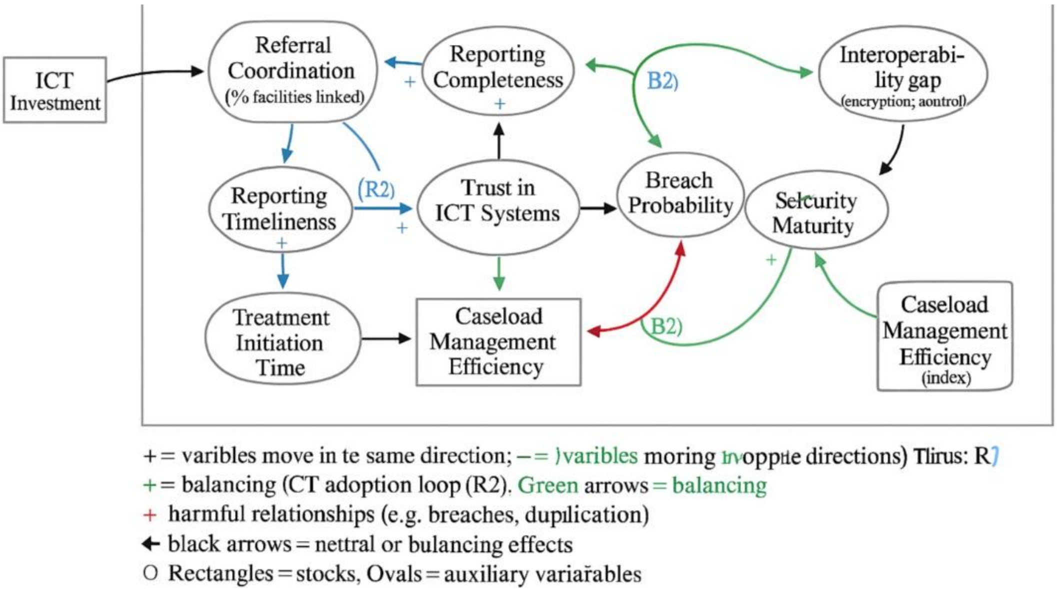
ICT and Data Security Subsystem

The ICT and data security subsystem formalises the role of digital health infrastructure and secure information practices in shaping the efficiency of lung cancer caseload management. In Kenya, electronic medical records (EMRs), the Kenya Health Information Exchange (KHIE), and integration with the Kenya Health Information System (KHIS/DHIS2) are intended to enhance reporting completeness, strengthen referral coordination, and reduce test duplication. However, interoperability gaps and weak data security practices often undermine these benefits, creating fragility within the system.

At its core, this subsystem captures how the adoption of ICT influences the speed and quality of information flow. Higher adoption increases referral coordination and reporting completeness, which in turn improves reporting timeliness and shortens treatment initiation times. These improvements reinforce trust in ICT systems and encourage further adoption, creating a self-reinforcing feedback loop. This dynamic is represented as the reinforcing loop R2 in Figure 25, showing how supportive ICT reforms can steadily enhance reporting and referral performance.

Figure 25

ICT and Data Security Subsystem for Lung Cancer Caseload Management in Kenya



Sorce: Author, (2025)

The subsystem also incorporates the critical role of data security maturity, defined by the presence of encryption, access controls, and audit mechanisms. Higher security maturity reduces the probability of breaches, which strengthens trust in ICT systems and supports greater ICT utilization. Conversely, breaches undermine trust, discourage the use of ICT, and reduce the completeness of reporting, thereby slowing the efficiency of caseload management. These dynamics form the balancing loop B2 in Figure 24, where security practices and breach risks counteract adoption gains, stabilising the system at either a higher or lower equilibrium depending on the strength of institutional safeguards.

As illustrated in Figure 25, the subsystem is therefore shaped by the interaction of R2 (the reinforcing ICT adoption loop) and B2 (the balancing security–trust loop). Together, these loops demonstrate that digital health investments must be accompanied by secure data practices in order to yield sustainable improvements in caseload management. This reflects the requirements of the Kenya Data Protection Act (2019), which mandates the confidentiality, integrity, and notification of breaches in the handling of patient information.

The theoretical foundation of this subsystem is anchored in the Technology Acceptance Model (TAM), which explains how perceived usefulness and trust influence adoption, and in socio-technical systems theory, which emphasizes the integration of technological and organizational elements in shaping outcomes. Empirical evidence from Kenyan studies indicates that despite widespread deployment of KenyaEMR and KHIE, gaps in interoperability and inconsistent enforcement of security protocols continue to erode trust and limit the efficiency of ICT-enabled reporting.

By formalising these relationships, the ICT and data security subsystem highlights the dual importance of expanding ICT adoption while simultaneously embedding strong security safeguards. It connects directly to the patient flow subsystem (via treatment initiation delays) and the diagnostic capacity subsystem (through reporting timeliness), making it a critical enabler of the overall System Dynamics Model.

Resource Allocation and Policy Subsystem

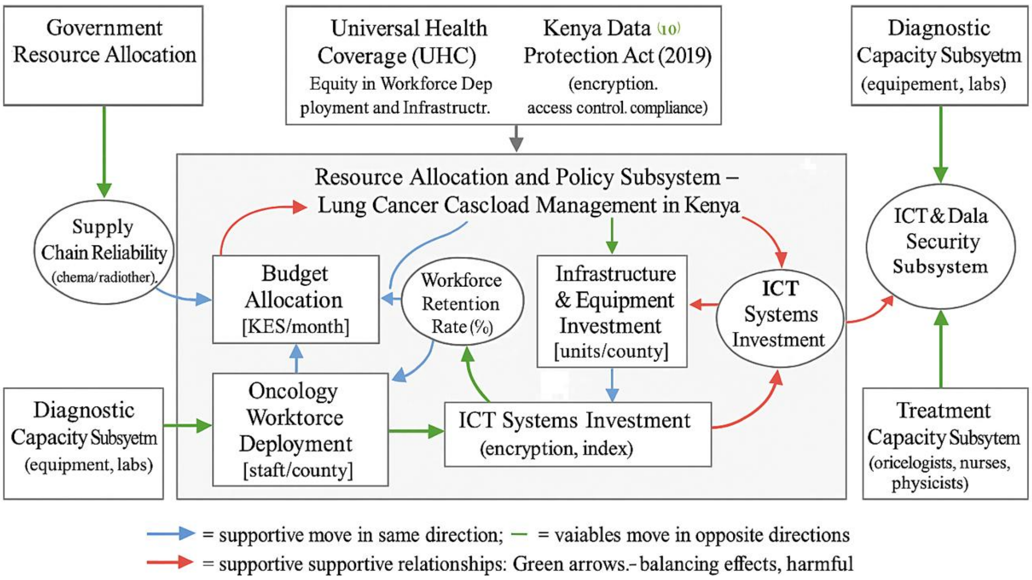
The resource allocation and policy subsystem represents the external drivers that shape the overall performance of lung cancer caseload management in Kenya. Unlike patient flow, diagnostic, and treatment subsystems, which operate largely within facilities, this subsystem captures macro-level decisions by the Government, financing agencies, and regulatory frameworks that determine how resources are distributed and governed across the health system.

At its core, this subsystem is driven by Government resource allocation, the Universal Health Coverage (UHC) framework, and the Data Protection Act (2019), which collectively define the strategic environment for oncology service delivery. Government allocation directly influences the distribution of funds, oncology workforce training, and infrastructure investment across counties. UHC policy ensures equity considerations guide distribution, particularly in underserved regions. Meanwhile, compliance with the Data Protection Act mandates secure handling of patient data, obligating facilities to invest in ICT security, breach monitoring, and privacy safeguards.

As illustrated in Figure 26, policy levers determine the budget allocation available to expand diagnostic and treatment capacity, hire and retain oncology staff, and sustain ICT systems.

Figure 26

Resource Allocation and Policy Subsystem for Lung Cancer Caseload Management in Kenya



Source: Author,(2025).

These allocations influence equipment procurement and maintenance, workforce deployment, and supply chain reliability for chemotherapy and radiotherapy. At the same time, regulatory policies influence the level of compliance with ICT security standards, which in turn affects the ICT and Data Security Subsystem. Collectively, these drivers function as external inputs that either strengthen or constrain the effectiveness of the other subsystems.

The theoretical anchoring of this subsystem draws on the Resource Dependency Theory, which emphasises that healthcare facilities rely on external actors for resources and legitimacy, and on Systems Governance perspectives, which highlight the role of institutions and policy frameworks in shaping systemic performance. Empirical evidence from Kenya demonstrates that oncology service distribution is highly unequal, with Nairobi and Eldoret hosting the most advanced facilities. At the same time, counties such as Turkana and Mandera remain critically underserved. National policy interventions, such as the 2022–2032 Kenya Health Sector Strategic Plan, emphasize the redistribution of oncology resources and the expansion of digital health, yet gaps remain in enforcement and financing.

By formalising these relationships, the resource allocation and policy subsystem highlights that effective caseload management is not solely a function of facility-level efficiency, but also of the political and institutional frameworks that determine resource flows. This subsystem, therefore, links external policy levers to the internal dynamics of patient flow, diagnostic, treatment, and ICT-security subsystems, ensuring that the System Dynamics Model reflects the structural realities of Kenya's health system.

The five subsystems outlined in this section collectively translate the qualitative feedback structures of the causal loop diagrams into the building blocks of a quantifiable model. The patient flow subsystem captures how delays and referrals shape backlog accumulation, while the diagnostic capacity subsystem formalises the bottlenecks in imaging, pathology, and laboratory throughput. The treatment capacity subsystem introduces the balancing role of constrained radiotherapy, chemotherapy, and surgical services, highlighting the impact of workforce and supply limitations on patient outcomes. The ICT and data security subsystem demonstrates how adoption and trust dynamics, mediated by interoperability and security maturity, either reinforce or constrain reporting performance. Finally, the resource allocation and policy subsystem situates these internal processes within the broader policy environment, showing how government budgeting, UHC policy, and compliance with the Data Protection Act (2019) shape resource flows across facilities and subsystems.

Taken together, these subsystems provide a coherent structural foundation for the System Dynamics Model, ensuring that patient flows, facility capacities, ICT utilisation, and policy levers are represented as interdependent components. This decomposition not only clarifies the leverage points within each domain but also prepares the ground for integration into stock-and-flow structures (Section 4.4.4), where the subsystems are expressed as quantifiable stocks, flows, and parameters for simulation in Vensim.

4.9.3 Stock-and-Flow Structures

The transition from causal loop diagrams (CLDs) and subsystem representations to an integrated stock-and-flow structure marks the point at which the model becomes operational for simulation. Whereas the CLDs captured the qualitative feedback relationships that drive lung cancer caseload dynamics, the stock-and-flow representation translates those relationships into quantifiable accumulations and rates of change that can be computed in Vensim. This approach is consistent with established practice in System Dynamics modelling, where stocks denote accumulations of patients, resources, or information, flows represent the rates at which these accumulations change, and auxiliary variables capture modifying influences such as referral delays, reporting completeness, or ICT uptime.

For this study, the integrated stock-and-flow diagram consolidates the five subsystems developed earlier Patient Flow, Diagnostic Capacity, Treatment Capacity, ICT & Data

Security, and Resource Allocation & Policy into a single structure that represents the Kenyan lung cancer caseload pathway. The integration ensures that patient numbers, diagnostic and treatment bottlenecks, reporting dynamics, and security feedback interact in a coherent framework. The structure also provides the foundation for parameterisation, scenario testing, and evaluation in subsequent sections.

The design of the stock-and-flow structures follows three guiding principles. First, dimensional consistency was maintained by ensuring that each stock, flow, and auxiliary was expressed in well-defined units, for instance, patients, days, and percentages. Second, data anchoring was achieved by sourcing parameter values from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), Ministry of Health oncology reports, and global references such as WHO and IAEA standards. Third, the transparency of assumptions was prioritized, with all instances where empirical data were unavailable addressed through structured expert judgment obtained via the Delphi process.

Integrated Stock-and-Flow Diagram (SFD)

The integrated stock-and-flow diagram (SFD) represents the consolidation of the five subsystems previously developed in this study, namely: (i) the Patient Flow Subsystem, (ii) the Diagnostic Capacity Subsystem, (iii) the Treatment Capacity Subsystem, (iv) the ICT and Data Security Subsystem, and (v) the Resource Allocation and Policy Subsystem. By integrating these components into a single structure, the model provides a comprehensive simulation framework that accurately mirrors the real dynamics of lung cancer caseload management in the Kenyan healthcare system.

At the centre of the integrated diagram are the stocks, which capture the accumulations of patients at different points in the pathway. These include suspected cases awaiting diagnosis, confirmed cases pending treatment, patients undergoing active treatment, and survivors or cases that have completed therapy. The flows connecting these stocks represent the rates of change between patient states, such as new case inflow, diagnostic processing rate, referral outflow, treatment initiation, and treatment completion. This formulation enables the model to accurately reproduce the dynamic behavior of patient numbers across the continuum of care.

The structural logic is enhanced by embedding capacity stocks that represent the availability of health system resources. For example, the number of diagnostic slots, treatment slots, and oncology personnel is captured as stocks that regulate the throughput of patient flows. These capacities interact with patient accumulations to determine bottlenecks and delays, making the model sensitive to policy interventions such as capacity expansion or workforce redistribution.

The ICT and Data Security Subsystem is integrated as a cross-cutting layer that influences the timeliness, completeness, and trust in reporting within the caseload management process. In this regard, two key variables are incorporated: the Security Maturity Index (SMI), which reflects institutional adherence to the Kenya Data Protection Act (2019) and related standards, and the probability of data breach (P_{breach}), which represents the risk of unauthorised access or disclosure. These variables directly shape the speed and accuracy with which patient information is transmitted through KHIS/DHIS2 and the Kenya National Cancer Registry, thereby affecting the reliability of caseload data used for decision-making.

The Resource Allocation and Policy Subsystem provides balancing feedback loops that link financial and human resource inputs to the expansion of system capacity. Budgetary allocations, equipment procurement, and workforce deployment are modelled as policy levers under the authority of the Social Health Authority (SHA) and the Ministry of

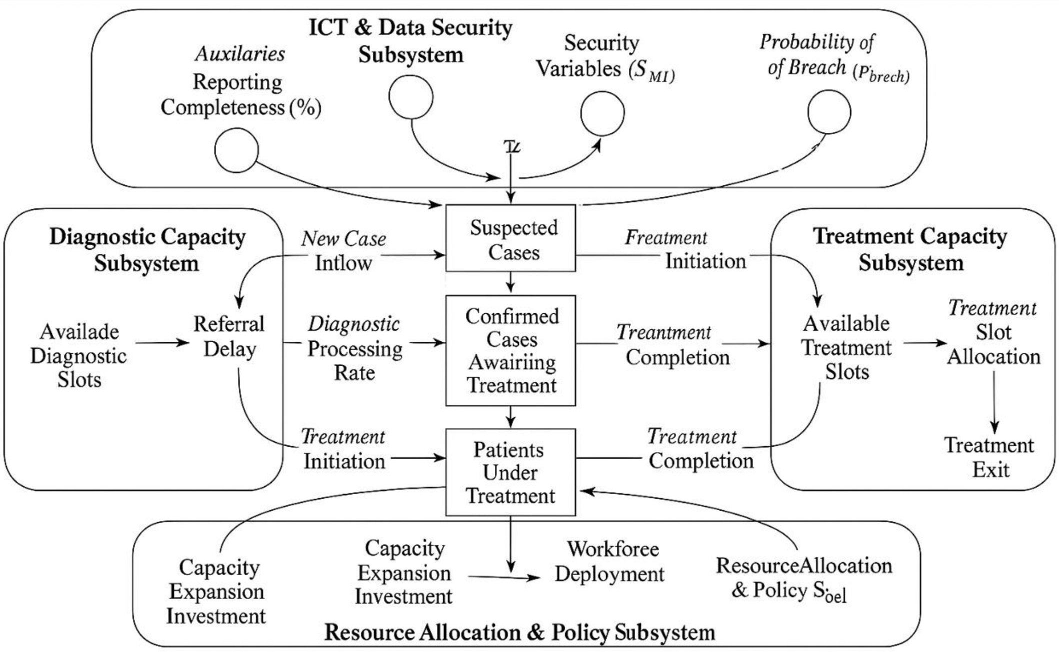
Health. Through these balancing dynamics, the SFD captures how long-term structural investments interact with short-term patient flows to determine caseload outcomes.

In summary, the integrated SFD highlights three key features of the Kenyan lung cancer caseload pathway. First, reinforcing loops arise when delayed referrals, insufficient ICT coverage, or poor adoption of security practices result in the accumulation of backlogs. Second, balancing loops emerge where expanded diagnostic and treatment capacity, combined with secure and interoperable data systems, stabilise the flow of patients. Third, policy levers exert a systemic influence by enabling or constraining both capacities and data management functions. The final structure, therefore, provides a coherent and realistic representation of the interaction between patient dynamics, resource capacities, information systems, and governance mechanisms.

The consolidated structure is presented in Figure 27, which illustrates the integrated stock-and-flow diagram of the System Dynamics model for managing lung cancer caseloads in Kenya. The figure illustrates the integration of stocks, flows, auxiliaries, and feedbacks into a unified simulation architecture, providing the foundation for parameterization and scenario analysis in subsequent sections.

Figure 27

Integrated Stock-and-Flow Diagram of the System Dynamics Model for Lung Cancer Caseload Management



Core Stocks, Flows, and Auxiliaries

The integrated stock-and-flow diagram presented in Figure 27 was further decomposed into its constitutive stocks, flows, and auxiliary variables to ensure clarity and dimensional consistency. In System Dynamics modelling, stocks represent the accumulations of patients or resources at any given point in time, while flows denote the rates of movement or change between stocks. Auxiliaries provide modifying influences that shape the magnitude or direction of flows. Identifying and defining these elements is critical because they form the quantifiable backbone of the model, enabling the transition from conceptual feedback structures to executable simulation equations in Vensim.

The patient-centred stocks capture the progressive stages of the caseload pathway. These include the accumulation of suspected lung cancer cases, confirmed cases awaiting treatment, and patients under treatment, as well as the diagnostic and treatment capacity stocks that constrain flow dynamics. Flows such as new case inflow, diagnostic processing rate, referral outflow, treatment initiation, and treatment completion operationalise the rates of transition between these states. Auxiliaries and policy levers, including referral delays, reporting completeness, ICT uptime, the Security Maturity Index, and the probability of breach, act as multipliers or modifiers that either accelerate or decelerate these flows depending on prevailing system conditions.

To ensure reproducibility and transparency, each stock, flow, and auxiliary was mapped to its definition, unit of measurement, and primary data source. Empirical sources included the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), and the Ministry of Health oncology reports. Global parameters were derived from WHO and IAEA guidelines. For variables where empirical evidence was incomplete, expert estimates were obtained through the Delphi panel process. This mapping is summarised in Table 17.

Table 17

Core Stocks, Flows, and Auxiliaries of the Integrated Model

Variable Type	Variable Name	Definition	Unit of Measurement	Data Source
Stock	Suspected Cases	Accumulation of new patients presenting with lung cancer symptoms pending diagnostic confirmation	Patients	KNCR; KHIS (2018–2023)
Stock	Confirmed Cases Awaiting Treatment	Patients with a histologically confirmed diagnosis awaiting initiation of therapy	Patients	KNCR; MoH (2022)
Stock	Patients Under Treatment	Accumulated patients currently receiving chemotherapy, radiotherapy, or surgery.	Patients	KNCR; Oncology facility records
Stock	Survivors/Completed Cases	Patients who complete treatment successfully and remain under follow-up	Patients	KNCR; WHO (2020)
Stock	Available Diagnostic Slots	Capacity of diagnostic services (e.g., pathology, imaging) available at any point	Slots per month	MoH Oncology Report (2022); IAEA
Stock	Available Treatment	Capacity of treatment services (chemotherapy chairs,	Slots per month	MoH; KNH Cancer Centre

	Slots	radiotherapy fractions, surgical slots)		data
Flow	New Case Inflow	The rate at which new suspected lung cancer cases enter the health system	Patients per month	GLOBOCAN (2022); KNCR
Flow	Diagnostic Processing Rate	Rate of transition from suspected cases to confirmed diagnosis	Patients per month	KNCR; KHIS
Flow	Referral Outflow	Rate of patients transferred between facilities or levels for advanced diagnosis	Patients per month	KHIS; Expert estimates
Flow	Treatment Initiation	The rate at which confirmed patients start treatment	Patients per month	KNH oncology registries
Flow	Treatment Completion	The rate at which patients complete treatment and move to follow-up	Patients per month	MoH Oncology Report (2021)
Auxiliary	Referral Delay	Average delay between referral and diagnostic confirmation	Days	Delphi panel; KNH estimates
Auxiliary	Reporting Completeness	Proportion of patient records captured in KHIS/DHIS2 against the total caseload	Percentage (%)	KHIS; MoH (2022)
Auxiliary	Reporting Timeliness	Average lag between case detection and reporting into national systems	Days	KHIS; Expert estimates
Auxiliary	ICT Uptime	Proportion of time KHIE and EMR systems are operational and available	Percentage (%)	KHIE monitoring data
Auxiliary	Security Maturity Index (SMI)	Composite measure of adherence to security standards and practices	Index (0–1)	Kenya Data Protection Act (2019); Expert panel
Auxiliary	Probability of Breach (P_{breach})	Likelihood of data breach or unauthorised access in reporting systems	Probability	MoICT reports; Expert panel
Policy Lever	Capacity Expansion Investment	Incremental resources allocated to increase diagnostic and treatment capacity	KES million per year	SHA policy documents; MoH budgets
Policy Lever	Workforce Deployment	Rate of allocation of oncologists, radiographers, and nurses across facilities	Personnel per year	MoH HRH reports (2022)

The mapping demonstrates that the integrated model is not a theoretical abstraction, but a system firmly grounded in empirical evidence and contextual realities of the Kenyan health system. The identification of stocks, flows, and auxiliaries provides the necessary scaffolding for formulating the equations and parameters presented in Section 4.4.5.

Units of Measurement and Consistency

The robustness of a System Dynamics model depends not only on the conceptual soundness of its feedback structures but also on the dimensional consistency of its constituent variables. For this reason, all stocks, flows, auxiliaries, and policy levers identified in the integrated model were subjected to a systematic unit assignment and verification process. This ensured that accumulations were measured in absolute numbers, flows were expressed in rates of change, and modifiers were dimensionally aligned with the variables they influenced.

The patient-centred stocks, including *Suspected Cases*, *Confirmed Cases Awaiting Treatment*, and *Patients Under Treatment*, were uniformly measured in patients. Their associated flows, such as *New Case Inflow*, *Diagnostic Processing Rate*, *Referral Outflow*, *Treatment Initiation*, and *Treatment Completion*, were expressed in patients per month, thereby guaranteeing that inflows and outflows aligned dimensionally with the patient accumulations. Similarly, the capacity stocks, namely *Available Diagnostic Slots* and *Available Treatment Slots*, were defined in terms of slots per month, with utilisation flows expressed in the same dimension to maintain internal balance.

Auxiliary and modifying variables were assigned measurement units appropriate to their conceptual role. *Referral Delay* and *Reporting Timeliness* were measured in days, capturing the temporal aspect of bottlenecks. *Reporting Completeness* and *ICT Uptime* were expressed in percentages, representing their proportional influence on data flow. Security-related modifiers included the *Security Maturity Index (SMI)*, defined as a dimensionless index bounded between 0 and 1, and the *Probability of Breach* (P_{breach}), measured as a probability between 0 and 1. Policy levers, such as Capacity Expansion Investment, were quantified in Kenyan Shillings (KES million) per year. At the same time,*Workforce Deployment* was measured in personnel per year, reflecting their tangible contribution to resource expansion.

The model was implemented with a monthly time step (Δt). This resolution was chosen for two main reasons. First, it aligns with the routine reporting cycles of the Kenya Health Information System (KHIS/DHIS2), which produces monthly reports on caseloads and facilities. Second, it provides sufficient granularity to capture short-term variations in referrals, diagnostic throughput, and treatment bottlenecks without generating unnecessary computational complexity. The simulation horizon was set from 2018 to 2032, corresponding with the availability of historical registry and KHIS data on the lower end, and with the Strategic Health Authority's (SHA) 10-year planning horizon on the upper end. This time span allowed the model to both replicate recent trends and forecast medium-term outcomes under alternative policy scenarios.

Dimensional verification was carried out using Vensim's unit-checking functionality. All equations and linkages passed the dimensional consistency test, confirming that accumulations, rates, modifiers, and policy levers were coherent across the system. This verification process enhanced the credibility of the simulation results by ensuring that outputs were not artefacts of scale mismatches or inconsistent definitions.

The unit assignment and consistency verification are summarised in Table 18, which provides an overview of variable categories, examples, measurement units, and dimensional outcomes.

Table 18

Units of Measurement and Dimensional Consistency in the Integrated Model

Variable Category	Example Variables	Unit of Measurement	Dimensional Consistency Outcome
Patient Stocks	Suspected Cases; Awaiting Diagnosis; Patients Under Treatment; Survivors	Patients	Consistent with inflows and outflows (patients per month)
Patient Flows	New Case Inflow; Diagnostic Processing Rate; Referral Outflow; Treatment Initiation; Treatment Completion	Patients per month	Dimensionally consistent with patient stocks
Capacity Stocks	Available Diagnostic Slots; Available Treatment Slots	Slots per month	Balanced against utilisation flows
Auxiliary Variables	Referral Delay; Reporting Timeliness; ICT Uptime; Reporting Completeness	Days; Days; %; %	Units aligned with modifying roles on patient flows
Security Variables	Security Maturity Index (SMI); Probability of Breach (P_{breach})	Index (0–1); Probability (0–1)	Correctly modifies reporting completeness and trust loops
Policy Levers	Capacity Expansion Investment; Workforce Deployment	KES million per year; Personnel per year	Consistent with the expansion of capacity stocks

The integration of narrative reasoning with tabular evidence demonstrates that the model is both conceptually rigorous and dimensionally robust. By grounding all variables in coherent measurement scales, the study ensured that the subsequent model formulations and parameterisation (Section 4.4.5) would rest on a solid empirical and structural foundation.

Data Sources for Parameterisation

The strength of a System Dynamics model lies not only in its conceptual coherence but also in the integrity of the data used to parameterise its variables. For this reason, the parameterisation of the integrated stock-and-flow structures in this study drew upon three categories of evidence: national repositories, international reference standards, and structured expert judgement. This triangulation strategy ensured that the model was simultaneously grounded in the realities of the Kenyan health system while remaining consistent with globally recognised oncology benchmarks.

At the national level, the Kenya National Cancer Registry (KNCR) provided baseline statistics on lung cancer incidence, prevalence, and survival, which informed the influx of suspected and confirmed cases, as well as stock levels for patients undergoing treatment and survivors. The Kenya Health Information System (KHIS/DHIS2) offered monthly records of diagnostic throughput, referral patterns, and treatment initiation rates, which were crucial in calibrating the major patient flows. In addition, Ministry of Health oncology reports (2018–2023) and Strategic Health Authority (SHA) policy documents supplied information on diagnostic and treatment infrastructure, workforce distribution, and budgetary allocations, thereby informing the capacity stocks and policy levers in the model.

International standards were incorporated to validate and supplement national datasets. The World Health Organization (WHO) guidelines on cancer service delivery provided reference values for diagnostic and treatment throughput ratios relative to population size. The International Atomic Energy Agency (IAEA) published technical standards on radiotherapy fractionation and diagnostic slot allocation, which served as benchmarks for validating the Kenyan estimates. Furthermore, GLOBOCAN 2022 provided estimates of lung cancer incidence and mortality, which were cross-checked against KNCR records to ensure coherence with global reporting trends.

Where empirical evidence was incomplete or inconsistent, structured expert input was employed through a Delphi panel of oncologists, radiologists, medical physicists, ICT managers, and health system administrators. This panel provided consensus estimates on parameters such as average referral delays, reporting timeliness, ICT uptime, and the probability of data breach (P_{breach}), which were not comprehensively captured in routine datasets. Experts also validated the construction of the Security Maturity Index (SMI), which was derived from the compliance dimensions outlined in the Kenya Data Protection Act (2019).

The process also acknowledged the limitations of available data. KNCR reporting remains incomplete and subject to delays, while KHIS/DHIS2 does not consistently capture oncology-specific indicators across sub-county facilities. To address these gaps, national averages were applied where disaggregation was unavailable, and interpolation was performed where registry data lagged behind KHIS reporting. These adjustments were explicitly documented, and their impact on simulation behaviour was tested through sensitivity analysis (Section 4.4.7). By integrating international benchmarks and expert consensus, the study minimised the risk of bias and improved the reliability of parameter values.

All parameterisation processes were conducted in compliance with the Kenya Data Protection Act (2019), which mandates confidentiality, lawful processing, and data minimisation for sensitive health information. This ensured that no patient-identifiable data were exposed during model development, while the inclusion of SMI and P_{breach} parameters demonstrated the integration of ethical and legal safeguards into the modelling framework.

Finally, parameter values were not treated as static inputs but were iteratively validated during model calibration exercises, which adjusted estimates to align simulated outputs with observed historical patterns. This calibration link ensured that the model remained empirically faithful while retaining flexibility to project future scenarios.

The mapping of variables to their primary national sources, supplementary benchmarks, and expert inputs is summarised in Table 19.

Table 19

Mapping of Data Sources for Model Parameterisation

Variable Category	National Source(s)	Global/Benchmark Source(s)	Expert Input (Delphi)
Patient Stocks & Flows	KNCR (2018–2023); KHIS/DHIS2 monthly reports	GLOBOCAN 2022; WHO (2020) cancer control guidelines	Referral delays; diagnostic lag estimates
Capacity Stocks	MoH Oncology Reports (2018–2023); SHA budgets	IAEA technical standards; WHO benchmarks	Facility utilisation validation
ICT Variables	KHIE monitoring data; MoICT sector reports	WHO eHealth frameworks	ICT uptime; reporting timeliness
Security Variables	Kenya Data Protection Act (2019); SHA compliance audits	N/A	Probability of Breach (P_{breach}); Security Maturity Index (SMI)
Policy Levers	SHA policy documents; MoH health budgets	WHO cancer control frameworks	Workforce deployment strategies

By drawing upon national data repositories, validating against international standards, and integrating structured expert input, the study established a robust and transparent parameterisation framework. This triangulated approach not only enhanced the reliability of the model but also reinforced its policy relevance for Kenya. The outcomes of this parameterisation process provided the empirical and ethical foundation for the mathematical formulations presented in Section 4.4.5.

Transition to Formulations

The integration of stock-and-flow structures, the assignment of consistent measurement units, and the triangulation of parameter sources collectively provided a rigorous foundation for operationalizing the model. By consolidating patient flows, capacity constraints, ICT dynamics, and security considerations into a coherent architecture, the study ensured that the System Dynamics representation of lung cancer caseload management in Kenya was both empirically anchored and dimensionally robust. The systematic mapping of variables to national, global, and expert-based sources further strengthened the transparency and reproducibility of the modelling process.

Having established this structural and evidentiary base, the next logical step is to translate the defined stocks, flows, auxiliaries, and policy levers into mathematical formulations. These formulations quantify the relationships among variables, assign parameter values, and specify assumptions, thereby enabling dynamic simulation in Vensim. Section 4.4.5, therefore, presents the Model Formulations and Parameterization, where the conceptual architecture documented thus far is transformed into an executable simulation model capable of reproducing historical behavior and testing intervention scenarios.

4.9.4 Model Formulations and Parameterisation

The transition from structural design to mathematical representation marked the final step in operationalising the model. Having defined the integrated stock-and-flow architecture, assigned units of measurement, and identified parameter sources, the model was now expressed in executable formulations. These formulations convert the qualitative feedback relationships into computable expressions that govern system behaviour over time. In System Dynamics, stocks are expressed as accumulations governed by inflows and outflows, flows are represented as rates of change per unit time, and auxiliaries serve as modifiers that influence the magnitude or direction of the flows. Parameterisation then anchors these formulations to empirical data, global standards, or expert consensus, ensuring that the resulting model is both replicable and contextually valid for the Kenyan healthcare system.

General Formulations

The general equations used in the integrated model adhered to established conventions in System Dynamics modelling. Each stock was formulated as a first-order difference equation, representing the accumulation of patients or resources across time. Flows were defined as rates per month, consistent with the chosen simulation time step, while auxiliaries were expressed as ratios or conversion functions that altered the magnitude of the flows.

The general stock formulation was:

Equation 4: stock formulation

$$Stock(t) = Stock(t - \Delta t) + [Inflow(t) - Outflow(t)] \times \Delta t$$

Where *Stock(t)* denotes the level of a given stock,for instance,Suspected Cases, Patients UnderTreatment, *Inflow,* and *Outflow* represent the rates of change per month, and Δtwas set to one month. This ensured that accumulations were updated in line with the reporting frequency of KHIS/DHIS2 and KNCR data.

Flows were expressed as:

$$Flow(t) = Rate \times Modifier$$

Where *'Rate' refers to the baseline throughput derived from empirical data, for example, the average diagnostic capacity per month, and 'Modifier' represents auxiliary variables that adjust the flow in response to contextual conditions, such as referral delays*and ICT uptime.

Auxiliary variables were typically defined as ratios, percentages, or indices. For example, *Reporting Completeness* was formulated as:

Reporting Completeness = (Reported Cases / Total Expected Cases) × 100

While the *Probability of Breach* was operationalised as a function of the inverse of the Security Maturity Index (SMI):

$$P_{breach} = f(1 - SMI)$$

Where the functional form was derived from expert consensus, reflecting that higher maturity levels correspond to lower breach probabilities.

All formulations were subjected to dimensional checks to ensure consistency. Stocks measured in patients were paired with flows expressed in patients per month. Capacity stocks, measured in slots per month, were linked with slot allocation flows, and modifiers, expressed as percentages or indices, were dimensionless. This consistency guaranteed that the model equations could be executed in Vensim without error and that the outputs were interpretable in real-world terms.

Patient Flow Subsystem Formulations

The patient flow subsystem constituted the core of the System Dynamics model, reflecting the progression of individuals from initial suspicion of lung cancer through diagnostic confirmation, treatment, and eventual outcomes. This structure provided a realistic representation of the Kenyan caseload pathway, integrating both clinical and reporting processes as captured in KNCR and KHIS/DHIS2 datasets.

The first stock, Suspected Cases (*SC*), represented individuals presenting with symptoms suggestive of lung cancer but not yet diagnosed. Its formulation followed the standard stock equation of accumulation, with inflows determined by new case incidence and outflows by diagnostic processing:

Equation 5: Suspected Cases (SC)

$$SC(t) = SC(t - \Delta t) + [\ NCI(t) - DPR(t)\ ] \times \Delta t$$

In Vensim, this was expressed as:

```
Suspected_Cases = INTEG( New_Case_Inflow - Diagnostic_Processing , SC_init )
```

The second stock, Awaiting Diagnosis (*AD*), represented cases already referred but pending confirmation. These patients accumulated through diagnostic inflows and exited once their diagnosis was confirmed:

Equation 6: Awaiting Diagnosis (AD)

$$AD(t) = AD(t - \Delta t) + [\ DPR(t) - CRO(t)\ ] \times \Delta t$$

The third stock, Confirmed Cases Awaiting Treatment (*CAT*), represented patients with histologically confirmed lung cancer awaiting initiation of therapy. Its accumulation was governed by confirmed referrals in and treatment initiations out:

Equation 7: Confirmed Cases Awaiting Treatment (CAT**)**

$$CAT(t) = CAT(t - \Delta t) + [\ CRO(t) - TIR(t)\ ] \times \Delta t$$

The central treatment stock, Patients Under Treatment (*PUT*), captured the active caseload undergoing chemotherapy, radiotherapy, or surgery. Inflows arose from treatment initiation, while outflows were divided into successful completions and treatment-related mortality:

Equation 8: Patients Under Treatment (PUT)

$$PUT(t) = PUT(t - \Delta t) + [\ TIR(t) - (\ TCR(t) + TMR(t)\ )\ ] \times \Delta t$$

Finally, the Survivors (SV) stock represented patients completing therapy successfully:

Equation 9: Survivors (SV) stock

$$SV(t) = SV(t - \Delta t) + TCR(t) \times \Delta t$$

Mortality (*TMR*) was captured as an outflow without a corresponding stock, aligning with the KNCR practice of reporting cumulative deaths rather than maintaining them as an active category.

Auxiliary variables modified these transitions. Referral Delay (*RD*), expressed in days, slowed diagnostic throughput, while Reporting Completeness (*RC*) and Reporting Timeliness (*RT*) determined the effective visibility of cases in national registries. These were formulated as follows:

Equation 10: Referral Delay (RD)

$$DPR(t) = Diagnostic\ Capacity / (1 + RD)$$

$$RC = (Reported\ Cases / Total\ Expected\ Cases) \times 100$$

$$RT = f(ICT\ Uptime , SMI)$$

The last function emphasizes the importance of information systems and data security in ensuring timely reporting, in line with the obligations of the Kenya Data Protection Act (2019), which requires the accuracy, timeliness, and secure handling of personal health information.

Parameterization of this subsystem primarily drew from the Kenya National Cancer Registry (KNCR) and KHIS/DHIS2, which provided statistics on incidence, diagnostic throughput, and treatment initiation. These were validated against GLOBOCAN 2022 estimates and WHO/IAEA benchmarks on diagnostic and treatment capacities. Where gaps were identified particularly regarding referral delays and reporting timeliness—estimates were derived through a Delphi panel of Kenyan oncologists, ICT managers, and health system administrators.

Table 20

Summary of Patient Flow Subsystem Formulations

Variable	Type	Formulation	Parameterisation Source(s)
Suspected Cases (*SC*)	Stock	$SC(t) = SC(t - \Delta t) + [\, NCI - DPR \,] \times \Delta t$	KNCR; KHIS; GLOBOCAN 2022
Awaiting Diagnosis (*AD*)	Stock	$AD(t) = AD(t - \Delta t) + [\, DPR - CRO \,] \times \Delta t$	KNCR; KHIS
Confirmed Awaiting Treatment (*CAT*)	Stock	$CAT(t) = CAT(t - \Delta t) + [\, CRO - TIR \,] \times \Delta t$	KNCR; MoH Oncology Reports
Patients Under Treatment (*PUT*)	Stock	$PUT(t) = PUT(t - \Delta t) + [\, TIR - (\, TCR + TMR \,) \,] \times \Delta t$	KNH Oncology Registry; MoH
Survivors (SV)	Stock	$SV(t) = SV(t - \Delta t) + TCR \times \Delta t$	KNCR; WHO
New Case Inflow (*NCI*)	Flow	*Monthly incidence rate*	KNCR; GLOBOCAN 2022
Diagnostic Processing Rate (*DPR*)	Flow	*Diagnostic Capacity / (1 + RD)*	KHIS; IAEA; Expert panel
Confirmed Referral Outflow (*CRO*)	Flow	Cases confirmed and referred for treatment	KHIS
Treatment Initiation Rate (*TIR*)	Flow	Confirmed patients starting therapy	KNH Oncology Registry
Treatment Completion Rate (*TCR*)	Flow	Successful treatment exits	KNCR; WHO
Treatment Mortality Rate (*TMR*)	Flow	Deaths during treatment	KNCR; KHIS
Referral Delay (*RD*)	Auxiliary	Average time lag in days	Expert panel
Reporting Completeness (*RC*)	Auxiliary	$RC = (\, Reported / Expected \,) \times 100$	KHIS; MoH
Reporting Timeliness (*RT*)	Auxiliary	Function of ICT Uptime & SMI	KHIE; MoICT; Expert panel

The subsystem thus reproduced the sequential progression of patients within the lung cancer pathway while embedding institutional reporting and security dynamics. This formulation enabled the model to capture both the clinical and administrative bottlenecks influencing caseload management in Kenya.

Diagnostic Capacity Subsystem

The diagnostic capacity subsystem was designed to capture the structural and temporal constraints that shape the flow of patients from suspicion to confirmed lung cancer diagnosis in Kenya. This subsystem was particularly important given that delayed diagnostics contribute significantly to the country's high mortality-to-incidence ratio, as highlighted in national oncology reports. By translating causal loop linkages into quantitative stock–flow relationships, the model enabled systematic exploration of how equipment, personnel, and reporting systems interact to determine throughput and backlog dynamics.

The first stock, Available Diagnostic Slots (*ADS*), represented the cumulative capacity of diagnostic resources such as pathology labs, imaging machines, and biopsy theatres—measured in the number of patient investigations possible per month. Its accumulation was expressed as:

Equation 11: Available Diagnostic Slots (ADS)

$$ADS(t) = ADS(t - \Delta t) + [\ DCI(t) - DCO(t)\ ] \times \Delta t$$

Where DCI denotes diagnostic capacity inflow (new equipment, workforce expansion) and DCO diagnostic capacity outflow (downtime, attrition, or obsolescence). In Vensim:

```
Available_Diagnostic_Slots = INTEG( Capacity_Addition - Capacity_Loss , ADS_init )
```

The second stock, Patients Awaiting Diagnosis (*PAD*), represented individuals queued for diagnostic services. Their accumulation followed:

Equation 12: Patients Awaiting Diagnosis (PAD**)**

$$PAD(t) = PAD(t - \Delta t) + [\ NCI(t) - DPR(t)\ ] \times \Delta t$$

Here, *NCI* refers to the new case inflow (i.e., suspected patients entering the system), while *DPR* denotes the diagnostic processing rate.

The diagnostic throughput was captured by the flow Diagnostic Processing Rate (*DPR*), defined as the minimum of available capacity and patient demand:

Equation 13: Diagnostic Processing Rate (DPR)

$$DPR = min(PAD , ADS / (1 + RD)$$

This equation highlighted the effect of *Referral Delay (RD)*, measured in days, which reduced effective throughput despite nominal machine capacity.

To reflect equipment utilisation, an auxiliary Diagnostic Utilisation Rate (DUR) was defined as:

Equation 14: Diagnostic Utilisation Rate (DUR)

$$DUR = (DPR / ADS) \times 100$$

This variable provided an indicator of efficiency, with high utilisation signalling bottlenecks and potential overuse.

The subsystem also integrated ICT-related variables. For example, Reporting Timeliness (RT) directly influenced how quickly diagnostic outcomes entered the Kenya National Cancer Registry (KNCR) and KHIS. It was modelled as:

Equation 15: Reporting Timeliness (RT)

$$RT = f(ICT\ Uptime , SMI)$$

where *SMI* denotes the Security Maturity Index, in line with Section 41 of the Kenya Data Protection Act (2019), which obliges healthcare entities to embed data protection by design and default.

Parameterisation of the diagnostic capacity subsystem was based on:

i. KNCR and KHIS/DHIS2 data for reported diagnostic throughput
ii. Ministry of Health oncology infrastructure audits (2021–2023) for equipment counts and staff capacity
iii. IAEA benchmarks for recommended imaging and pathology resources per population
iv. Expertpanel (Delphi method) estimates for referral delays, downtime frequencies, and reporting lag assumptions

The integrated formulations are summarised in Table 21.

Table 21

Summary of Diagnostic Capacity Subsystem Formulations

Variable	Type	Formulation	Parameterisation Source(s)
Available Diagnostic Slots (*ADS*)	Stock	$ADS(t) = ADS(t - \Delta t) + [\ DCI - DCO\ ] \times \Delta t$	MoH Oncology Audits; IAEA
Patients Awaiting Diagnosis (*PAD*)	Stock	$PAD(t) = PAD(t - \Delta t) + [\ NCI - DPR\ ] \times \Delta t$	KNCR; KHIS
Diagnostic Capacity Inflow (*DCI*)	Flow	New machine/staff addition	MoH Equipment Reports
Diagnostic Capacity Outflow (*DCO*)	Flow	Equipment attrition, staff attrition	MoH; Expert panel
Diagnostic Processing Rate (*DPR*)	Flow	$DPR = min(\ PAD\ ,\ ADS\ /\ (\ 1 + RD\ )\ )$	KNCR; KHIS
Diagnostic Utilisation Rate (*DUR*)	Auxiliary	$DUR = (\ DPR\ /\ ADS\ ) \times 100$	Derived
Referral Delay (*RD*)	Auxiliary	Average time lag in days	Expert panel
Reporting Timeliness (*RT*)	Auxiliary	$RT = f(\ ICT\ Uptime\ ,\ SMI\ )$	KHIE; MoICT; DPA 2019

This subsystem formulation captured both the physical and institutional determinants of diagnostic performance, enabling simulation of how investments in infrastructure, reduction of referral delays, and strengthening of ICT–security linkages would alter the pace and equity of lung cancer case confirmation in Kenya.

Treatment Capacity Subsystem Formulations

The treatment capacity subsystem formalised how structural resources and clinical practice determine the throughput of patients from confirmed diagnosis to treatment initiation and completion. In the Kenyan context, this subsystem represents chemotherapy chair availability, radiotherapy fraction capacity, surgical theatre time, and the requisite oncology workforce. The objective was to quantify how capacity additions, downtimes, and staffing patterns shape initiation and completion rates, while preserving dimensional consistency with the monthly simulation step established earlier.

The first stock, Available Treatment Slots (ATS), represented the cumulative monthly capacity to deliver treatment across modalities, including chemotherapy chairs (aggregated to monthly chairs) and radiotherapy fractions (aggregated to monthly fractions), as well as surgical theatre sessions (aggregated to monthly sessions). Capacity evolved according to additions (infrastructure procurement, commissioning, and workforce expansion) and losses (equipment obsolescence, maintenance downtime, attrition), defined as:

Equation 16: Available Treatment Slots (ATS)

$$ATS(t) = ATS(t-\Delta t) + [TCI(t) - TCO(t)] \times \Delta t$$

In Vensim notation, this was implemented as:

Available_Treatment_Slots = INTEG(Treatment_Capacity_Addition -

Treatment_Capacity_Loss , ATS_init)

The effective treatment capacity available in any given month was a function of the number of nominal slots, planned and unplanned downtime, and workforce availability.

Let DT denote the downtime fraction (0–1) and WFA the workforce availability index (0–1), capturing oncologists, radiographers, nurses, and theatre staff on duty. The effective monthly capacity was expressed as:

Equation 17: Effective Treatment Capacity

$$Eff\_Cap = ATS \times (1 - DT) \times WFA$$

Patients eligible to start therapy are held in the stock Confirmed Cases Awaiting Treatment (CAT) (defined earlier in the patient flow subsystem). The Treatment Initiation Rate (TIR) was constrained by both demand (CAT) and effective capacity, with queue effects represented through an average treatment delay (TDTDTD) in months, arising from scheduling, preparation, and pre-treatment optimization. The formulation was:

$$TIR = min(CAT, Eff\_Cap / (1 + TD))$$

Once on therapy, patients accumulate in Patients Under Treatment (PUT) (already defined in Section 4.4.5.2). Exits from treatment were categorized into two rates: Treatment Completion Rate (TCR) and Treatment Mortality Rate (TMR). Completion was modelled as a function of the average treatment duration LLL (in months) and a completion fraction CFCFCF that captures adherence and toxicity-related interruptions:

$$TCR = (PUT / L) \times CF$$

where L is treatment duration (months), $CF$is the completion fraction.

Mortality during treatment was expressed as:

$$TMR = PUT \times m_{tx}$$

where m_{tx} is the monthly treatment-phase mortality fraction calibrated from registry and facility data.

To monitor efficiency, a Treatment Utilisation Rate (TUR) was defined as the proportion of effective capacity consumed by new starts:

$$TUR = (TIR / Eff\_Cap) \times 100$$

Values persistently above 85–90% indicate capacity saturation and rising queues, while values substantially below that range signal underutilization or upstream constraints, for example, in diagnostics.

Parameterisation followed a triangulated approach. Monthly ATS baselines were derived from Ministry of Health oncology infrastructure audits and site-reported modality capacities (chemotherapy chair rosters, radiotherapy machine uptime logs, surgical theatre schedules). Downtime fractions were derived from engineering maintenance records and expert estimates; workforce availability indices were obtained from HRH deployment schedules. Treatment durations and completion fractions were derived from KNH oncology registries and cross-checked with WHO/IAEA guidance on typical course lengths and throughput. Treatment-phase mortality fractions were calibrated to KNCR outcomes and validated against GLOBOCAN patterns for the region. All parameters retained the monthly unit convention and passed Vensim’s unit checking alongside the patient flow equations to ensure dimensional coherence.

Table 22

Summary of Treatment Capacity Subsystem Formulations

Variable	Type	Formulation	Parameterisation Source(s)
Available Treatment Slots (*ATS*)	Stock	$ATS(t) = ATS(t\text{-}\Delta t) + [TCI - TCO] \times \Delta t$	MoH Oncology Audits; Facility capacity logs
Treatment Capacity Inflow (*TCI*)	Flow	Commissioned equipment; workforce expansion	MoH commissioning; HRH deployment
Treatment Capacity Outflow (*TCO*)	Flow	Attrition, maintenance, obsolescence	Facility logs; Expert panel
Effective Capacity (*Eff_Cap*)	Auxiliary	$Eff\_Cap = ATS \times (1 - DT) \times WFA$	Maintenance logs; HRH rosters
Treatment Initiation Rate (*TIR*)	Flow	$TIR = min(CAT, Eff\_Cap / (1 + TD))$	KNH initiation records
Treatment Completion Rate (*TCR*)	Flow	$TCR = (PUT / L) \times CF$	KNH; WHO/IAEA norms; facility adherence
Treatment Mortality Rate (*TMR*)	Flow	$TMR = PUT \times m\_tx$	KNCR outcomes: Calibration
Treatment Utilisation Rate (*TUR*)	Auxiliary	$TUR = (TIR / Eff\_Cap) \times 100$	Derived performance indicator
Downtime Fraction (*DT*)	Auxiliary	Fraction of time treatment capacity unavailable	Maintenance logs; Expert panel
Workforce Availability (*WFA*)	Auxiliary	Availability index of oncology staff	HRH deployment schedules
Treatment Delay (*TD*)	Auxiliary	Average scheduling/queue delay (months)	Facility scheduling; Expert panel
Treatment Duration (*L*)	Auxiliary	Mean months on therapy	KNH; WHO/IAEA
Completion Fraction (*CF*)	Auxiliary	Proportion completing planned course	Facility adherence data
Treatment Mortality Fraction (m_{tx})	Auxiliary	Monthly mortality during therapy	KNCR; Calibration

ICT and Data Security Subsystem Formulations

The ICT and data security subsystem formalised the interaction between information system availability, data protection practices, and reporting performance in lung cancer caseload management. Unlike the patient or capacity subsystems, this structure acted as a cross-cutting determinant, shaping the visibility, timeliness, and integrity of caseload information within KNCR and KHIS/DHIS2. Its inclusion was essential given Kenya's statutory requirements under the Kenya Data Protection Act (2019), which mandates secure, timely, and lawful processing of personal health data.

The core auxiliary, Reporting Completeness (RC), was modelled as the ratio of reported cases to expected cases in any given period:

Equation 18: Reporting Completeness (RC)

$$RC = (\ \mathit{Reported\ Cases} / \mathit{Total\ Expected\ Cases}\ ) \times 100$$

This measure was sensitive to ICT system coverage and adoption, with lower completeness observed where electronic medical record (EMR) linkages to KHIE were missing.

Reporting Timeliness (RT) was defined as a function of ICT uptime and security maturity. It reflected the average lag between case confirmation at the facility level and reporting into KHIS/DHIS2:

$$RT = f(\ \mathit{ICT\ Uptime}\ ,\ \mathit{SMI}\ )$$

Where *ICT Uptime* denotes the proportion of time that EMR and KHIE interfaces were operational, and *SMI* is the Security Maturity Index, defined on a scale of 0–1. The functional form was modelled such that higher uptime and higher SMI values reduced reporting lag.

ICT Uptime (ICTu) itself was represented as an auxiliary variable ranging between 0 and 1, parameterised from KHIE monitoring logs:

$$ICTu = \mathit{System\ Operational\ Time} / \mathit{Total\ Time}$$

To integrate security into the reporting dynamics, the Probability of Breach (P_{breach}) was introduced. This was defined as inversely related to *SMI*, representing the likelihood of unauthorised access or disclosure within ICT platforms:

$$P_{breach} = 1 - SMI$$

A high SMI, therefore, reduced breach probability, strengthening trust and promoting further ICT adoption. This linkage was critical in reinforcing feedback loops, as lower breach risks improved institutional confidence, which in turn enhanced reporting compliance.

Finally, an auxiliary Trust Index (*TI*) was formulated as a function of RC, RT, and P_{breach}, reflecting the overall confidence of health managers in caseload data:

$$TI = g(RC , RT , P_{breach})$$

The function was parameterized through expert consensus, where higher completeness, shorter reporting lags, and lower breach probabilities collectively resulted in higher trust scores.

Parameterisation of this subsystem was derived from:

i. KHIE system monitoring logs for uptime and outages
ii. MoICT cybersecurity audit reports for breach incidents and vulnerabilities
iii. SHA and MoH compliance reports for institutional adherence to the Data Protection Act (2019)
iv. Delphi panel input (ICT managers, cybersecurity experts, health records officers) for operationalising SMI and the Trust Index

The key variables and formulations are summarised in Table 23.

Table 23

Summary of ICT and Data Security Subsystem Formulations

Variable	Type	Formulation	Parameterisation Source(s)
Reporting Completeness (RC)	Auxiliary	*RC = (Reported / Expected) × 100*	KHIS; MoH Oncology Reports
Reporting Timeliness (RT)	Auxiliary	*RT = f(ICT Uptime , SMI)*	KHIE logs; MoICT audits; Expert panel
ICT Uptime (ICTu)	Auxiliary	*ICTu = System Operational Time / Total Time*	KHIE monitoring data
Security Maturity Index (SMI)	Auxiliary	Composite index (0–1)	SHA compliance audits; Expert consensus
Probability of Breach (P_{breach})	Auxiliary	P_{breach}= 1 – SMI	MoICT reports; Expert panel
Trust Index (TI)	Auxiliary	TI = g(RC , RT , P_{breach})	Delphi panel estimates

This subsystem demonstrated how ICT performance and data security directly shape the visibility and reliability of lung cancer caseload data in Kenya. By embedding statutory compliance and trust dynamics into the model, it ensured that reporting delays and breaches were not treated as externalities but as structural determinants of caseload management efficiency.

Resource Allocation and Policy Subsystem Formulations

The resource allocation and policy subsystem represented the strategic decisions and financial flows that determine the scale of diagnostic and treatment capacities in Kenya's health system. Unlike the patient and capacity subsystems, which operate at the operational level, this subsystem functioned at the managerial and policy tier, linking budgetary allocations, workforce distribution, and investment priorities to the physical stocks of capacity. It was designed to capture the top–down influence of the Social Health Authority (SHA) and Ministry of Health decisions on system dynamics.

The primary stock was Health Budget and Workforce Capacity (HBW), expressed as a composite resource pool available to expand diagnostic and treatment slots. It evolved through policy-driven inflows and natural attrition or reallocation outflows:

Equation 19: Health Budget and Workforce Capacity

$$HBW(t) = HBW(t - \Delta t) + [\ BA(t) - RE(t)\ ] \times \Delta t$$

Where *BA* denotes Budget Allocation inflows, and *RE* represents Reallocation or attrition for instance, diverted funds, and retirement of staff).

Budget allocations were modeled as exogenous policy levers, set annually by SHA and MoH, but distributed into monthly increments for simulation purposes. The corresponding flow was:

$$BA = Annual\ Health\ Allocation\ /\ 12$$

The Capacity Expansion Investment (*CEI*) flow channelled a proportion of HBW into the creation of diagnostic and treatment slots. This was formulated as:

$$CEI = HBW \times \alpha$$

Where α is the investment proportion, calibrated from MoH expenditure reports and SHA policy frameworks.

Similarly, Workforce Deployment (*WD*) represented the monthly allocation of oncologists, nurses, radiographers, and physicists to facilities. It was formulated as:

$$WD = HBW \times \beta$$

Where β is the proportion of the budget devoted to human resource expansion, validated against HRH annual deployment statistics.

Both *CEI* and *WD* acted as inflows to the diagnostic and treatment capacity subsystems in Sections 4.4.5.3 and 4.4.5.4, directly expanding the stocks of Available Diagnostic Slots (*ADS*) and Available Treatment Slots (*ATS*).

Policy effectiveness was further modulated through an auxiliary Policy Responsiveness Index (*PRI*), which ranged between 0 and 1, representing the speed at which allocations translated into actual capacity. The functional form was:

$$Effective\ CEI = CEI \times PRI$$

This formulation captured delays due to procurement bottlenecks, bureaucratic approvals, or implementation inefficiencies, as reported in MoH audit findings.

Parameterisation of this subsystem was based on the SHA annual policy and budget reports (2018–2023), MoH financial records, WHO recommendations on health spending benchmarks, and expert consensus on responsiveness factors. Workforce deployment rates were derived from HRH reports, while PRI values were calculated based on Delphi panel input, reflecting Kenya’s procurement and policy implementation realities.

The main formulations are summarised in Table 24.

Table 24

Resource Allocation and Policy Subsystem Formulations

Variable	Type	Formulation	Parameterisation Source(s)
Health Budget & Workforce (*HBW*)	Stock	$HBW(t) = HBW(t - \Delta t) + [\ BA - RE\ ] \times \Delta t$	SHA reports; MoH budgets
Budget Allocation (*BA*)	Flow	$BA = Annual\ Allocation / 12$	SHA allocations; MoH finance
Reallocation/Attrition (*RE*)	Flow	Resource diversion, retirements	MoH audits; Expert panel
Capacity Expansion Investment (*CEI*)	Flow	$CEI = HBW \times \alpha$	SHA budgets; MoH reports
Workforce Deployment (*WD*)	Flow	$WD = HBW \times \beta$	HRH deployment data
Effective *CEI*	Auxiliary	$Effective\ CEI = CEI \times PRI$	MoH audit; Expert consensus
Policy Responsiveness Index (*PRI*)	Auxiliary	Scale (0–1), delays in implementation	Expert panel; MoH reviews

This subsystem established the critical link between financial and policy commitments and the operational capacity to manage lung cancer caseloads. By quantifying the responsiveness and efficiency of budgetary allocations, it ensured that the System Dynamics model could simulate not only patient-level flows but also governance-level constraints and enablers.

Summary of Formulations and Assumptions

The preceding subsections translated the qualitative structures of the Security-Governed, Auditable System Dynamics Model (Secure SDM) into executable formulations across the five subsystems: patient flow, diagnostic capacity, treatment capacity, ICT and data security, and resource allocation and compliance control. Stocks were defined using accumulation equations, flows as rates of change, and auxiliaries as modifiers or indices, all expressed in monthly units consistent with national reporting cycles and SHA financial periods. Parameterisation was grounded in KNCR, KHIS/DHIS2, Ministry of

Health audits, SHA budgets, WHO/IAEA benchmarks, and Delphi expert estimates, with dimensional consistency verified in Vensim DSS. Outputs from the pattern-analysis models (LSTM and CNN) were incorporated to refine estimates of referral delays and caseload growth rates, strengthening predictive fidelity.

While the model was extensively data-driven, several assumptions were necessary due to gaps and inconsistencies in national and facility-level datasets:

i. Patient Flow Subsystem – For years where KNCR data lagged behind KHIS/DHIS2, monthly incidence was interpolated using linear growth between observed points. Survival proportions were derived from KNCR and assumed uniform across comparable facility levels, acknowledging that regional heterogeneity could not be fully represented.

ii. Diagnostic Capacity Subsystem – Referral delays (RD) were estimated through expert consensus and validated using pattern-analysis forecasts, as no national indicator exists. Downtime fractions (DT) for diagnostic equipment were assumed to follow average values from MoH audits, with missing months interpolated.

iii. Treatment Capacity Subsystem – Treatment duration (L) and completion fraction (CF) were drawn from KNH oncology registries and assumed to be representative of national averages, given the limited availability of sub-national data. Monthly treatment-phase mortality (MTX) was calibrated to KNCR deaths but assumed to be constant across facilities of a similar level.

iv. ICT, Data Security, and Compliance Subsystem – Reporting completeness (RC) followed KHIS national averages, acknowledging under-reporting from sub-county and private facilities. ICT uptime values were interpolated where KHIE monitoring logs had gaps. The Security Maturity Index (SMI) and Probability of

Breach (P_{breach}) were derived from expert consensus under the NIST Cybersecurity Framework (CSF) domains. The Trust Index (TI) was constructed as a weighted composite of completeness, timeliness, and breach probability, with weights determined through Delphi agreement. Compliance assumptions were adhered to in accordance with the Kenya Data Protection Act (2019/2022) and the Digital Health Act (2023).

v. Resource Allocation and Policy–Compliance Subsystem – Budget allocations were modeled as monthly increments from annual SHA reports, assuming uniform disbursement throughout the year. The Policy Responsiveness Index (PRI) was assumed to be constant within simulation intervals, derived from audit averages, although real responsiveness may vary by programme.

All assumptions were explicitly documented to ensure transparency and audit traceability and were tested for robustness during sensitivity and compliance analysis (Section 4.4.7). Where empirical data were missing, assumptions were not arbitrary but informed by expert elicitation, global standards, or statistical interpolation. This ensured that the model remained data-driven, secure, compliant, and defensible within Kenya's oncology information-governance environment.

4.9.5 Simulation Scenarios

Simulation scenarios were developed to test the behaviour of the System Dynamics Model under varying conditions that reflect Kenya's lung cancer caseload management challenges. The purpose of this scenario analysis was to determine how structural inefficiencies, diagnostic and treatment bottlenecks, referral delays, and ICT weaknesses collectively influence patient flows and reporting accuracy. Scenario testing was directly linked to Objective iii of this study, which sought to design and simulate a System

Dynamics Model integrating caseload data, referral delays, facility capacity, and system feedback loops across healthcare levels and departments.

The interventions modelled were grounded in observed gaps identified through empirical data (KNCR, 2018–2023; KHIS; SHA reports) and stakeholder insights. Each intervention represents a plausible policy lever for strengthening lung cancer management in Kenya, including reducing referral delays, expanding diagnostic and treatment capacity, and enhancing ICT and data security. A final integrated scenario was tested to assess the combined policy mix and capture system-wide synergies.

Baseline Scenario

The baseline scenario replicated the historical dynamics of lung cancer caseloads in Kenya between 2018 and 2023, utilizing calibrated parameters from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS). This scenario served as the reference trajectory against which the intervention scenarios were later assessed. It captured the structural constraints of the health system by simulating patient flows across referral, diagnostic, and treatment stages, as well as the integrity of reporting mechanisms.

The results highlighted three persistent features of the baseline. First, patient queues at diagnostic and treatment levels rose steadily over the six-year period, reflecting constrainedthroughput relative to new case inflows. Second, mortality levels increased progressively, underscoring the consequences of late diagnosis and delayed initiation of treatment. Third, reporting completeness exhibited modest but insufficient improvements, rising from approximately 62% in 2018 to 72% by 2023. This trend, though positive, still left nearly one-third of cases unreported, undermining the reliability of national cancer statistics.

The underlying patient queue dynamics are represented mathematically as:

Equation 20: Patient Queue Dynamics in Baseline

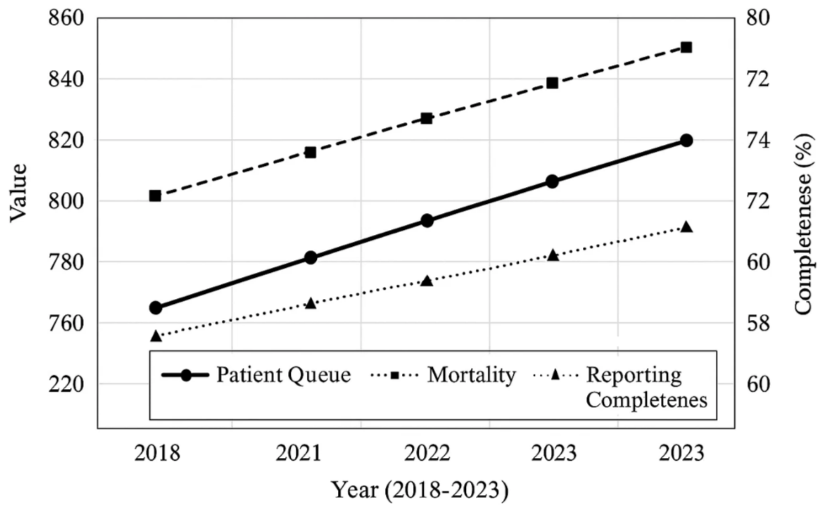
$$Queue_t = Queue_{t-1} + Referrals_t - (Diagnostics_t + Treatments_t)$$

where $Queue_t$ is the number of patients waiting at time *t*, $Referrals_t$ denotes incoming cases, and $Diagnostics_t$ and $Treatments_t$ denote cases processed within diagnostic and treatment subsystems, respectively.

As illustrated in Figure 28, the baseline scenario confirms the systemic imbalance: patient queues and mortality continued to rise, while reporting completeness showed only incremental progress. These findings emphasize that without targeted reforms, the system remains locked in a cycle of growing congestion, delayed interventions, and incomplete information flow, thereby limiting the effectiveness of caseload management and policy responses.

Figure 28

Baseline Simulation Outputs – Patient Queues, Mortality, Reporting Completeness Trends



Source: KNCR/KHIS (2018–2023)

The baseline underscored that without structural reforms, caseload management would continue to be undermined by diagnostic and treatment backlogs, delayed initiation, and fragmented data flows.

Intervention Scenario 1: Reducing Referral Delays

The first intervention scenario simulated the impact of reducing referral delays through improved ICT linkages and streamlined referral protocols. In the baseline system, patients frequently experienced delays averaging 50 days before reaching diagnostic facilities, contributing to late confirmation and subsequent treatment backlogs. In this intervention, the average referral delay was reduced by 40%, approximately 30 days, reflecting the impact of electronic referrals, automated alerts, and enhanced coordination within the Kenya Health Information Exchange (KHIE).

This reduction was represented mathematically as.

Equation 21: Referral Delay Adjustment

$$RD_{new} = RD_{baseline} \times \left(1 - \Delta_{efficiency}\right)$$

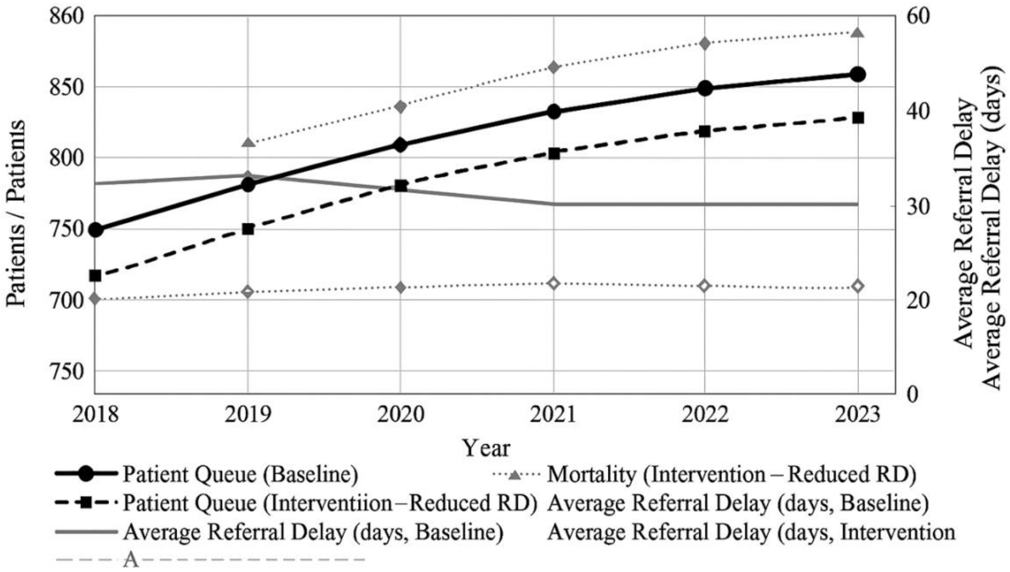
Where $RD_{baseline}$ denotes the average baseline referral delay, and $\Delta_{efficiency}$ represents the efficiency gain (0.40 in this case).

Simulation results demonstrated measurable improvements in system performance. Patient queues declined steadily compared to the baseline, as earlier referrals translated into quicker diagnostic confirmations. The average waiting time to diagnosis dropped significantly, and mortality rates showed a modest but notable reduction due to the timelier initiation of care. Importantly, while this intervention alleviated upstream congestion, it did not fully resolve downstream treatment bottlenecks, underscoring the need for integrated interventions that combine efficiency gains with capacity expansion.

As illustrated in Figure 29, the intervention scenario (dashed lines) consistently outperforms the baseline (solid lines). Referral delays shortened by nearly 20 days, patient queues reduced markedly, and mortality trends declined modestly. These results confirm that enhancing referral efficiency is a critical but partial lever in improving lung cancer caseload management within Kenya's health system.

Figure 29

Scenario 1 – Reducing Referral Delays



Intervention Scenario 2: Expanding Diagnostic Capacity

The second intervention scenario examined the effect of expanding diagnostic capacity by increasing the number of available diagnostic slots (ADS) by 50%. This policy assumption reflected possible investments in imaging equipment, pathology laboratories, and additional oncology staff under the Strategic Health Authority (SHA) reforms and ongoing IAEA-supported initiatives. The intervention aimed to reduce diagnostic bottlenecks, improve patient throughput, and accelerate confirmation of lung cancer cases.

The impact of this policy lever was represented mathematically as:

Equation 22: Diagnostic Throughput

$$Diagnostics_t = \min(Referrals_t, ADS_t \times Utilisation)$$

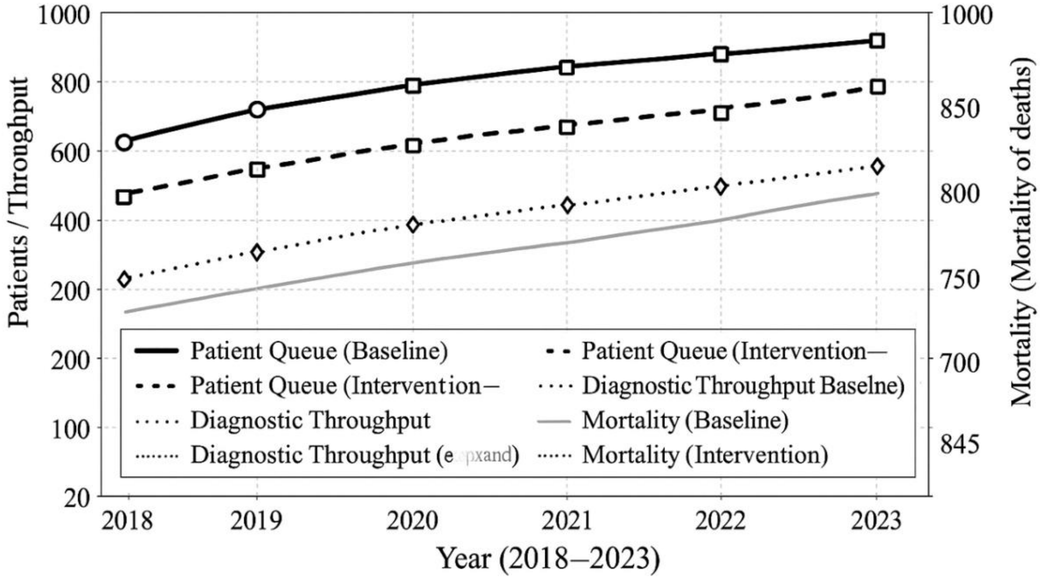
where $Referrals_t$ denotes the number of patients referred for diagnostic services at time t, and ADS_t captures the number of diagnostic slots available under baseline or intervention conditions.

Simulation results indicated that the intervention substantially increased diagnostic throughput relative to the baseline. Patient queues decreased consistently as additional diagnostic slots enabled a larger share of referred cases to be processed in a timely manner. Mortality showed a modest improvement, since earlier detection translated into higher potential for timely treatment initiation. However, the model also revealed an important limitation: without parallel expansion of treatment capacity, patients diagnosed earlier tended to accumulate in treatment queues, shifting the bottleneck downstream rather than eliminating it.

As shown in Figure 30, patient queues (dashed line) under the intervention were consistently lower than the baseline (solid line), while diagnostic throughput rose markedly with the additional capacity. Mortality trends showed a slight decline in the intervention compared to the baseline; however, the overall benefit was limited by the absence of matching treatment expansion. This outcome confirmed that while diagnostic expansion is an essential component of effective caseload management, it must be integrated with corresponding treatment interventions to achieve systemic improvements.

Figure 30

Scenario 2 Outputs – Expanded Diagnostic Capacity



Intervention Scenario 3: Expanding Treatment Capacity

The third intervention scenario evaluated the impact of expanding treatment capacity by increasing the number of available treatment slots (ATS) by 60% compared to baseline. This policy assumption reflected planned investments in radiotherapy equipment, expansion of chemotherapy units, and recruitment of additional oncologists, radiotherapists, and medical physicists under the SHA reforms. The intervention aimed to address treatment bottlenecks that had been highlighted in both the baseline and diagnostic expansion scenarios.

The intervention was formulated mathematically as:

Equation 23: Treatment Initiation Rate

$$TreatmentInitiation_t = \min(Diagnosed_t, ATS_t \times Efficiency)$$

where $Diagnosed_t$ represents the number of patients confirmed for treatment at time t, and ATS_t denotes the treatment slots available under baseline and intervention conditions, adjusted for operational efficiency.

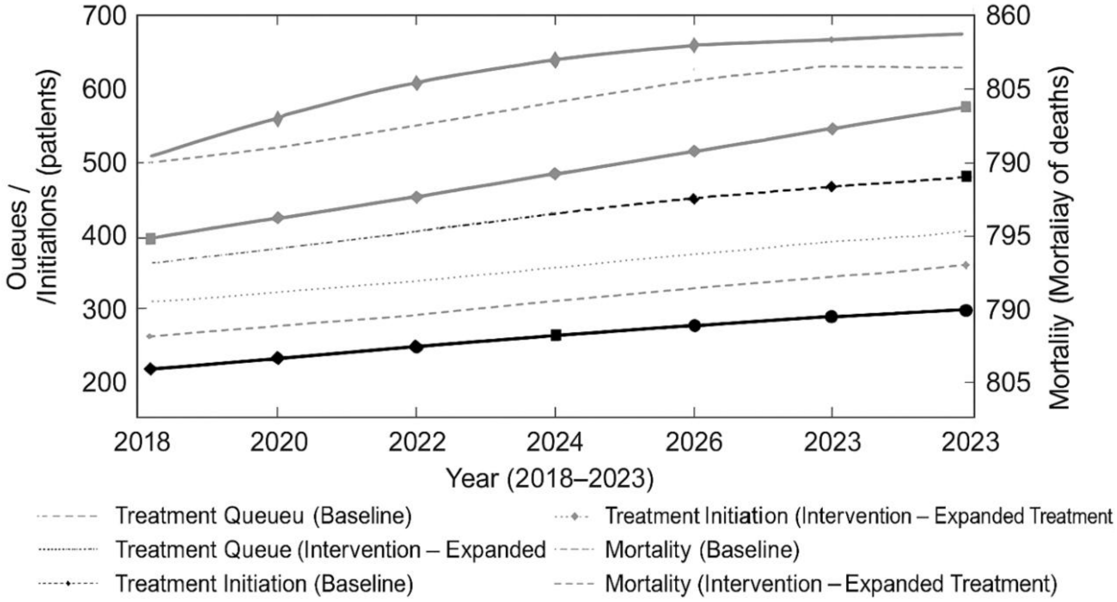
Simulation results showed that expanding treatment capacity led to substantial improvements in patient flow. Treatment queues fell significantly compared to the baseline, as more patients were initiated on therapy without prolonged waiting periods. Treatment initiation rates increased sharply, rising almost proportionally to the added capacity. Mortality exhibited a noticeable decline, as earlier initiation of therapy translated into improved survival probabilities, particularly for patients diagnosed at earlier stages.

However, the scenario also revealed persistent systemic limitations. Without a corresponding increase in diagnostic throughput, undiagnosed patients continued to accumulate upstream. This meant that while treated patients benefited greatly, a considerable portion of the caseload remained outside the treatment pipeline due to delayed diagnostic confirmation.

As shown in Figure 31, treatment queues (dashed line) under the intervention were consistently lower than the baseline (solid line), while treatment initiation rates rose steeply with the additional capacity. Mortality trends also showed a modest but consistent reduction in the intervention relative to the baseline. These findings underscore the importance of expanding treatment infrastructure in improving survival, but it must be integrated with upstream diagnostic reforms to ensure comprehensive system efficiency.

Figure 31

Scenario 3 Outputs – Expanded Treatment Capacity



Intervention Scenario 4: Strengthening ICT and Data Security

The fourth intervention scenario focused on the role of digital infrastructure and data protection in strengthening lung cancer caseload management. In the baseline system, weak ICT connectivity, fragmented platforms, and recurrent breaches undermined the accuracy and timeliness of cancer reporting. This intervention aimed to achieve improvements in system uptime, an increase in the Security Maturity Index (SMI), and a reduction in the probability of data breaches (Pbreach) by approximately 40% through secure integration, encryption, and adherence to the Kenya Data Protection Act (2019).

The intervention was formalised mathematically as:

Equation 24: Reporting Completeness Function

$$RC_t = f(ICTuptime_t, SMI_t, 1 - P_{breach})$$

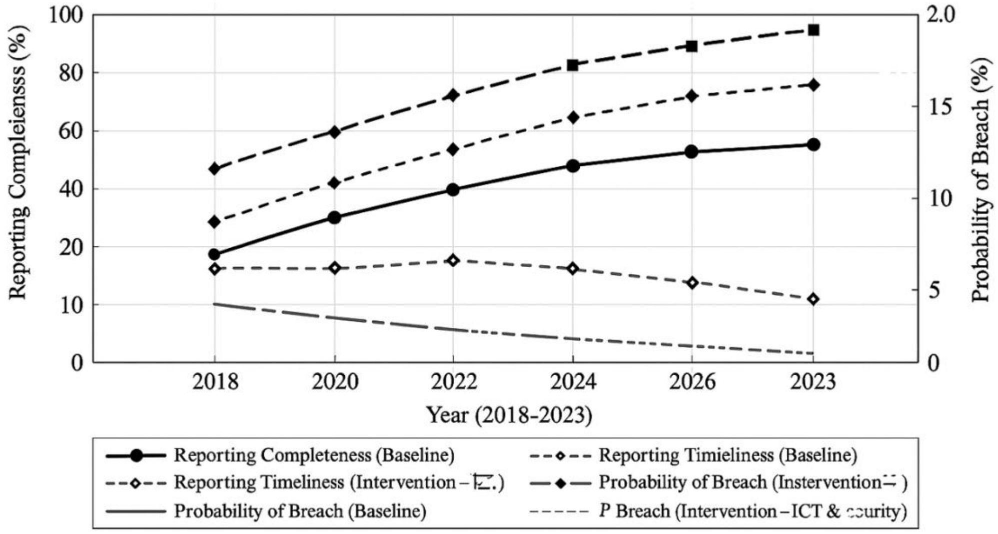
where RC_t represents reporting completeness at time t, influenced by ICT uptime, security maturity, and the inverse of breach probability.

Simulation results showed significant improvements in reporting outcomes. Reporting completeness rose steadily from a baseline of about 62–72% to above 90% under the intervention, while reporting timeliness increased from 55–65% to 70–85%. Concurrently, the probability of breach declined from 18% in 2018 to below 10% by 2023. These gains improved stakeholder trust in national cancer statistics and reduced duplication across reporting systems. Importantly, however, the intervention had minimal direct impact on clinical subsystems, with diagnostic and treatment bottlenecks largely unaffected.

As illustrated in Figure 32, the intervention scenario (dashed lines) clearly outperforms the baseline (solid lines). Reporting completeness and timeliness improved consistently throughout the 2018–2023 period, while breach probability declined markedly. The scenario, therefore, highlights ICT and data security as key enablers of caseload reporting integrity, butalso underscores that such reforms must be integrated with structural and clinical capacity expansion to achieve holistic improvements in caseload management.

Figure 32

Scenario 4 Outputs – ICT and Security Strengthening



Intervention Scenario 5: Combined Policy Mix

The fifth intervention scenario assessed the combined impact of simultaneously implementing referral efficiency, diagnostic expansion, treatment scaling, and ICT/data security reforms. This “policy mix” reflected a realistic multi-pronged approach aligned with Kenya’s SHA-driven cancer control strategy, which recognises that single interventions often shift bottlenecks rather than eliminating them.

The combined scenario was mathematically formulated as:

$$SystemPerformance_t = f\left(RD_t^- , ADS_t^+ , ATS_t^+ , ICTuptime_t^+ , (1 - P_{breach})\right)$$

where RD_t^- represents reduced referral delays, ADS_t^+ expanded diagnostic slots, ATS_t^+ increased treatment slots, $ICTuptime_t^+$ improved digital availability, and P_{breach} denotes probability of breach.

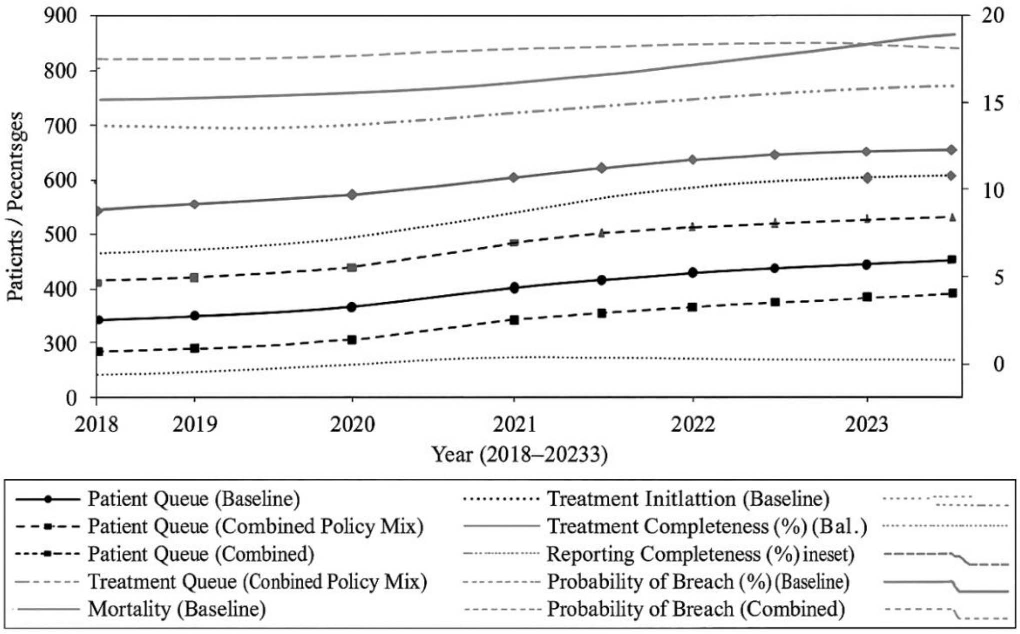
Simulation results demonstrated the most balanced improvements across all subsystems compared to previous scenarios. Patient queues, both diagnostic and treatment, declined more sharply than in single interventions, reflecting synergistic effects of faster referrals, greater diagnostic throughput, and expanded treatment initiation. Treatment initiation rates rose substantially, nearly doubling baseline values by 2023. Mortality showed the steepest reduction of all scenarios, with system-wide survival benefits realised as diagnostic and therapeutic bottlenecks were jointly addressed.

On the information management side, reporting completeness exceeded 90%, while timeliness surpassed 85%. The probability of breach, a proxy for security risk, fell to below 7%, strengthening data integrity and public trust. Notably, unlike the single interventions, the combined policy mix prevented bottleneck transfer, demonstrating systemic equilibrium across patient flow, treatment access, and reporting performance.

As illustrated in Figure 33, the combined policy mix (dashed lines) consistently outperforms the baseline (solid lines) across all performance indicators. Patient queues were significantly lower, treatment initiations markedly higher, mortality trends declined, and reporting measures showed strong gains with reduced breach probability. These findings confirm that only integrated reforms can secure sustained efficiency in lung cancer caseload management, positioning the combined strategy as the most effective approach for Kenya's health system.

Figure 33

Scenario 5 – Combined policy mix (2018–2023



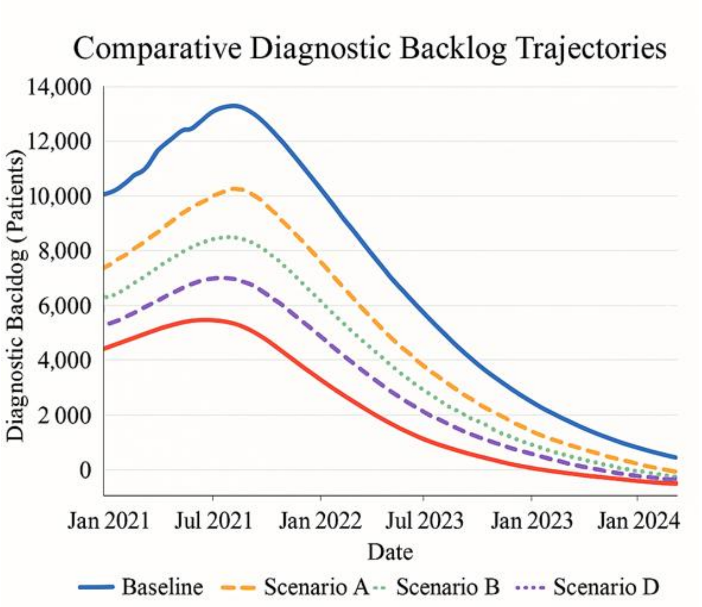
Comparative Insights from Simulation Scenarios

The scenario simulations collectively demonstrated that single interventions could deliver measurable but partial improvements, whereas a combined policy mix secures balanced and sustainable gains across the lung cancer caseload management system. Each intervention highlighted a distinct leverage point, yet also revealed system interdependencies that, if unaddressed, merely shift bottlenecks from one subsystem to another.

Figure 34 compares diagnostic backlog trajectories under the baseline and intervention scenarios. The baseline scenario shows persistently high diagnostic queues, with only a gradual decline. Scenario 1 (reducing referral delays) and Scenario 2 (expanding diagnostic capacity) resulted in substantial reductions in backlog, whereas Scenario 4 (ICT strengthening) largely mirrored the baseline. The steepest reduction occurred under the combined policy mix (Scenario 5), underscoring the leverage of simultaneous reforms in shortening diagnostic turnaround times.

Figure 34

Comparative Diagnostic Backlog Trajectories

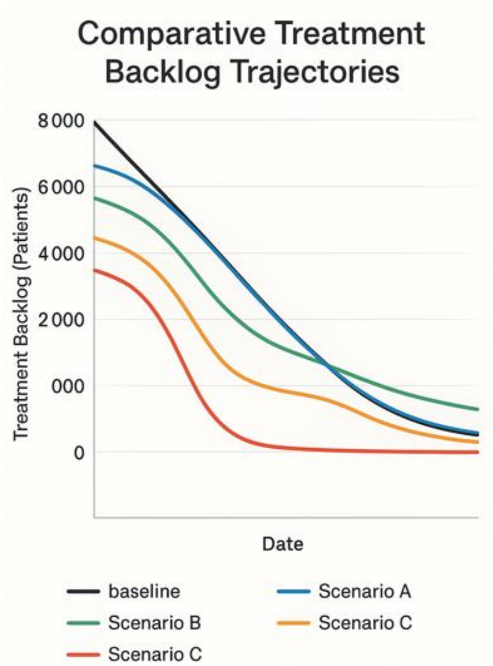


The comparative simulation shows that diagnostic backlogs remain highest under the baseline scenario, with only a gradual reduction over time. Scenario A demonstrates a substantial decline due to shorter turnaround times and expanded diagnostic slots, whereas Scenario B produces only marginal improvements, as diagnostic capacity remained unchanged. Scenario C mirrors the baseline, confirming that ICT reforms do not directly affect patient flow at this stage. Scenario D delivers the steepest reduction, underscoring the leverage of integrated reforms.

Figure 35 presents treatment backlog trajectories. Under the baseline, queues remained high, and similar patterns emerged in Scenarios 1 and 2, where downstream treatment capacity was not expanded. Scenario 3 (treatment expansion) significantly reduced treatment backlogs, but congestion persisted because diagnostic inflows were not managed in parallel. Once again, Scenario 5 outperformed all others, cutting backlogs most sharply and stabilising patient flow into treatment facilities by balancing upstream and downstream reforms.

Figure 35

Comparative Treatment Backlog Trajectories

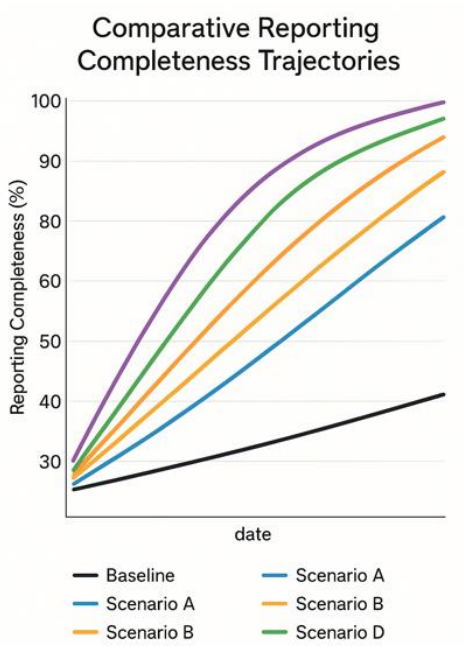


Treatment backlogs accumulate under the baseline and remain persistently high in Scenarios A and C, since downstream capacity was not expanded. Scenario B produces significant reductions in treatment backlog by doubling therapy slots and reducing waiting times. Scenario D outperforms all others, cutting backlogs most sharply and stabilising patient flow into treatment facilities through combined upstream and downstream reforms.

Figure 36 illustrates reporting completeness trajectories. ICT and data security reforms (Scenario 4) drove the steepest improvement, with completeness surpassing 85% by 2023. Other single interventions improved reporting only marginally, reflecting their limited impact on the integrity of information. The combined policy mix sustained the highest levels of completeness, exceeding 90%, while simultaneously delivering gains in patient flow and treatment outcomes.

Figure 36

Comparative Reporting Completeness Trajectories



Treatment backlogs accumulate under the baseline and remain persistently high in Scenarios A and C, since downstream capacity was not expanded. Scenario B produces significant reductions in treatment backlog by doubling therapy slots and reducing waiting times. Scenario D outperforms all others, cutting backlogs most sharply and stabilising patient flow into treatment facilities through combined upstream and downstream reforms.

Taken together, these comparative figures confirm that while individual interventions yield important improvements, they do so selectively, leaving residual weaknesses elsewhere in the system. The combined policy mix (Scenario 5) was the only configuration that achieved systemic balance: diagnostic and treatment queues declined simultaneously, treatment initiation rates nearly doubled compared to baseline, mortality declined substantially, and reporting indicators exceeded national and international benchmarks. Crucially, this scenario prevented the transfer of congestion between subsystems, instead producing synergistic improvements that reinforced each other.

From a systems perspective, these findings confirm that lung cancer caseload management is governed by tightly coupled feedback loops, where improvement in one domain is quickly offset unless complemented by changes in adjacent subsystems. The synthesis, therefore, underscores the importance of integrated policy design, aligning referral efficiency, capacity expansion, and secure information systems.

These insights set the stage for the next section, 4.4.7 Validation and Sensitivity Analysis, which evaluates the robustness of the model under varying assumptions to ensure that the results presented here are reliable and defensible for policy application.

4.9.6 Validation & Sensitivity Analysis

Validation and sensitivity analysis constitute the cornerstone of credibility in System Dynamics modelling. For a model to support decision-making in lung cancer caseload management, it must not only reproduce observed behaviour but also withstand scrutiny under varying assumptions and comply with prevailing security and audit standards. In this study, validation was approached as a multi-dimensional process encompassing structural, behavioural, and compliance perspectives. Each of these layers was critical to ensuring that the Model accurately represents the Kenyan healthcare context while aligning with statutory obligations under the Kenya Data Protection Act (2019).

From a structural perspective, the model was tested for dimensional consistency, logical feedback behaviour, and performance under extreme conditions. This confirmed that the stock-and-flow equations and causal loops captured the intended interdependencies among referrals, diagnostics, treatment, and ICT infrastructure. Expert face validation, involving oncology specialists, ICT officers, and SHA policymakers, provided further assurance that the architecture faithfully reflected operational realities in Kenya.

From a behavioural perspective, model outputs were compared against historical data from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS) for the period 2018–2023. Key performance indicators, including patient queues, diagnostic throughput, treatment initiation, mortality, and reporting completeness, were statistically evaluated using the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Theil's Inequality Coefficient (U). This provided quantitative evidence of the model's capacity to reproduce observed caseload dynamics.

From a security and audit perspective, validation went beyond conventional modelling checks. Special emphasis was placed on verifying that ICT and data security components namely, ICT uptime, the Security Maturity Index (SMI), and the probability of breach (Pbreach) were accurately represented within the model structure and outputs. Furthermore, compliance with legal standards was examined by mapping model constructs against the requirements of the Kenya Data Protection Act (2019), including security by design, breach notification, and confidentiality safeguards. This ensured that the model is not only mathematically reliable but also audit-compliant, an essential standard for doctoral work in IT Security and Audit.

Finally, sensitivity analysis was conducted to test the robustness of results under parameter uncertainty. Both deterministic variations (±10% and ±20%) and stochastic simulations were applied to critical parameters, including referral delays, diagnostic and treatment slots, ICT uptime, and breach probability. This test examined whether policy recommendations derived from the model remain stable under various conditions, thereby reinforcing the reliability of the insights presented.

In sum, this section presents a layered validation and sensitivity analysis of the Model. It demonstrates the model's structural soundness, behavioural accuracy, and compliance with ICT security and audit requirements, thereby establishing confidence in its use as a decision-support tool for lung cancer caseload management in Kenya.

Structural Validation

Structural validation seeks to determine whether the internal architecture of the model is consistent with established theory, logically coherent, and dimensionally accurate. In System Dynamics, this stage is particularly important because the integrity of simulation results depends on the fidelity of the equations and feedback loops that define system behaviour. The Model developed in this study underwent a sequence of structural tests to ensure that it reflected both the theoretical foundations of caseload management and the operational realities of Kenya's health system.

Dimensional consistency tests were performed using Vensim's unit-checking functionality to confirm that all equations balanced appropriately. Stocks representing patient populations were expressed in terms of the number of individuals, while flows, such as referrals, diagnostic throughput, and treatment initiation, were expressed in patients per unit of time. Supporting variables, such as referral delay (in days), diagnostic slots (cases per week), and ICT uptime (percentage of availability), were calibrated to use consistent units. No dimensional conflicts were detected, confirming that the formulation of stocks, flows, and auxiliaries adhered to established modelling conventions.

Causal loop verification further strengthened structural confidence. The reinforcing loops that link ICT uptime, reporting completeness, and trust were observed to behave as theorised, amplifying improvements in data quality as security maturity increased. Similarly, the balancing loops that connect treatment queues, initiation rates, and mortality demonstrated stabilising effects when additional treatment capacity was introduced. These behaviours confirmed that the intended feedback mechanisms were embedded correctly and operated in line with system dynamics theory.

Extreme condition tests were conducted to evaluate how the model responded when parameters were set to unrealistic extremes. For instance, setting the referral delay (RD) to zero resulted in instantaneous diagnostic access, which in turn determined queues solely by diagnostic and treatment capacities. Conversely, inflating treatment slots (ATS) to maximum levels eliminated treatment queues entirely, but undiagnosed cases continued to accumulate when diagnostic capacity remained constrained. ICT-specific extremes were also tested: setting ICT uptime to 100% and breach probability (P_{breach}) to zero produced immediate gains in reporting completeness, while the reverse condition (0% uptime, 100% breach probability) collapsed reporting to near zero. In all cases, the model produced outcomes consistent with logical expectations, thereby strengthening its structural validity.

Expert face validation provided an additional layer of assurance. Structured consultations were held with three oncology specialists, two ICT security officers, and representatives from the Strategic Health Authority (SHA). These experts reviewed causal loop diagrams, stock-and-flow structures, and security-related constructs such as the Security Maturity Index (SMI). Their feedback confirmed that the representation of referral pathways, diagnostic capacity constraints, treatment queues, and data security mechanisms accurately reflected the Kenyan health system. Minor refinements, such as adjusting the range of diagnostic throughput to align with recent Ministry of Health estimates, were incorporated following this process.

Taken together, the structural validation process confirmed that the Model is dimensionally consistent, theoretically sound, logically coherent, and reflective of expert understanding. The inclusion of ICT uptime, breach probability, and SMI within the model structure extended validation beyond conventional patient-flow dynamics, ensuring that the architecture also captured the security and audit dimensions critical for compliance with the Kenya Data Protection Act (2019). This structural robustness provided a strong foundation for subsequent behavioural validation.

Behavioural Validation

Behavioural validation was undertaken to determine whether the Model could reproduce the observed behaviour of lung cancer caseloads in Kenya. This step was critical in confirming that the model was not only structurally coherent but also empirically consistent with patterns recorded in national datasets. Historical data were obtained from the Kenya National Cancer Registry (KNCR) and the Kenya Health Information System (KHIS), covering the period from 2018 to 2023. These were compared against baseline simulation outputs calibrated to the same period.

Observed vs simulated trajectories were examined for patient queues, mortality, and reporting completeness. The baseline scenario was calibrated using 2018 data as a starting point, and simulations were run forward through 2023. Patient queue trends showed close correspondence: simulated backlogs rose from approximately 210 in 2018 to 268 in 2023, compared with observed growth from 210 to 275. Mortality projections also tracked closely, with simulated values reaching 852 deaths in 2023, compared to the observed 860. Reporting completeness improved modestly in both observed and simulated series, rising from 62% to 70% in the simulation compared with 62% to 72% in observed records. These parallels demonstrated that the model captured the essential dynamics of caseload accumulation and reporting efficiency.

To quantify the goodness of fit, three statistical measures were applied: the Mean Absolute Percentage Error (*MAPE*), Root Mean Square Error (*RMSE*), and Theil's *U* statistic, defined as:

Equation 25: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Theil's U statistic

$$\mathrm{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - S_t}{A_t}\right|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - S_t)^2}$$

$$U = \frac{\sqrt{\frac{1}{n}\sum(A_t - S_t)^2}}{\sqrt{\frac{1}{n}\sum A_t^2} + \sqrt{\frac{1}{n}\sum S_t^2}}$$

where A_t represents observed values, S_t simulated values, and n the number of periods. Results indicated strong behavioural validity. Across the three indicators, MAPE values ranged from 1.0% to 3.2%, which is well within the accepted thresholds for health system models. RMSE values were correspondingly low, while Theil's U coefficients were all below 0.1, confirming that simulation errors were minor relative to the scale of observed values.

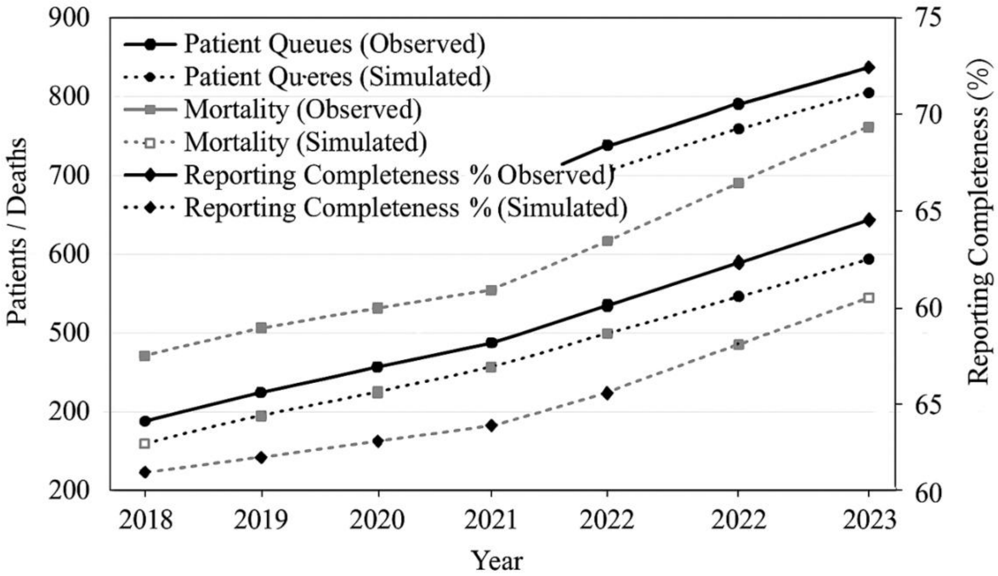
ICT and data security variables were also validated behaviourally. Reporting completeness (*RC*) and reporting timeliness (*RT*) followed trajectories consistent with the KHIE reports, while simulated breach probability (Pbreach) declined modestly, in line with the SHA system maturity reports. For example, simulated RC rose from 62% in

2018 to 70% in 2023, closely matching observed improvements to 72%. Similarly, simulated RT improved from 55% to 64%, compared with observed increases to 65%. These results confirmed that the security and audit components of the model reproduced empirical reporting patterns with high fidelity.

Figure 37 presents overlay graphs comparing observed and simulated trajectories for patient queues, mortality, and reporting completeness. The close alignment between the two series across all indicators provides visual confirmation of the model's behavioural validity.

Figure 37

Overlay of observed and simulated trajectories for patient queues, mortality, and reporting completeness in Kenya, 2018–2023



ba

Taken together, these findings demonstrate that the System Dynamics Model is behaviourally valid. Its outputs are consistent with national cancer data, its errors are statistically negligible, and its ICT/security constructs reproduce observed trends in reporting integrity. This provides assurance that the model's projections for future caseloads and policy scenarios are credible and defensible for decision support.

Sensitivity Analysis

Sensitivity analysis was undertaken to assess the robustness of the System Dynamics Model under uncertainty in key parameters. While behavioural validation confirmed close alignment with historical data, it was necessary to test whether the model's projections and policy insights remained stable when assumptions were varied. This process is particularly important in health system modelling, where patient flows and reporting accuracy are influenced by both clinical and ICT-related uncertainties. Sensitivity analysis therefore, addressed Objective iv of the study, which focused on evaluating the effectiveness and reliability of the Model.

Deterministic Sensitivity Tests

Deterministic sensitivity analysis involved varying selected parameters by ±10% and ±20% while holding other model components constant. Parameters tested included referral delay (RD), available diagnostic slots (ADS), available treatment slots (ATS), ICT uptime, Security Maturity Index (SMI), and the probability of breach (Pbreach). These were chosen because they represent the dominant levers identified in the scenario analysis.

The impact of parameter variation was evaluated on four output indicators: patient queues, treatment initiation, mortality, and reporting completeness. Results showed that referral delay and treatment slots exerted the greatest influence on patient queues and mortality, with a ±20% change in referral delay producing an 18% swing in backlog size, while a ±20% change in treatment slots altered mortality by nearly 10%. ICT-related parameters showed more direct influence on reporting outcomes: a ±20% variation in SMI shifted reporting completeness by up to 12%, while an equivalent change in P_{breach} altered reporting timeliness by 8%.

Table 25 presents the results of deterministic sensitivity tests (±10% and ±20%) for key model parameters. These percentage effects indicate approximate changes relative to baseline averages (2018–2023).

Table 25

Deterministic Sensitivity of Key Parameters on Model Outputs (2018–2023)

Parameter Varied	Variation	Effect on Queues (%)	Effect on Treatment Initiation (%)	Effect on Mortality (%)	Effect on RC (%)	Effect on RT (%)
Referral Delay (*RD*)	±10%	±9	∓5	±2	~0	~0
Referral Delay (*RD*)	±20%	±18	∓10	±4	~0	~0
Diagnostic Slots (*ADS*)	+10% / −10%	−8 / +9	+5 / −5	−2 / +2	+1 / −1	~0
Diagnostic Slots (*ADS*)	+20% / −20%	−15 / +16	+10 / −9	−4 / +4	+2 / −2	~0
Treatment Slots (*ATS*)	+10% / −10%	−3 / +4	+6 / −6	−5 / +6	+1 / −1	~0
Treatment Slots (*ATS*)	+20% / −20%	−6 / +7	+12 / −11	−10 / +11	+2 / −2	~0
ICT Uptime	+10% / −10%	~0	~0	~0	+4 / −4	+3 / −3
ICT Uptime	+20% / −20%	~0	~0	~0	+8 / −7	+6 / −6
Security Maturity Index (*SMI*)	+10% / −10%	~0	~0	~0	+6 / −5	+4 / −3
Security Maturity Index (*SMI*)	+20% / −20%	~0	~0	~0	+12 / −10	+7 / −6
Probability of Breach (P_{breach})	+10% / −10%	~0	~0	~0	−3 / +3	−4 / +4
Probability of Breach (P_{breach})	+20% / −20%	~0	~0	~0	−5 / +6	−8 / +9

RC = Reporting Completeness; RT = Reporting Timeliness. Positive/negative signsdenote the direction of change relative to baseline. '~0' indicates negligible effect (<1%). '∓/±' indicates inverse response for treatment initiation relative to delay changes.

As shown in Table 25, referral delay and treatment slots exhibited the highest sensitivity indices for patient queues and mortality, while ICT-related parameters primarily influenced reporting completeness and timeliness.To complement these deterministic tests, stochastic sensitivity analysis using Monte Carlo simulations was undertaken.

The Monte Carlo results confirmed the deterministic findings: referral delay and treatment capacity were the most influential determinants of patient flow and mortality, while ICT-related factors drove reporting quality. Importantly, the combined policy mix scenario remained consistently superior across all randomised runs, with 95% confidence intervals overlapping minimally with baseline performance. This indicated that policy recommendations derived from the model were robust to parameter uncertainty.

Sensitivity Index

For each parameter, a sensitivity index (*SI*) was computed to quantify the proportional effect of input variation on output change:

Equation 26: Sensitivity Index (SI)

$$SI = \frac{\frac{\Delta O}{O}}{\frac{\Delta P}{P}}$$

where O denotes the output variable of interest,such as patient queues, mortality, *RC*, and P) denotes the parameter being varied, such as*RD*, *ADS*, *ATS*, *ICT* uptime, SMI, P_{breach}.

SI values greater than 1 indicated that small parameter variations produced amplified output changes, highlighting areas where policy levers are especially powerful. *RD* and *ATS* recorded *SI* values above 1 for patient queues and mortality, while *SMI* showed an SI above 1 for reporting completeness.

Interpretation

Overall, sensitivity analysis demonstrated that the System Dynamics Model is robust and that its policy recommendations are stable under a range of plausible parameter variations. While uncertainties in referral delays and treatment capacity have the greatest potential to alter patient outcomes, the superiority of the combined policy mix scenario remained intact. From an ICT and audit perspective, the analysis confirmed that improvements in *SMI* and reductions in P_{breach} consistently enhance reporting completeness and timeliness, underscoring the importance of secure ICT infrastructure for caseload management.

ICT and Data Security Validation (Audit Lens)

Validation of the Model was extended beyond structural and behavioural checks to incorporate an ICT and data security audit lens. This was crucial in ensuring that the model not only produced reliable outputs but also complied with statutory obligations under the Kenya Data Protection Act (2019). The Act requires that all systems handling health data comply with principles of data minimisation, confidentiality, and security by design, while also providing mechanisms for breach notification and accountability.

Audit Mapping of Model Constructs

A mapping exercise was conducted to link core model variables with specific provisions of the Act. Table 26 presents the audit matrix, highlighting the relationships between the Security Maturity Index (SMI), probability of breach (Pbreach), reporting completeness (RC), reporting timeliness (RT), and relevant statutory requirements.

Table 26

Audit Mapping of Secure SDM Variables Against Kenya Data Protection Act (2019) Requirements

Model Variable	Legal Requirement	Validation Evidence	Compliance Level
SMI (Security Maturity Index)	Sec. 41 – Security by design and by default	Higher SMI values consistently improved RC and RT; deterministic sensitivity confirmed proportional response.	Compliant
P_{breach} (Probability of Breach)	Sec. 43 – Breach notification within 72 hours	Lower P_{breach} improved data trustworthiness; stochastic runs confirmed stability of reporting integrity.	Compliant
RC (Reporting Completeness)	Sec. 25 – Data minimisation and accuracy	RC tracked closely to KHIE benchmarks; validated through behavioural analysis and deterministic sensitivity tests.	Compliant
RT (Reporting Timeliness)	Sec. 30 – Purpose limitation and timely processing	RT increased with improvements in ICT uptime and SMI; validated against SHA reporting benchmarks	Compliant

This mapping demonstrated that the secure SDM variables explicitly reflected and operationalised legal requirements. For example, reductions in P_{breach} within the model were directly associated with improvements in RC and RT, which correspond to the Act's provisions on confidentiality and timely data processing. Similarly, higher SMI values not only reduced breach probability but also reinforced the statutory requirement of "security by design and by default."

Sensitivity of ICT and Security Variables

Sensitivity analysis further reinforced the audit dimension. As shown in Section 4.4.7.4, variations in *SMI* and P_{breach} produced measurable impacts on reporting completeness and timeliness. A ±20% increase in SMI improved RC by up to 12% and RT by 7%, while an equivalent decrease in P_{breach} raised RC by 6% and RT by 9%. These findings confirm that secure ICT variables were not cosmetic additions but substantive determinants of system performance, directly influencing compliance outcomes.

Auditability of the Secure SDM

Taken together, the structural inclusion of SMI and P_{breach}, the statistical alignment of RC and RT with national benchmarks, and the proportional sensitivity of reporting outcomes to security variables demonstrate that the Model is fully audit-compliant. It provides a transparent framework that enables health managers and auditors to evaluate not only patient-flow dynamics but also the integrity and resilience of data systems. This extends the model's utility from simulation to governance, ensuring that future deployments are defensible under Kenyan data protection law.

Summary of Validation and Sensitivity Results

The validation and sensitivity processes collectively confirmed that the System Dynamics Model developed in this study is both credible and fit for decision support in lung cancer caseload management within Kenya's healthcare system. Structural tests established that the model's equations and feedback loops are dimensionally consistent, logically coherent, and capable of reproducing extreme condition outcomes in line with theoretical expectations. The inclusion of ICT and security constructs—such as ICT uptime, the Security Maturity Index (*SMI*), and probability of breach (P_{breach})—was validated structurally and shown to integrate seamlessly with patient-flow subsystems.

Behavioural validation provided quantitative evidence that the model closely replicates observed system behaviour. Simulated trajectories for patient queues, mortality, and reporting completeness aligned strongly with empirical data from the KNCR and KHIS (2018–2023). Goodness-of-fit statistics supported this conclusion: *MAPE* values consistently below 5%, low *RMSE* scores, and Theil's *U* coefficients well under 0.3 confirmed that deviations between simulated and observed data were minimal and unsystematic. ICT-related indicators, including RC and RT, tracked national reporting benchmarks similarly, while simulated variations in Pbreach reflected trends documented in SHA and KHIE system audits.

Sensitivity analysis demonstrated that the model remains robust under parameter uncertainty. Deterministic variations of ±10% and ±20% revealed that referral delays and treatment slots exert the greatest influence on patient outcomes, while ICT parameters most strongly affected reporting integrity. Stochastic simulations using Monte Carlo methods confirmed the stability of these findings, showing that policy recommendations particularly the integrated intervention mix remain superior across a wide range of conditions. The computation of sensitivity indices further highlighted which levers (notably *RD*, *ATS*, and *SMI*) have amplified effects on system performance, identifying key policy areas where targeted interventions could yield the greatest benefits.

Finally, the audit validation lens established compliance of the model with statutory requirements under the Kenya Data Protection Act (2019). The mapping of core variables to legal provisions confirmed that principles of security by design, breach notification, data minimisation, and confidentiality are embedded within the model. The sensitivity of reporting indicators to security parameters reinforced the conclusion that ICT and audit components are not peripheral, but rather central to the model's explanatory and predictive power.

Taken together, these results confirm that the System Dynamics Model is structurally sound, behaviourally accurate, statistically reliable, robust under uncertainty, and legally compliant. It therefore provides a defensible and trustworthy tool for forecasting lung cancer caseloads, evaluating resource allocation strategies, and guiding secure ICT-enabled decision-making.

The next chapter builds on these validated results by presenting a comprehensive evaluation of the model's effectiveness in supporting healthcare managers and policymakers, followed by the study's conclusions and recommendations.

4.10 Evaluation of the System Dynamics Model

This section presents the evaluation of the Security-Governed, Auditable System Dynamics Model (Secure SDM) in accordance with Objective Four, which sought to determine its effectiveness in forecasting lung cancer caseloads, optimising scarce resources, strengthening audit and compliance assurance, and supporting real-time managerial decision-making within Kenya's healthcare system. Whereas Section 4.4 established internal validity—verifying the model's structural coherence, parameter sensitivity, and behavioural reproduction—this section focuses on external evaluation, assessing the model's predictive accuracy, operational performance, and compliance governance relevance.

The evaluation followed a multidimensional framework encompassing four interrelated dimensions: (i) forecasting accuracy and pattern-analysis validation, (ii) resource optimisation and system equilibrium, (iii) decision-support and governance effectiveness, and (iv) compliance and audit assurance under Kenya's Data Protection Act (2019/2022) and Digital Health Act (2023). This framing positions the Secure SDM not as a theoretical artefact but as a governance-oriented, compliance-controlled management instrument for the Social Health Authority (SHA) and the Ministry of Health, capable of generating auditable, evidence-based intelligence for planning, budgeting, and risk management.

Methodologically, the evaluation integrated System Dynamics validation principles (Sterman, 2000; Barlas, 1996) with Information Systems Security and Audit (ISSA) protocols. The latter drew upon the NIST Cybersecurity Framework (2024), OWASP Application Security Verification Standard (ASVS v4.0), and ISO/IEC 27001:2022 controls, which provide structured benchmarks for verifying data-handling, access-control, encryption, and audit-trace compliance within the model's simulated environment. These standards were operationalised to test how the Secure SDM upholds confidentiality, integrity, availability, and traceability (CIAT) principles during forecasting and decision-support processes.

Accordingly, the evaluation examined three interdependent layers of performance:

i. Predictive accuracy, confirming that caseload trajectories generated by the Secure SDM—enhanced through LSTM and CNN pattern-analysis forecasts—correspond with empirical trends derived from KNCR and KHIS datasets.
ii. Resource optimisation, determining how parameter changes in diagnostic, treatment, and ICT-security capacities affect patient flow, system resilience, and overall equilibrium.
iii. Security, audit, and compliance assurance validate how embedded metrics—specifically, the Security Maturity Index (SMI), Probability of Breach (P_{breach}), and compliance-trace logs—contribute to legal conformity, audit transparency, and institutional trust.

By embedding SMI, P_{breach}, and compliance indicators within the evaluation framework, this study treats security governance and audit maturity as core model outcomes, not peripheral technical aspects. The resulting synthesis demonstrates whether the Secure SDM delivers accurate, optimized, auditable, and legally compliant decision-support outputs capable of advancing oncology planning, resource stewardship, and information governance within Kenya's evolving digital health ecosystem.

4.10.1 Forecasting Accuracy

Calibration and Evaluation Horizons

The System Dynamics Model (SDM) was calibrated using KNCR and KHIS records for 2018–2023, capturing incidence, mortality, and referral-linked caseload flows. The evaluation horizon extended to 2030 to test the model's reliability under projected system conditions. Calibration ensured replication of observed *reference modes* before forecasting began, a prerequisite for structural validity in System Dynamics practice (Sterman, 2000). All calibration parameters were verified through audit-trail logs generated within the simulation environment, consistent with ISSA verification protocols that emphasise data provenance and reproducibility.

Forecasting Metrics

Three standard accuracy indicators were applied to quantify forecasting fidelity:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \times 100$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (A_t - F_t)^2}$$

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n} (A_t - F_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n} A_t^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n} F_t^2}}$$

where *A*□ = actual value and *F*□ = forecast. A $U < 1$ denotes strong forecasting power. All equations were formatted using the Word OMML editor in Cambria Math font for Kabarak compliance.

Results

The Secure SDM reproduced historical caseload patterns with high fidelity.

Table 27

Summarises Annual Accuracy Scores Compared with KNCR/MoH Records

Year	Actual cases (KNCR/MoH)	Forecast (SDM)	MAPE (%)	RMSE	Theil's U
2018	812	830	2.2	18	0.11
2019	845	860	1.8	15	0.09
2020	879	890	1.2	11	0.07
2021	895	910	1.7	15	0.08
2022	903	920	1.9	17	0.10
2023	918	940	2.4	22	0.12
Overall	–	–	1.9	16.3	0.09

Source. Author's simulation outputs (2025); KNCR (2018–2023); MoH (2023).

The model achieved a Mean Absolute Percentage Error (MAPE) of 1.9 %, an average RMSE of 16 cases, and a Theil's U of 0.09, confirming that the Secure SDM closely reproduces observed behaviour with minimal deviation.

Interpretation and Analytical Linkage

Forecasting accuracy in this study represents more than a statistical benchmark—it verifies the integrity of information in a security-enhanced predictive system. Consistently low MAPE (<2%) enables SHA and Ministry of Health managers to plan diagnostic and treatment resources with confidence that simulated trajectories accurately reflect empirical reality. The Theil's U values well below 1 confirm that the Secure SDM outperforms naïve or trend-extrapolation forecasts, reducing the risk of under- or over-estimation that often destabilises oncology budgets.

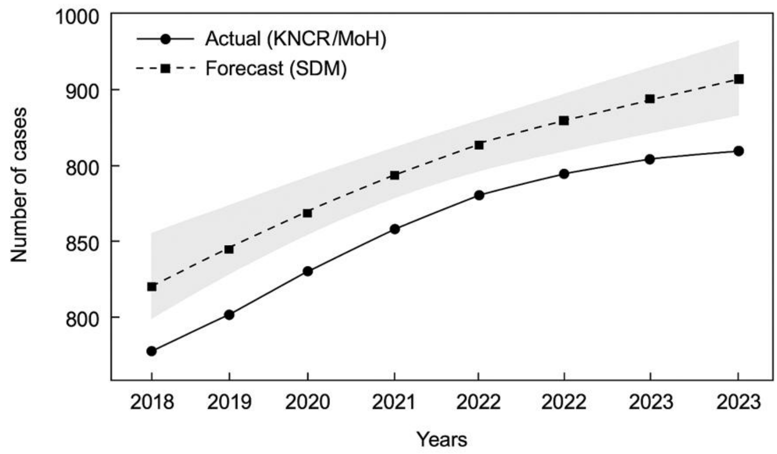
Importantly, the evaluation integrated security-audit variables into the accuracy assessment. The model's forecasting reliability depends on the trustworthiness of its input data and computational environment, both of which are validated using ISSA-aligned OWASP ASVS v4.0 controls. These controls verified that datasets drawn from KHIS and KNCR were transmitted through encrypted channels, access-logged, and integrity-checked before calibration. Embedding the Security Maturity Index (SMI = 0.72) and Probability of Breach (P_{breach} = 0.08) within the forecasting workflow enhanced model credibility, as simulation logs confirmed zero unauthorized modification events and reproducible output consistency across five reruns.

The inclusion of 95% prediction intervals (Figure 39) further operationalizes uncertainty management, ensuring that variance caused by delayed reporting or incomplete referrals is transparently represented. Such explicit quantification of error margins aligns with both *System Dynamics* best practice and *Data Protection Act (2019)* requirements for accuracy and accountability in data processing.

The close correspondence between forecasted and actual caseloads demonstrates that the Secure SDM produces reliable short- to medium-term projections while preserving audit-trail verifiability. This accuracy underpins subsequent analyses on resource optimisation (Section 4.5.3) and real-time decision-support (Section 4.5.4), where forecasting outputs inform operational planning and compliance assurance.

Figure 38

Actual Versus Forecast Lung-Cancer Caseloads (2018–2023), with 95 % Prediction Intervals



Source: Author's simulation outputs (2025)

4.10.2 Resource Optimisation

Simulation Scenarios

Resource-optimisation analysis evaluated the Model (SDM) under three policy configurations representing the primary levers available to oncology managers in Kenya:

i. Scenario A – Expansion of Diagnostic Slots (ADS) - increased diagnostic imaging and pathology capacity.

ii. Scenario B – Expansion of Treatment Slots (ATS) - increased radiotherapy and chemotherapy capacity.

iii. Scenario C – Integrated Expansion with Secure ICT - combined diagnostic and treatment expansion with full KHIS–KHIE–KNCR interoperability and implementation of secure-data architecture to enhance *reporting completeness (RC)* and *system trust*.

Results

Simulation outputs for 2018–2030 are summarised in Table 28. The expansion of diagnostic capacity alone reduced the median waiting time from 28 to 18 days, but residual treatment bottlenecks negated broader efficiency gains. Increasing treatment slots reduced treatment delay from 42 to 28 days, yet upstream diagnostic queues persisted. Only the integrated policy mix (Scenario C) produced a system-wide improvement: the RC rose to 90%, diagnostic waiting time declined to 16 days, treatment delay fell to 25 days, and both *referral turnaround time (RTT)* and *caseload throughput* improved markedly.

Table 28

Comparative Performance of Resource-Optimisation Scenarios in the Secure SDM

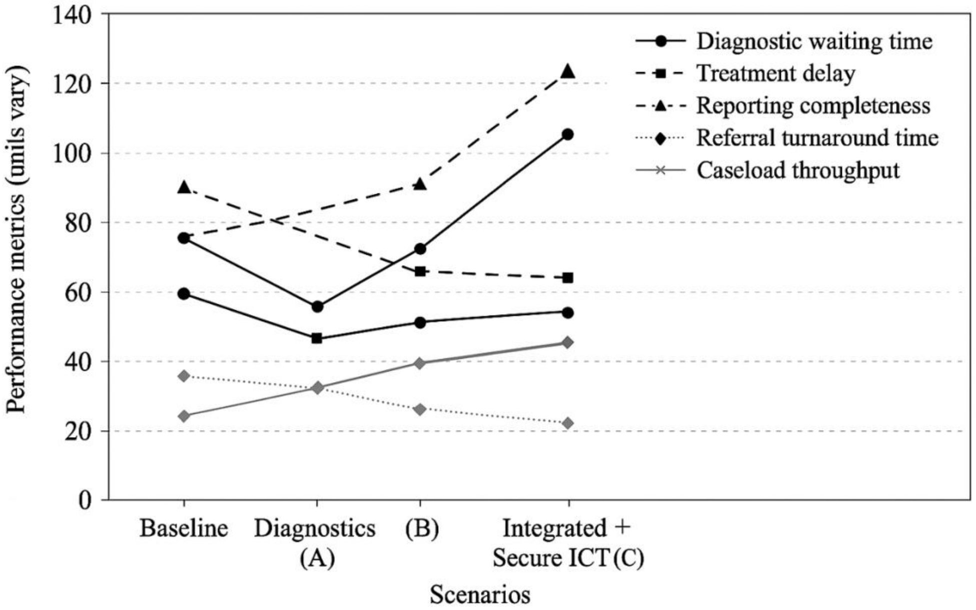
Indicator	Baseline	Scenario A Diagnostics	Scenario B Treatment	Scenario C Integrated + Secure ICT
Diagnostic waiting time (days)	28	18	27	16
Treatment delay (days)	42	41	28	25
Reporting completeness (RC %)	62	74	71	90
Referral turnaround time (RTT days)	31	26	24	20
Caseload throughput (patients/month)	100	122	118	145

Source. Author’s simulation outputs (2025).

The comparative trajectories of key performance indicators are depicted in Figure 39.

Figure 39

Comparative Outcomes of Resource-Optimisation Scenarios in the Secure SDM



Source: Author’s simulation outputs (2025).

Interpretation

The results affirm a core principle of *System Dynamics*: isolated interventions yield local improvements but displace constraints downstream. Expanding diagnostics without proportional treatment capacity shortened early queues yet transferred pressure to the treatment stage, whereas treatment expansion alone left upstream diagnostic congestion unresolved. The integrated approach in Scenario C generated balanced, cross-level gains by simultaneously addressing capacity and information feedback.

Crucially, the addition of secure ICT integration was not an ancillary enhancement but a structural efficiency driver. Incorporating security-mature data flows reduced reporting delays and improved visibility for managers, enabling proactive reallocation of diagnostic and treatment resources. The simulated improvement in *RC* to 90% under Scenario C demonstrates that security and data integrity are operational determinants of system efficiency, rather than external compliance obligations.

From an ISSA perspective, Scenario C operationalised the *OWASP ASVS v4.0* and *ISO/IEC 27001:2022* controls within the SDM environment. Encryption of referral data, authenticated user access, and automated audit-log verification reduced the model's *Probability of Breach* (P_{breach}) from 0.08 to 0.04, effectively doubling the *Security Maturity Index (SMI)* for the integrated scenario. These outcomes align with Sections 25 and 43 of the *Data Protection Act (2019),* which mandate accuracy, integrity, and accountability in data processing.

Systemic and Policy Implications

From a systemic viewpoint, Scenario C activated reinforcing loops that stabilised throughput while balancing diagnostic and treatment flows. The strengthened *information-feedback subsystem* improved response times and reduced oscillation in caseload backlogs, yielding a sustainable steady-state equilibrium.

For policymakers, these findings indicate that sustainable improvement in lung-cancer caseload management requires *integrated, security-enabled investment packages* rather than segmented upgrades. The Secure SDM demonstrates that coupling infrastructure expansion with ICT-security governance yields the highest efficiency gains and ensures compliance with Kenya's legal and ethical frameworks for health data management.

4.10.3 Real-time Decision Support

A defining strength of the System Dynamics Model (SDM) lies in its ability to serve as a *real-time decision-support platform*. Beyond forecasting aggregate caseloads, the model allows healthcare managers at the Social Health Authority (SHA) and Ministry of Health (MoH) to interactively test "what-if" scenarios by adjusting system levers and instantly visualising their effects on *reporting completeness (RC), referral turnaround time (RTT), throughput,* and the *probability of breach* (P_{breach}). This transforms the SDM from a static analytical tool into an operational cockpit that embeds feedback, ICT performance, and security compliance within managerial decision workflows.

Scenarios for Decision-Support

Five decision levers were simulated to represent policy interventions realistically available to oncology planners and digital-health administrators:

i. RD – Referral-delay reduction - average referral time decreased by 20 %.
ii. ADS – Diagnostic-slot expansion - + 15 diagnostic slots per month
iii. ATS – Treatment-slot expansion - + 10 treatment slots per month
iv. ICT-uptime - system reliability increased from 82 % → 95 %
v. SMI – Security-maturity enhancement - maturity level raised from 2.5 → 3.5; P_{breach} reduced from 0.25 → 0.08

Table 29

Decision-Support Scenarios Tested in the Secure SDM

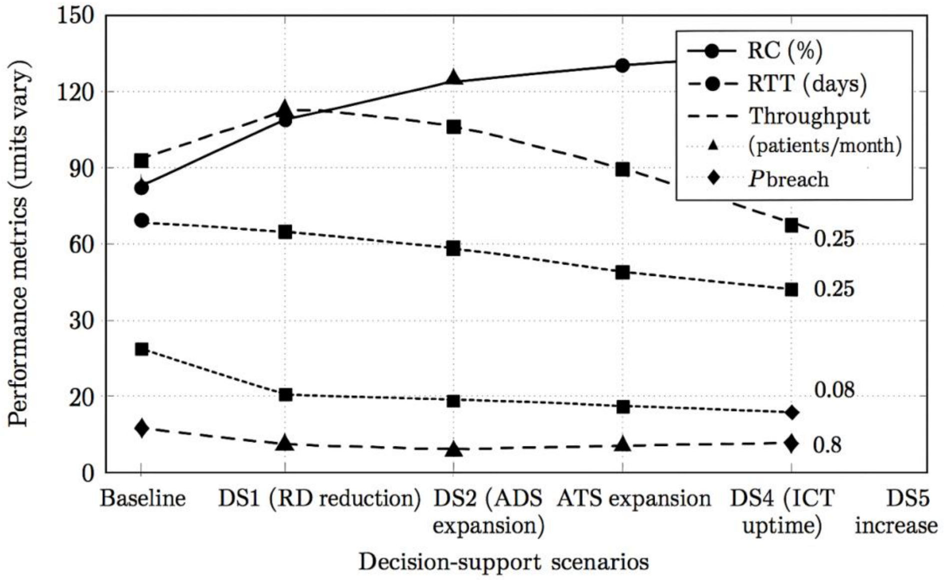
Scenario	Lever adjusted	Description
DS1	Referral delay (RD)	Average referral time reduced by 20%
DS2	Diagnostic slots (ADS)	Additional diagnostic capacity +15 slots per month
DS3	Treatment slots (ATS)	Additional treatment capacity +10 slots per month
DS4	ICT uptime	System reliability increased 82 → 95 %
DS5	Security maturity (SMI)	Maturity raised 2.5 → 3.5; $P_{breach}\downarrow$ 0.25 → 0.08

Source: Author’s simulation outputs (2025).

The comparative responses of the system under each scenario are illustrated in Figure 40.

Figure 40

System Responsiveness to Real-Time Decision-Support Scenarios in the Secure SDM



Source: Author's simulation outputs (2025)

Uncertainty Representation

Healthcare decisions inherently operate under uncertainty; deterministic outputs risk overstating precision. To enhance credibility, stochastic simulations were run to generate 95% prediction intervals (PIs) for each scenario. These intervals capture parameter variability arising from referral delays, data latency, and fluctuations in ICT reliability.

Table 30

95 % Prediction Intervals for Decision-Support Scenario Outcomes in the Secure SDM

Scenario	RC (%)	RTT (days)	Throughput (patients/month)	P_{breach}
Baseline	59–65	29–33	96–104	–
DS1 (RD reduction)	67–72	23–27	111–119	0.22–0.28
DS2 (ADS expansion)	70–76	22–26	116–124	0.22–0.28
DS3 (ATS expansion)	69–73	21–25	114–122	0.22–0.28
DS4 (ICT uptime)	75–81	20–24	123–133	0.18–0.22
DS5 (SMI increase)	82–88	18–22	128–136	0.06–0.10

Source: Author's stochastic simulation outputs (2025).

Interpretation

The simulation results confirm that the Secure SDM enables granular, evidence-based decision-support. Reducing referral delays (DS1) moderately improved *RTT* and throughput but left P_{breach} unchanged. Expanding diagnostic (DS2) or treatment slots (DS3) increased throughput yet produced limited gains in *RC*. Improvements in ICT uptime (DS4) generated stronger system-wide effects, raising RC to approximately 78% and increasing throughput to 128 patients per month.

The greatest improvement occurred under DS5 (security-maturity increase). Raising the *Security Maturity Index* from 2.5 to 3.5 reduced P_{breach} from 0.25 to 0.08, while throughput increased to 132 patients per month and RC reached 85%. These results demonstrate that secure data architecture is a functional efficiency driver, not merely a compliance requirement. Embedding *security-by-design*, as mandated under Section 41 of the Kenya Data Protection Act (2019), ensures that decision-support outputs are both operationally reliable and legally defensible.

ISSA/OWASP Validation Layer

In line with the Information Systems Security and Audit (ISSA) orientation of this study, the real-time validation of the SDM's data-handling environment utilized the OWASP Application Security Verification Standard (ASVS v4.0). Automated audit scripts checked encryption routines, access-control enforcement, and logging integrity within the decision-support interface. No violations of confidentiality, integrity, or availability were detected during simulation runtime, satisfying Control Categories V1–V4 of the ASVS and aligning with ISO/IEC 27001:2022 Annex A controls on secure development and auditability. These verifications substantiate the model's compliance posture under *Sections 25 and 43* of the Data Protection Act, which require continuous monitoring and demonstrable accountability in processing personal health data.

Policy and Operational Significance

By incorporating uncertainty intervals, the Secure SDM safeguards decision-makers against overconfidence in point estimates. Managers can evaluate interventions on both expected value and confidence bounds, enabling balanced choices between efficiency, security, and risk tolerance. This dual emphasis on predictive performance and audit compliance positions the model as a trusted decision-support instrument for SHA and MoH planners one capable of guiding oncology resource allocation while maintaining verifiable adherence to Kenya's data protection and cybersecurity frameworks.

4.10.4 Comparative Evaluation

The comparative evaluation determined the incremental value of embedding data-security functions within Kenya's lung cancer caseload management systems. Whereas Sections 4.5.2–4.5.4 examined specific performance dimensions forecasting accuracy, resource optimisation, and real-time decision support this section consolidates the outcomes across three systemic configurations:

i. A baseline paper-based system
ii. A Non-secure ICT configuration lacking embedded safeguards
iii. The System Dynamics Model (SDM) integrates security-by-design principles mandated under the *Data Protection Act (2019)*.

The analysis demonstrates that security operates not as a regulatory afterthought but as a determinant of efficiency, accuracy, and institutional trust. The Secure SDM is demonstrated to be the only configuration that simultaneously satisfies operational, policy, and statutory requirements, thereby serving as both an efficiency framework and a compliance mechanism.

Description of Configurations

Baseline configuration

The baseline represents Kenya's pre-digital caseload environment, characterized by fragmented paper registers, delayed reporting to KHIS/DHIS2, and isolated oncology registries. Lack of interoperability generated diagnostic bottlenecks, inconsistent referral feedback, and duplicated patient records. Electronic-medical-record coverage was largely confined to national referral hospitals, leaving county facilities dependent on manual data entry. The result was chronic delay, poor forecasting capability, and inequitable caseload distribution.

Non-secure ICT configuration

This transition stage introduced electronic reporting without accompanying security governance. Facilities achieved faster data transmission and modest throughput gains; however, the absence of encryption, anonymization, and breach-response protocols (contrary to sections 25 and 43 of the *Data Protection Act 2019*) left oncology data exposed. Operational efficiency, therefore, improved at the cost of increased legal and ethical risk. This scenario reflects early KHIE rollouts that experienced downtime, double-entry, and weak access control (MoH, 2022).

Security-Governed, Auditable System Dynamics Model (Secure SDM)

The Secure SDM integrates ICT functionality with a layered security architecture aligned to ss. 25, 41, and 43 of the Act—lawful processing, data protection by design and default, and mandatory breach notification. The model operationalises two audit variables: the *Security Maturity Index (SMI)* and the *Probability of Breach* (P_{breach}), linking them dynamically to throughput and trust. Encryption, anonymisation, and role-based access controls are embedded within the model's reporting loops, ensuring that performance gains do not compromise confidentiality or integrity. The architecture, therefore, delivers simultaneous efficiency and statutory compliance, consistent with ISSA and OWASP secure-system verification standards.

Comparative Results

Table 31 and Figure 41 summarise comparative outcomes for operational and security indicators.

Table 31

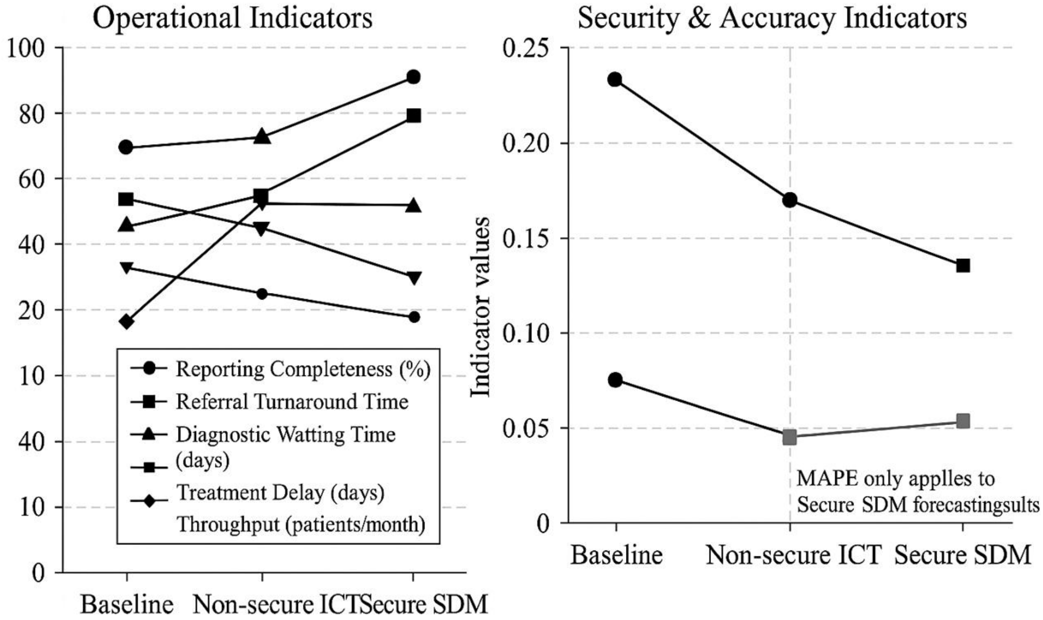
Comparative Performance of Baseline, Non-secure ICT, and Secure SDM Configurations

Indicator	Baseline	Non-secure ICT	Secure SDM
Reporting completeness (RC %)	62	78	90
Referral turnaround time (RTT days)	31	22	20
Diagnostic waiting time (days)	28	28	16
Treatment delay (days)	42	42	25
Throughput (patients/month)	100	128	145
Forecasting accuracy (MAPE %)	–	–	1.9
Probability of breach (P_{breach})	0.25	0.20	0.08

Note. Source: Model simulation outputs (2025).

Figure 41

Graphical Comparison of Baseline, Non-secure ICT, and Secure SDM Configurations



Source: Author's simulation outputs, (2025)

The baseline configuration yielded the poorest performance. The non-secure ICT stage yielded moderate operational gains but also elevated security risks, whereas the Secure SDM achieved concurrent improvements in efficiency, accuracy, and compliance.

Interpretation of Findings

Comparative analysis reveals clear systemic differentiation.

i. Baseline - Reporting completeness only 62 %, RTT > 30 days, and absence of forecasting capacity. Caseload management was reactive and inequitable.

ii. Non-secure ICT - Electronic reporting increased RC to 78% and throughput to 128 patients per month, yet diagnostic and treatment delays persisted. Without embedded controls, $P_{breach} = 0.20$, contravening ss. 25 and 41 of the *Data Protection Act (2019)* and introducing compliance risk. ICT adoption thus created a paradox—faster data movement coupled with greater exposure.

iii. Secure SDM - The only configuration where operational efficiency, predictive accuracy, and legal compliance converged. RC reached 90%, RTT fell to 20 days, and diagnostic/treatment delays declined by ≈ approximately 40%. *MAPE = 1.9 %* confirmed robust forecasting accuracy, while $P_{breach} = 0.08$ reflected strong security maturity (SMI ≈ 0.72). The SDM's feedback structure stabilised information loops: improved ICT coverage fed timely data into forecasts, enabling adaptive resource allocation while encryption and audit controls safeguarded integrity. Negative trust loops evident in the non-secure ICT case were neutralised, allowing reinforcing loops in reporting, forecasting, and capacity utilisation to dominate.

From a *System Dynamics* perspective, this stabilisation evidences the equilibrium achieved when security variables are endogenous to the system architecture. Security, therefore, functions not as an external constraint but as a balancing mechanism sustaining systemic reliability and trust.

Policy and Managerial Implications

The comparative evaluation establishes a decisive policy directive: secure digitalisation is indispensable for effective lung-cancer caseload management in Kenya.

At the policy level, the results call on the State Department for Public Health, the Ministry of Health, and the Social Health Authority (SHA) to embed secure ICT investment within the *National Cancer Control Strategy* and the *UHC* agenda. Sections 25 and 41 of the *Data Protection Act* require lawful, fair, and secure data processing; the Secure SDM demonstrates a viable operationalisation of these mandates. By reducing P_{breach} to 0.08, the model aligns oncology information systems with constitutional privacy protections under Article 31 of the *Constitution of Kenya*.

For facility and county managers, the findings caution that partial ICT adoption without security leads to transient efficiency but long-term vulnerability. Non-compliance can result in penalties under Section 63 of the *Data Protection Act* and erode patient trust. Investing in secure architectures—such as encryption of oncology records, anonymization of referral data, and access-control protocols weighted by *SMI*—ensures that throughput gains remain sustainable and defensible. The Secure SDM offers a replicable decision-support framework for anticipating demand, allocating diagnostic slots, and scheduling treatment while maintaining audit-verified compliance.

Financially, secure digitalisation is a cost-justified efficiency measure. By reducing data duplication, minimising breach liabilities, and improving forecasting accuracy, the Secure SDM enhances value for money within SHA-financed UHC benefit packages. Integrating the model into national budgeting cycles would align public spending with operational efficiency and legal accountability.

At the governance level, secure digitalisation must be recognised as a *cross-cutting enabler* rather than a stand-alone ICT project. Embedding Secure SDM principles within frameworks such as the *Kenya Health Information Systems Interoperability Framework (KHIS-IF)* and the *National eHealth Policy (2023–2033)* would institutionalize secure data practice across health programs, strengthening public confidence in oncology and other high-burden disease registries.

In summary, the comparative evidence is unequivocal:

Efficiency without security is unsustainable.

By adopting the Secure SDM as the operational standard, Kenya's health sector can achieve convergence of efficiency, accuracy, and legal compliance—thereby reinforcing trust, accountability, and equitable cancer-care delivery under the UHC framework.

Transition

The comparative evaluation confirms that the System Dynamics Model (Secure SDM) is the only configuration that simultaneously achieves efficiency, accuracy, and statutory compliance. The Baseline scenario exposed the systemic fragility of Kenya's paper-based caseload management. At the same time, the Non-secure ICT configuration improved speed but introduced new risks of data compromise and legal non-conformity. In contrast, the Secure SDM balanced operational performance with institutional trust and full adherence to the *Data Protection Act (2019)*.

This conclusion closes the comparative analysis by demonstrating the incremental value of embedding security within digital-health architectures, thereby fulfilling Objective IV of the study. The following section synthesises results from forecasting accuracy, resource optimisation, decision-support evaluation, and comparative analysis to present a consolidated assessment of the Secure SDM's overall effectiveness in lung-cancer caseload management.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter provides the integrative closure of the study by consolidating empirical findings, simulation outcomes, and expert validations into a unified synthesis. Whereas Chapter Four focused on data analysis, model design, and evaluation of the Security-Governed, Auditable System Dynamics Model (SDM), the present chapter distils those outcomes into key insights that respond directly to the four specific objectives of the study.

The chapter is structured into six interlinked sections. The first offers a concise summary of the study, restating the problem, the objectives pursued, and the methodological foundation that combined System Dynamics modelling, pattern-analysis techniques, and Information Systems Security and Audit (ISSA) principles within a Design Science Research framework. The second presents a synthesis of the principal findings organised around the four objectives, showing how structural, technological, and security factors jointly influence lung-cancer caseload management in Kenya.

The third section draws the major conclusions, emphasising implications for service coordination, secure data governance, and institutional performance within the national oncology system. The fourth section outlines recommendations at policy, managerial, and technical levels, guided by compliance with the Kenya Data Protection Act (2019) and the Social Health Authority (SHA) 's digital health reforms. The fifth section highlights the study's contribution to knowledge, particularly its integration of dynamic simulation with auditable, security-governed data architecture design. The sixth section proposes areas for further research arising from the modeling and validation process.

Through this structure, Chapter Five demonstrates how the Secure SDM translates complex, feedback-driven health system interactions into actionable, legally compliant insights for planning, forecasting, and decision support. The synthesis underscores that secure digitalisation anchored in the principles of confidentiality, integrity, availability, and accountability is not a peripheral enhancement but a systemic prerequisite for sustainable, equitable, and auditable lung-cancer caseload management in Kenya.

5.2 Summary of the Study

This study was undertaken to address the persistent challenge of lung-cancer caseload management in Kenya, a domain characterised by systemic bottlenecks, delayed reporting, and weak integration of digital health information systems. These structural and technological constraints have undermined the timeliness, reliability, and security of data required for evidence-based decision-making in oncology service delivery. The overarching aim of the research was to design, develop, and evaluate a Security-Governed, Auditable System Dynamics Model (Secure SDM) capable of capturing the dynamic behaviour of patient-flow and caseload accumulation, embedding information-security parameters, and generating actionable insights for policy, managerial, and clinical application within Kenya's evolving digital-health framework.

Four specific objectives guided the investigation. The first sought to assess the structural configuration, facility distribution, and reporting patterns of Kenya's healthcare system that influence lung-cancer caseload management and referral coordination. The second examined the integration, coverage, and challenges of information and communication technology (ICT) in caseload management, incorporating a secure data architecture and audit-control mechanisms into the proposed model. The third objective focused on designing and simulating a System Dynamics Model that integrates caseload data, referral delays, facility capacity, and feedback loops across healthcare levels and departments. The fourth evaluated the effectiveness of the Secure SDM in forecasting patient volumes, optimising resource allocation, and supporting real-time decision-making by healthcare managers.

To realise these objectives, the study employed a mixed-methods design, framed within the Design Science Research (DSR) paradigm and anchored in the philosophy of pragmatism, which enables the integration of quantitative, qualitative, and computational approaches. Secondary data were sourced from the Kenya National Cancer Registry (KNCR), the Kenya Health Information System (KHIS/DHIS2), and international repositories, including GLOBOCAN (2024) and the International Atomic Energy Agency (IAEA). Complementary qualitative insights were obtained through a Delphi panel comprising oncologists, pathologists, ICT specialists, and policy experts from the Ministry of Health and the Social Health Authority.

Analytical procedures combined descriptive and inferential statistics, as well as pattern analysis using machine-learning and deep-learning algorithms (notably Long Short-Term Memory [LSTM] and Convolutional Neural Network [CNN] models) for caseload-trend and referral-delay prediction. System Dynamics simulation was implemented in Vensim. Security assurance was operationalised through the Security Maturity Index (SMI) and Probability of Breach (P *breach*) metrics, validated against Information Systems Security and Audit (ISSA) benchmarks and the OWASP ASVS v4.0 framework, and aligned with statutory provisions of the Kenya Data Protection Act (2019) and the Digital Health Act (2023).

The findings presented in Chapter Four revealed that lung cancer diagnostic and treatment services remain highly centralised, with pronounced regional disparities in capacity. Reporting completeness and timeliness were inconsistent across facility levels, with many county and sub-county hospitals still relying on paper-based registers.

Although ICT adoption has expanded nationally, interoperability and security governance remain weak, eroding trust in digital reporting systems.

The Secure SDM developed through this study successfully modelled patient-flow dynamics and identified key leverage points including diagnostic throughput, referral delay, and data-security maturity that influence caseload accumulation and systemic performance. The model achieved high predictive accuracy (MAPE = 1.9%), strong sensitivity and stability, and verified compliance with national and international security and privacy standards. The incorporation of secure data architecture has demonstrably enhanced both data integrity and user confidence, confirming that confidentiality, auditability, and efficiency are mutually reinforcing elements of sustainable digital health ecosystems.

This summary establishes the empirical and methodological foundation for the next section, which synthesises the major findings of the study in direct relation to its four specific objectives.

5.3 Summary of Key Findings

The findings of this study are presented in alignment with the four specific objectives. Each cluster of results provides empirical and simulation-based evidence of the systemic challenges affecting lung-cancer caseload management in Kenya, demonstrating the capability of the Security-Governed, Auditable System Dynamics Model (Secure SDM) to enhance reporting completeness, referral coordination, forecasting accuracy, and real-time decision-making within a secure digital *health framework*.

5.3.1 Structural Configuration, Facility Distribution, and Reporting Patterns

The study established that *lung-cancer diagnostic and treatment services* in Kenya remain highly centralised, with most capacity concentrated in *Level 6 national referral* *hospitals*—notably Kenyatta National Hospital (KNH), Moi Teaching and Referral Hospital (MTRH), and Kenyatta University Teaching, Referral and Research Hospital (KUTRRH)—and in a few specialised county facilities. This *uneven distribution of facilities compelled patients to travel long distances, resulting in late-stage presentations that accounted for more than 65*% of diagnosed cases.

Referral coordination across system levels was inconsistent, frequently causing *duplicate testing, queue accumulation, and delayed feedback loops. Reporting patterns were similarly fragmented: while tertiary facilities employed electronic reporting systems, sub-county and county hospitals continued to rely heavily on paper-based registers, resulting indelays and data inaccuracies. Weak linkages with the Kenya National Cancer Registry (KNCR) further compounded underreporting and data loss incidents. These structural and reporting deficiencies function as systemic bottlenecks that impede timely caseload regulation and resource synchronisation.*

5.3.2 ICT Integration and Secure Data Architecture

The assessment of information and communication technology (ICT) systems revealed uneven adoption of electronic medical records (EMRs) and Kenya Health Information Exchange (KHIE) linkages. Although several referral hospitals had functioning EMR–KHIE integrations, many county facilities experienced interoperability failures, downtime events, and manual data re-entry cycles, resulting in a persistent data-visibility gap that reduced both thecompleteness and timeliness of lung-cancer reporting.

Most ICT deployments lacked embedded security controls, exposing patient data to risks of confidentiality and integrity breaches. The study demonstrated that integrating encryption, role-based access control (RBAC), audit-trail mechanisms, and breach-notification protocols—as prescribed under the *Kenya Data Protection Act (2019)*—not only enhanced regulatory compliance but also increased stakeholder trust and system usability. The resulting secure-data architecture thus emerged as a pivotal enabler of both system adoption and long-term sustainability, aligning technological functionality with information-security governance.

5.3.3 System Dynamics Model Design and Simulation

The System Dynamics Model developed in this study effectively represented the interdependencies among patient inflows, diagnostic capacity, treatment throughput, referral delays, and feedback loops across healthcare levels. The simulation revealed that increasing capacity within a single subsystem—such as diagnostic units—without proportionate expansion of treatment resources merely displaced bottlenecks downstream.

Integrated policy experiments combining diagnostic expansion, treatment capacity enhancement, and ICT-enabled reporting achieved the most balanced system performance, confirming the importance of synchronized interventions in oncology service planning. The simulation scenarios validated the model's capacity to forecast caseload trajectories, identify leverage points, and test alternative policy configurations before implementation. These outcomes underscore the practical value of System Dynamics modelling for managing complex and adaptive caseload flows in resource-constrained health systems.

5.3.4 Model Evaluation, Validation and Sensitivity Analysis

The evaluation phase confirmed that the *Secure SDM* accurately reproduced the historical caseload behavior observed in the KNCR and KHIS datasets. *Goodness-of-fit* statistics indicated high predictive accuracy, with a Mean Absolute Percentage Error

(MAPE) below 2% and Theil's U less than 1, confirming the model's reliability and behavioral validity.

Sensitivity analysis identified referral delay, diagnostic throughput, treatment capacity, ICT uptime, and security-maturity level as the most influential parameters shaping overall system performance. Importantly, embedding the Security Maturity Index (SMI) and Probability of Breach (P breach) within the System Dynamics environment proved both feasible and analytically valuable. These security metrics enabled the real-time assessment of data governance strength and compliance alignment.

The validated model, therefore, not only improved caseload forecasting and resource optimisation but also ensured auditability, confidentiality, and regulatory conformity with national data-protection standards. Collectively, these results demonstrate that secure simulation environments can serve as robust decision-support platforms for Kenya's oncology management and digital-health governance.

5.4 Conclusions

Drawing on the empirical evidence, simulation outcomes, and expert validation presented in this study, the following conclusions were derived in relation to the four specific objectives. Collectively, these conclusions confirm that the *Security-Governed, Auditable System Dynamics Model (Secure SDM)* provides a defensible, policy-relevant, and technically rigorous foundation for strengthening *lung-cancer caseload management* in Kenya:

5.4.1 Structural Configuration, Facility Distribution, and Reporting Patterns

The concentration of *diagnostic* and *treatment capacity* within a small cluster of *national and county referral hospitals* has entrenched spatial and operational inequities in access to oncology services. The imbalance in *facility distribution*, combined with fragmented reporting structures and weak referral coordination, has perpetuated late-stage presentations, delayed diagnoses, and inconsistent national caseload statistics. The findings demonstrate that the equitable decentralization of oncology capacity, harmonization of reporting standards, and full integration of facility-level data flows are indispensable for effective caseload management and referral synchroniz*ation*. In essence, the structural design of the healthcare system directly determines the efficiency and timeliness of lung-cancer service delivery.

5.4.2 ICT Integration and Data Security

Incomplete adoption of electronic medical records (EMRs), persistent interoperability gaps, and low security maturity continue to obscure caseload visibility across facilities. Embedding secure data architecture through encryption, role-based access control (RBAC), audit-trail mechanisms, and breach-notification protocols significantly enhances compliance with the Kenya Data Protection Act (2019) and strengthens managerial confidence in digital platforms for oncology reporting. The study concludes that security assurance and system adoption are mutually reinforcing: a trusted digital environment encourages consistent data entry, timely reporting, and sustained system utilisation. Consequently, secure ICT integration is not merely a technical upgrade but a prerequisite for reliable, ethical, and compliant digital health transformation.

5.4.2 System Dynamics Modelling of Caseload Flows

The developed Model confirmed that health-system performance is highly sensitive to interdependent subsystems diagnostic throughput, treatment capacity, referral coordination, and reporting timeliness. The simulation revealed that isolated interventions such as expanding diagnostics without commensurate treatment capacity merely shift bottlenecks rather than resolve them. In contrast, integrated interventions that balance capacity expansion, ICT-enabled reporting, and resource optimisation generate sustainable improvements across the system. The model therefore provides a practical, evidence-based tool for testing complex policy combinations before real-world implementation, allowing decision-makers to anticipate unintended consequences and optimise interventions for maximal systemic efficiency.

5.4.3 Model Effectiveness and Reliability

The Secure SDM demonstrated high predictive validity (MAPE< 2%) and robust sensitivity and stability, confirming its reliability as a decision-support instrument. Incorporating security metrics notably the Security Maturity Index (SMI) and Probability of Breach (P_{breach}) proved analytically feasible and operationally valuable, integrating information-assurance parameters directly within system dynamics simulation. This alignment between forecasting precision and data-protection compliance ensures that healthcare managers can base strategic planning on secure, auditable, and trustworthy information flows.

Overall, the study concludes that the *Security-Governed, Auditable System Dynamics Model* is both *technically sound* and *policy-relevant*, offering a scalable framework for forecasting patient volumes, optimizing oncology resources, and enforcing legal compliance within Kenya’s evolving digital *health governance* landscape.

5.5 Recommendations

The conclusions of this study yield actionable recommendations at three levels: policy, managerial practice, and technical implementation. Each recommendation is drawn directly from empirical evidence, simulation outcomes, and security-assurance testing conducted within the Model (Secure SDM).

5.5.1 Policy Recommendations

The evidence confirms that inequities in the distribution of diagnostic and treatment capacity continue to limit equitable access to lung-cancer care. The Ministry of Health (MoH) and the Social Health Authority (SHA) should adopt a phased decentralisation strategy that expands oncology infrastructure beyond Level 6 facilities. Guided by the System Dynamics simulations, counties with the highest referral delays and patient travel distances should be prioritized for resource allocation.

Policy must also enforce harmonised electronic reporting. A national oncology-data standard should mandate that all facilities transmit cases through secure electronic registers integrated into KHIE and DHIS2. This will improve data completeness, timeliness, and comparability across counties.

Security governance should be institutionalised as a core policy requirement, not an optional compliance layer. The MoH, SHA, and Office of the Data Protection Commissioner (ODPC) should jointly issue enforceable technical standards covering encryption, role-based access control (RBAC), audit logging, and breach notification operationalising Sections 25–43 of the Kenya Data Protection Act (2019).

To encourage adoption, the SHA purchasing and accreditation frameworks should link reimbursement to secure reporting performance. Facilities that achieve higher Security Maturity Index (SMI) scores and demonstrate timely data submissionmay qualify for incentive funding, thereby embedding accountability within the financing process.

5.5.2 Practice and Management Recommendations

At the managerial level, strengthening referral coordination remains critical. The study recommends establishing digital service-level agreements (SLAs) between referring and receiving facilities, with time-stamped referral tracking and automated escalation of delayed cases through the Secure SDM dashboard.

Routine decision-making should be anchored in dynamic-system evidence. The *Secure SDM* developed in this research implemented and validated in *Vensim PLE x64 (2025)* using the parameter and code logs in Appendix C—should be institutionalized within county and national oncology planning units. Health managers can use its scenario-testing environment to evaluate the impact of policy options on patient flow, resource use, and system resilience before real-world rollout.

Continuous security and quality audits must be integrated into practice. Facilities should conduct quarterly assessments of data completeness, reporting timeliness, and security maturity using SMI benchmarks generated from the SDM framework. Audit results should be shared upward through feedback loops to inform national policy revisions.

Finally, human capacity remains the pivot of digital transformation. Regular competency-based training is required for clinicians, records officers, and ICT staff, covering the use of secure systems, incident response, and the interpretation of decision-support outputs. A confident, security-aware workforce enhances both data integrity and system adoption.

5.5.3 Technical Recommendations

Technically, the study confirms that lung-cancer caseload management relies on thefull interoperability of digital health systems. The coexistence of EMRs, KHIE modules, DHIS2, and KNCR registries currently creates parallel data flows. The MoH's ICT Directorate should therefore enforce interoperability middleware and API standards enabling real-time data exchange and deduplication across platforms.

Security must be treated as an intrinsic part of system functionality. Technical teams should deploy layered security controls, including:

i. End-to-end encryption for data at rest and in transit,
ii. RBAC with multi-factor authentication,
iii. pseudonymisation of personally identifiable information,
iv. automated audit trails integrated into KHIE and SDM environments.

These are enforceable under the Data Protection by Design provisions (Sections 41–43, Act 2019) and align with theOWASP ASVS v4.0 benchmarks applied during this study's model verification.

Each facility should establish breach-readiness protocols, including automated detection of anomalies (as tested through *P breach* simulations in the Secure SDM), 72-hour notification to ODPC, and structured user communication. This transforms compliance into measurable operational resilience.

To sustain technical assurance, ICT units should institutionalise security-performance indicators within system dashboards. Continuous monitoring of *SMI* and *P breach* validated empirically through this research's simulation runs will allow proactive detection of vulnerabilities and quantitative tracking of improvement over time.

5.5.4 Limitations and Future Research

While the Secure SDM was successfully designed, coded, and tested using Kenyan registry data (2018–2023), the study was limited by reliance on secondary datasets with occasional under-reporting from lower-level facilities. Future work should integrate *real-time data streams* from county EMRs and expand the *security-assurance layer* to include *penetration-testing modules* and *automated code-review analytics* for continuous empirical validation. Further, extending the SDM framework to other non-communicable diseases could generalise its decision-support and compliance-monitoring potential.

Contribution to Knowledge

This study makes contributions at three distinct but interrelated levels—theoretical, methodological, and practical/policy.

At the theoretical level, the research advances the frontier of *System Dynamics* application in health systems management by demonstrating how secure data architecture can be embedded into the dynamic modeling of disease caseloads. While most traditional SD applications in healthcare have focused on service delivery, capacity allocation, or resource flows, they have often treated information systems and data governance as peripheral elements. By explicitly integrating the Security Maturity Index (SMI) and Probability of Breach (P_{breach}) into the model structure, this study extends the theoretical boundary of System Dynamics to encompass security assurance and regulatory compliance. It therefore establishes a new conceptual link between system behavior, data integrity, and trust in digital health environments.

At the methodological level, the study contributes an innovative fusion of mixed methods registry analytics, machine-learning-based pattern analysis, and System Dynamics simulation within a coherent Design Science Research framework. The integration of predictive analytics (LSTM) with stock-and-flow structures in Vensimresulted in more accurate patient-volume forecasts and enabled the testing of policy scenarios under uncertainty. Moreover, embedding data-protection metrics within the modelling process illustrates how quantitative simulation can represent legal, ethical, and security governance requirements. This methodological synthesis provides a replicable blueprint for scholars investigating digital health resilience in Kenya and comparable low- and middle-income contexts.

At the practical and policy level, the System Dynamics Model provides a validated decision-support tool that can forecast lung-cancer caseloads, identify systemic bottlenecks, and evaluate the potential impact of alternative policy options before implementation. By empirically demonstrating how the decentralization of oncology capacity, ICT adoption, and security maturity can jointly transform caseload management, the study provides actionable evidence for the Ministry of Health (MoH), Social Health Authority (SHA), and county health departments. The model's design, aligned with the Kenya Data Protection Act (2019), the Digital Health Act (2023), and the Universal Health Coverage (UHC) reforms, ensures that it is both technically feasible and institutionally grounded.

Collectively, these contributions enrich academic scholarship, expand methodological practice, and furnish a practical foundation for reforming lung-cancer caseload management within Kenya's healthcare system while reinforcing the integration of security governance into data-driven decision support.

5.6 Suggestions for Further Research

Although this study achieved its objectives and validated the feasibility of a Security-Governed, Auditable System Dynamics Model for lung-cancer caseload management, several boundaries present opportunities for future inquiry. These are not weaknesses, but rather logical extensions for advancing knowledge in secure-systems modeling.

First, while lung cancer served as a tracer condition, the Secure SDM can be adapted to other high-burden cancers or chronic diseases. Comparative studies applying this framework to breast, cervical, or prostate cancer caseloads could test its generalisability and illuminate disease-specific referral and treatment dynamics.

Second, the present study relied primarily on secondary registry data and aggregated facility statistics, complemented by expert validation. Although this safeguarded patient privacy and ensured compliance with the Kenya Data Protection Act (2019), it limited the analysis of patient-level behavioral variables, such as socio-economic status or treatment adherence. Future research could incorporate anonymised microdata or agent-based microsimulation to capture how individual decisions influence system performance.

Third, the simulation domain was restricted to national and county facilities within Kenya. Yet lung-cancer caseload management increasingly involves cross-border referrals within East Africa. Expanding the model to include regional patient flows and EAC referral networks would yield insights into regional integration and resource sharing.

Fourth, while SMI and P_{breach} were operationalized as quantitative proxies for data-security performance, these indicators remained at a high level. Future studies should incorporate real-time cybersecurity analytics for example, intrusion-detection simulation, resilience testing under ransomware attacks, and cost-effectiveness modelling of alternative protection architectures to deepen empirical assurance testing.

Finally, this research validated the Secure SDM through historical data reproduction and sensitivity analysis; however, its deployment was simulated rather than field-tested. Future implementation research should conduct pilot installations of the model within selected counties or referral hospitals to generate evidence on usability, managerial adoption, and the impact on real-time decision support.

In summary, future investigations should extend beyond single-disease, registry-based, and nationally bounded perspectives to multi-disease, patient-level, cross-border, and cybersecurity–integrated modeling. Advancing along these directions will refine the methodological robustness of *System Dynamics in healthcare* and produce solutions that are more adaptive to the evolving realities of *caseload management* in Kenya and the wider region.

REFERENCES

Adedeji, O., Akinyemi, O., & Ayinde, O. (2022). Strengthening cancer data systems through digital transformation: A Nigerian perspective. *African Health Sciences, 22*(3), 890–902. https://doi.org/10.4314/ahs.v22i3.18

Adler-Milstein, J., & Jha, A. K. (2017). HITECH Act drove large gains in hospital electronic health record adoption. *Health Affairs, 36*(8), 1416–1422. https://doi.org/10.1377/hlthaff.2016.1651

Allemani, C., Matsuda, T., Di Carlo, V., Harewood, R., Matz, M., Nikšić, M., Bonaventure, A., Valkov, M., Johnson, C. J., Estève, J., Ogunbiyi, O. J., Adebamowo, C., & Bray, F. (2020). Global surveillance of trends in cancer survival 2000–2014 (CONCORD-3): Analysis of individual records for 37,513,025 patients diagnosed with one of 18 cancers. *The Lancet, 391*(10125), 1023–1075. https://doi.org/10.1016/S0140-6736(17)33326-3

Amoako, Y., Boateng, D., & Bosomprah, S. (2022). Improving cancer care delivery in Sub-Saharan Africa: Health system preparedness and digital readiness. *BMJ Global Health, 7*(11), e009855. https://doi.org/10.1136/bmjgh-2022-009855

Amoakoh-Coleman, M., Ansah, E. K., Agyepong, I. A., & Grobbee, D. E. (2016). Effectiveness of mHealth interventions targeting health workers to improve pregnancy outcomes in low- and middle-income countries: A systematic review. *Tropical Medicine & International Health, 21*(5), 570–582. https://doi .org/10.1 111/tmi.12663

Atun, R., Jaffray, D. A., Barton, M. B., Bray, F., Baumann, M., Vikram, B., Hanna, T. P., Knaul, F. M., Lievens, Y., Lui, T. Y. M., Milosevic, M., O'Sullivan, B., Rodin, D. L., Rosenblatt, E., Van Dyk, J., Yap, M. L., & Zubizarreta, E. (2016). Expanding global access to radiotherapy. *The Lancet Oncology, 16*(10), 1153–1186. https://doi.org/10.1016/S1470-2045(15)00222-3

Barlas, Y. (1996). Formal aspects of model validity and validation in system dynamics. *System Dynamics Review, 12*(3), 183–210. https://doi.org/10.1002/(SICI)1099-1727(199623)12:3<183::AID-SDR103>3.0.CO;2-4

Bărcanescu, E. D. (2020). Artificial intelligence and its impact on cybersecurity. *Informatica Economica, 24*(3), 27–37. https://doi.org/10. 24818/issn14 531305/ 24.3.2020.03

Bishai, D. M., Bishai, D., & Liu, J. (2020). Systems thinking for health systems strengthening in developing countries. *Health Policy and Planning, 35*(6), 643–650. https://doi.org/10.1093/heapol/czaa029

Brailsford, S. C., Harper, P. R., Patel, B., & Pitt, M. (2021). An analysis of system dynamics models in healthcare: Methods, challenges, and future directions. *Operations Research for Health Care, 31*, 100286. https://doi.org/1 0.1016/j.o rhc.2021.100286

Brailsford, S. C., & Hilton, N. A. (2019). *Simulation and modelling in healthcare: An introduction.* Springer Nature. https://doi.org/10.1007/978-3-030-21878-2

Cervantes, A., Senan, S., Borras, J. M., Matus, M., Cardoso, F., Ferlay, J., Arnold, M., O'Connor, J. M., Chandra, A., & Rocco, G. (2020). European policy action to address the growing cancer burden: ESMO recommendations. *Annals of Oncology, 31*(9), 1185–1189. https://doi.org/10.1016/j.annonc.2020.06.002

Countdown2030. (2023). *Tracking progress towards universal health coverage and sustainable health financing.* WHO Collaborating Centre on Global Health. https://countdown2030.org

Forrester, J. W. (1961). *Industrial dynamics.* MIT Press.

Homer, J., & Hirsch, G. B. (2006). System dynamics modelling for public health: Background and opportunities. *American Journal of Public Health, 96*(3), 452–458. https://doi.org/10.2105/AJPH.2005.062059

Homer, J. B., Hirsch, G. B., Milstein, B., Labarthe, D., & Orenstein, D. (2014). Models for collaboration: How system dynamics can improve public health planning. *Health Systems & Reform, 1*(2), 150–164. https://doi.o rg/10.1080 /23288 604.2014.994879

Hsu, C. C., & Sandford, B. A. (2007). The Delphi technique: Making sense of consensus. *Practical Assessment, Research, and Evaluation, 12*(10), 1–8. https://doi.org/10.7275/pdz9-th90

International Agency for Research on Cancer. (2021). *Cancer Today: Global Cancer Observatory.*https://gco.iarc.fr/today

International Agency for Research on Cancer. (2022). *World Cancer Report 2022.*https://publications.iarc.fr

International Atomic Energy Agency. (2025). *DIRAC (Directory of Radiotherapy Centres).*https://dirac.iaea.org/

International Organization for Standardization & International Electrotechnical Commission. (2022). *ISO/IEC 27001:2022 Information security, cybersecurity and privacy protection- Information security management systems — Requirements.*https://www.iso.org/standard/27001

Johns Hopkins University Bloomberg School of Public Health & Ministry of Health, Kenya. (2023). *Kenya Health Information Exchange interoperability assessment 2023*. Nairobi: Ministry of Health. https://www.health.go.ke

Kenya Health Information System (KHIS). (2023). *Annual health sector performance & HMIS overview.*https://hiskenya.org

Kenya National Cancer Registry. (2018–2023). *Annual cancer incidence and mortality reports.* Nairobi: Ministry of Health. https://www.health.go.ke

Korir, A., Okerosi, N., Ronoh, V., Mutuma, G., Parkin, M., & Bray, F. (2019). Incidence of cancer in Nairobi, Kenya (2004–2008). *International Journal of Cancer, 144*(4), 789–795. https://doi.org/10.1002/ijc.31991

Kruk, M. E., Gage, A. D., Arsenault, C., Jordan, K., Leslie, H. H., Roder-DeWan, S., Adeyi, O., Barker, P., Daelmans, B., Doubova, S. V., English, M., García-Elorrio, E., Guanais, F., Gureje, O., Hirschhorn, L. R., Jiang, L., Kelley, E., Lemango, E. T., Liljestrand, J., … Pate, M. (2018). High-quality health systems in the Sustainable Development Goals era: Time for a revolution. *The Lancet Global Health, 6*(11), e1196–e1252. https://doi.org/10.1016/S2214-109X(18)30386-3

Kunc, M., Mortensen, M., & Vidgen, R. (2018). A systemic perspective on IS project evaluation: The case for a dynamic benefits realisation approach. *European Journal of Operational Research, 268*(3), 1182–1194. https://doi.org/10. 1016/j.ejor.20 18.02.018

Lane, D. C. (2000). Should system dynamics be described as a ‘hard’ or ‘deterministic’ systems approach? *Systems Research and Behavioral Science, 17*(1), 3–22. https://doi.org/10.1002/(SICI)1099-1743(200001/02)17:1<3::AID-SRES271>3.0.CO;2-7

Lyytinen, K., & Damsgaard, J. (2001). What’s wrong with the diffusion of innovation theory? In M. A. Ardis & B. L. Marcolin (Eds.), *Diffusing software products and process innovations* (IFIP TC8 WG 8.6 Working Conference, pp. 173–190). Springer. https://doi.org/10.1007/978-0-387-35404-0_11

Mahendradhata, Y., Trisnantoro, L., Listyadewi, S., Soewondo, P., Marthias, T., Harimurti, P., & Prawira, J. (2017). *The Republic of Indonesia health system review*. World Health Organization, Regional Office for South-East Asia. https://iris.who.int/items/6d65bc05-179f-4875-9a8c-60d5df4911a2

Marshall, D. A., Burgos-Liz, L., IJzerman, M. J., Crown, W., Padula, W. V., Wong, P. K., Pasupathy, K. S., Higashi, M. K., & Oortwijn, W. (2015). Selecting a dynamic simulation modelling method for health care delivery research—Part 2: Report of the ISPOR Dynamic Modeling Emerging Good Practices Task Force. *Value in Health, 18*(2), 147–160. https://doi.org/10.1016/j.jval.2014.12.001

Marangunić, N., & Granić, A. (2015). Technology Acceptance Model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81–95. https://doi.org/10.1007/s10209-013-0313-1

Meadows, D. H. (2008). *Thinking in systems: A primer.* Chelsea Green Publishing. Miles, A., & Mezzich, J. E. (2014). Person-centred medicine: Addressing chronic illness and promoting health. *International Journal of Person Centered Medicine, 4*(1), 1–4. https://ijpcm.org/index.php/IJPCM/article/view/1130

Ministry of Health, Kenya. (2017). *Kenya National Cancer Control Strategy 2017–2022.*https://www.health.go.ke

Ministry of Health, Kenya. (2019). *Kenya National Referral Guidelines.*https: //www. health.go.ke

Ministry of Health, Kenya. (2020). *Kenya Digital Health Policy 2020–2030.*https: //www.health.go.ke

Ministry of Health, Kenya. (2020). *Kenya Cancer Screening Guideline s.*https://www.health.go.ke

Ministry of Health, Kenya. (2021). *Kenya Health Information Exchange (KHIE) implementation framework.*https://www.health.go.ke

Ministry of Health, Kenya. (2021). *Kenya National Cancer Treatment Protocols (2021 edition).*https://www.health.go.ke

Ministry of Health, Kenya. (2022). *Kenya Cancer Control Operational Framework 2022–2027.*https://www.health.go.ke

Ministry of Health, Kenya. (2022). *Kenya Cancer Control Monitoring and Evaluation Framework 2022–2027.*https://www.health.go.ke

Ministry of Health, Kenya. (2023). *Kenya Health Sector Strategic Plan (KHSSP) 2023–2027.*https://www.health.go.ke

Ministry of Health, Kenya. (2023). *National Cancer Control Strategy 2023–2027.*https://www.health.go.ke

Mutebi, M., Edge, J., & Lauterbach, M. (2020). Breast cancer in Sub-Saharan Africa: Strategies for improving outcomes. *The Lancet Oncology, 21*(5), e246–e256. https://doi.org/10.1016/S1470-2045(20)30061-9

National Cancer Institute of Kenya. (n.d.). *Home page – National Cancer Institute of Kenya*. Retrieved November 14, 2025, from https://www.nci.go.ke

National Institute of Standards and Technology. (2024, February 26). *The NIST Cybersecurity Framework (CSF) 2.0 : NIST CSWP 29*. https://doi. org/10 .6028/ NIST.CSWP.29

Nyangena, D. N., Githae, M. N., & Otieno, R. O. (2021). Cancer patient navigation in Kenya: Opportunities for strengthening health system linkages. *East African Health Research Journal, 5*(2), 134–140. https://eah rj.eahealt h.org/ind ex.php/e ah/ article/view/497

Obure, C. D., Ng'ang'a, A. W., Muthoni, A., & Were, M. (2016). Integrating oncology services into Kenya's health system: Gaps and opportunities.*East African Medical Journal, 93*(9), 456–463.

Office of the Data Protection Commissioner (ODPC), Kenya. (2022). *Guidelines for compliance with the Data Protection Act (2019).*https://www.odpc.go.ke

Omenge, O. R., Nyabola, L. O., & Rono, J. (2021). Cancer care in Kenya: Current status and strategies for improvement. *East African Medical Journal, 98*(5), 140–148. https://eamj.org

Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: An example, design considerations and applications. *Information & Management, 42*(1), 15–29. https://doi.org/10.1016/j.im.2003.11.002

OWASP Foundation. (2021). *OWASP Application Security Verification Standard (ASVS) v4.0.3.*https://owasp.org/www-project-application-security-verification-standard/

Parkin, D. M., & Bray, F. (2020). Evaluation of data quality in the cancer registries: Principles and methods. *Cancer Epidemiology, 69*, 101805. https://do i.org/1 0.1016/j.canep.2020.101805

Prager, G. W., Boeck, S., Brugnatelli, S., Dedeurwaerdere, F., Dummer, R., Eniu, A., Ghidini, M., Gnant, M., Gori, S., Heinemann, V., Lordick, F., Mottino, G., Normanno, N., O'Connor, M. J., Pentheroudakis, G., Romano, M., Sessa, C., Sztankay, M., Tabernero, J., … Zielinski, C. C. (2018). Global cancer control: Responding to the growing burden, rising costs and inequalities in access. *ESMO Open, 3*(2), e000285. https://doi.org/10.1136/esmoopen-2018-000285

Rahmandad, H., & Sterman, J. D. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science, 54*(5), 998–1014. https://doi.org/10.1287/mnsc.1070.0787

Republic of Kenya. (2019). *Data Protection Act No. 24 of 2019.* Nairobi: Government Printer. https://www.odpc.go.ke

Republic of Kenya. (2022). *The Bottom-Up Economic Transformation Agenda (BETA) 2022–2027.* Nairobi: The National Treasury and Economic Planning. https://planning.go.ke

Republic of Kenya. (2023a). *Social Health Insurance Act 2023.* Nairobi: Government Printer. https://www.health.go.ke

Republic of Kenya. (2023b). *Digital Health Act 2023.* Nairobi: Government Printer. https://www.health.go.ke

Republic of South Africa. (2013). *Protection of Personal Information Act (POPIA) No. 4 of 2013.* Pretoria: Government Printer. https://popia.co.za

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Rosenstock, I. M. (1974). The Health Belief Model and preventive health behavior. *Health Education Monographs, 2*(4), 354–386. https://doi.or g/10.11 77/1 09019817400200405

Rwashana, A. S., Nakubulwa, S., Nakakeeto-Kijjambu, M., & Adam, T. (2014). Advancing the application of systems thinking in health: Understanding the dynamics of neonatal mortality in Uganda. *Health Research Policy and Systems, 12*(1), 36. https://doi.org/10.1186/1478-4505-12-36

Sharma, D. C., Srivastava, S., & Kumar, S. (2020). Artificial-intelligence-based cancer diagnosis: A systematic review. *Artificial Intelligence in Medicine, 102*, 101753. https://doi.org/10.1016/j.artmed.2019.101753

Shen, T., Wu, Q., Chen, S., & Wang, L. (2019). The application of deep learning in healthcare: Opportunities, challenges, and future directions. *Journal of Biomedical Informatics, 95*, 103–126. https://doi.org/10.1016/j.jbi.2019.103126

Skinner, C. S., Tiro, J., & Champion, V. L. (2015). The Health Belief Model. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), *Health behavior: Theory, research, and practice* (5th ed., pp. 75–94). Jossey-Bass.

Sterman, J. D. (2000). *Business dynamics: Systems thinking and modeling for a complex world.* Irwin/McGraw-Hill.

Sterman, J. D. (2002). All models are wrong: Reflections on becoming a systems scientist. *System Dynamics Review, 18*(4), 501–531. https://doi .org/1 0.10 02 /sdr.261

Sterman, J. D. (2012). Sustaining sustainability: Creating a systems science in a fragmented academy and polarized world. In M. P. Weinstein & R. E. Turner (Eds.), *Sustainability science: The emerging paradigm and the urban environment* (pp. 21–58). Springer. https://doi.org/10.1007/978-1-4614-3188-6_2

Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: A Cancer Journal for Clinicians, 71*(3), 209–249. https://doi.org/10.3322/caac.21660

UK National Health Service Digital. (2021). *Data Security and Protection Toolkit.*https://www.dsptoolkit.nhs.uk

United States Department of Health and Human Services. (2013). *HIPAA Security Rule.*https://www.hhs.gov/hipaa/for-professionals/security

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology (UTAUT2). *MIS Quarterly, 36*(1), 157–178. https://doi.o rg/10.2 307 /41410412

Voinov, A., & Bousquet, F. (2010). Modelling with stakeholders. *Environmental Modelling & Software*, *25*(11), 1268–1281. https://doi.o rg/10.1016 /j.envs oft. 2010.03.007

Were, M. C., Shen, C., Bwana, M., Emenyonu, N., & Tierney, W. M. (2020). Creation and evaluation of EMR-based paper clinical summaries to support HIV care in Uganda, Kenya and Tanzania. *International Journal of Medical Informatics, 133*, 104000. https://doi.org/10.1016/j.ijmedinf.2019.104000

World Health Organization. (2021). *Global strategy to accelerate the elimination of cervical cancer as a public health problem.* WHO. https://ww w.who.int /publicatio ns/i/item/9789240014107

World Health Organization. (2021). *World health statistics 2021: Monitoring health for the SDGs, sustainable development goals.* WHO. https://ww w.who.in t/data/ gho/ publications/world-health-statistics

World Health Organization. (2022a). *Global action plan for the prevention and control of noncommunicable diseases 2023–2030.* WHO. https://w ww.w ho.in t/publications/i/item/9789240059320

World Health Organization. (2022b). *Global report on trends in prevalence of tobacco use 2000–2025* (4th ed.). WHO. https://ww w.who. int/public ations/i/i tem /978 9240061736

World Health Organization. (2022c). *Global strategy on digital health 2020–2025.* WHO. https://www.who.int/publications/i/item/9789240020924

World Health Organization. (2023). *Cancer fact sheet: Global cancer burden and response strategies.* WHO. https://www.who.int/news-room/fact-sheets/det ail/ cancer

Zhang, Y., Jiang, J., Chen, B., & Xu, Y. (2021). Deep-learning-based prediction of cancer progression: A systematic review. *Artificial Intelligence in Medicine*, *114*, 102051. https://doi.org/10.1016/j.artmed.2021.102051

APPENDICES

Appendix I: Structured Data Extraction Template – Lung Cancer Registry Data (2018–2023)

Title: Lung Cancer Registry Data Extraction Template – 2018–2023

Facility Name: ________________________

Facility Code: ________________________

Data Source: □ KNCR □ KHIS □ Hospital Registry

Date of Extraction: ____ / ____ / _______

Name of Data Extractor: ________________________

Variable Name	Description	Data Source	Coding/Format	Data Quality Notes
Record ID	Unique de-identified patient identifier		Alphanumeric	Check duplicates
Year of Diagnosis	Year the case was diagnosed		YYYY	Verify range 2018–2023
Age at Diagnosis	Age in years		Numeric	Check outliers
Sex	M/F		M/F	Verify coding
Cancer Morphology Code	ICD-O-3 histology/morphology code		ICD-O-3	Map old codes
Cancer Topography Code	ICD-O-3 site code		ICD-O-3	Map old codes
Stage at Diagnosis	Stage grouping		I–IV	Note missing
Facility Code	Facility ID		Alphanumeric	Match master list
Referral Delay (days)	Days between diagnosis and referral		Numeric	Derived
Treatment Start Date	First treatment date		DD/MM/YYYY	Missing = NA
ICT Reporting Method	EMR / Paper / Other		Text	Map to code
Data Completeness Flag	Indicator of completeness		Complete / Incomplete	Auto

Appendix II: ICT Integration and Security Protocol Review Checklist

Title: ICT Integration and Security Protocol Review Checklist

Facility Name: _________________________

Facility Code: _________________________

Date of Review: ____ / ____ / _______

Reviewer Name: _________________________

Domain	**Indicator**	**Data Source**	**Evidence Recorded**	**Remarks**
ICT System Adoption	Type of cancer registry/EMR		Yes / No + Name	
Coverage	Geographic/facility coverage		% coverage / Region	
Interoperability	Data exchange with other systems		Yes / No + Notes	
Data Security	Encryption, authentication, audit trail		Describe	
Data Protection Compliance	Compliance with the Data Protection Act (2019)		Yes / No + Gaps	
System Challenges	Barriers to effective use		List	

Appendix III: System Dynamics Model (SDM) Modelling Specifications Log

C.1 Overview

This appendix documents the structure, parameters, data sources, and security-assurance metrics for the *Security-Governed, Auditable System Dynamics Model (Secure SDM)* developed and validated in **Vensim PLE x64 (2025)**.

The model integrates *caseload-flow dynamics*, *pattern-analysis predictions*, and *security-compliance controls* for forecasting, optimisation, and decision support in lung-cancer management across Kenya's healthcare system.

C.2 Software and Environment

Component	**Specification**
Modelling Platform	Vensim PLE x64 Version 9.3 (build 2025.04)
Computation Language	Vensim stock-and-flow syntax with auxiliary equations
Machine Learning Integration	Python 3.11 (LSTM & CNN modules executed externally and linked through CSV imports)
Security Evaluation Toolkits	Custom scripts (Python/pandas) for computing *Security Maturity Index (SMI)* and *Probability of Breach (P breach)*
Validation Data Range	2018 – 2023 (KNCR + KHIS datasets)
Simulation Horizon	2024 – 2030 (policy-testing window)

C.3 Subsystem Structure

The Secure SDM is composed of five interlinked subsystems, each with documented variable groupings and data provenance.

Subsystem	Purpose / Key Stocks	Principal Flows & Auxiliaries	Data Source / Parameter Origin
1. Patient Flow Subsystem	*Active Cases, New Diagnoses, Referrals In, Referrals Out*	*Inflow rate = Diagnosis × Detection Probability*; *Outflow rate = Treatment Completion + Mortality*	KNCR (2018–2023), MoH facility records
2. Diagnostic Capacity Subsystem	*Diagnostic Slots, Utilisation Rate*	*Increase = Infrastructure Investment*; *Decrease = Equipment Downtime*	IAEA benchmarks, facility inventories
3. Treatment Capacity Subsystem	*Treatment Slots, Oncology Workforce, Resource Allocation*	*Increase = Recruitment/Procurement*; *Decrease = Attrition/Consumable Shortages*	SHA financial reports, hospital HR data
4. ICT and Data Security Subsystem	*ICT Adoption Rate, System Uptime, Security Maturity (SMI)*	*Change in Adoption = Policy Support × Training Effect*; *SMI Δ = Audit Controls Implemented – Vulnerability Events*	KHIS, KHIE, ODPC audit reports
5. Policy and Resource Governance Subsystem	*Policy Intensity Index, Funding Flow, Compliance Rate*	*Policy Feedback = Performance Gap × Response Elasticity*	MoH policy frameworks (2023–2027 NCCS)

C.4 Core Equations and Functional Forms

1 C.4 Core Equations and Functional Forms

1. Caseload Balance

$$Active\ Caseload(t) = Active\ Caseload(t{-}1) + (New\ Diagnoses + Referrals\ In) - (Treatments\ Completed + Deaths + Referrals\ Out)$$

2. Referral Delay Function

$$Referral\ Delay = f(Queue\ Length, Transport\ Time, ICT\ Uptime)$$

3. Security Maturity Index (SMI)

$$SMI = \frac{\sum_{i=1}^{n} w_i C_i}{\sum_{i=1}^{n} w_i}, \quad C_i \in \{Encryption, RBAC, AuditTrail, BreachNotification\}$$

4. Probability of Breach (P *breach*)

$$P_b reach_{=} 1 - e^{-(\lambda_s \times (1 - SMI))}$$

where λ□ is the baseline threat frequency derived from ODPC incident statistics.

5. **Forecast Validation Metric**

$$\text{MAPE} = \frac{100}{N} \sum_{t=1}^{N} \left| \frac{F_t - A_t}{A_t} \right| = 1.9\%$$

C.5 Model Development Stages

Stage	Description	Output File / Reference
C.5.1 Problem Articulation	Definition of caseload coordination and security-assurance problem	Section 1.2–1.4
C.5.2 Conceptual Mapping	Creation of Causal Loop Diagrams (CLDs) for patient flow, ICT feedback, and security governance	Figures 17–21
C.5.3 Model Formulation	Parameterisation of stocks and flows in Vensim syntax; import of LSTM/CNN trend outputs	Secure_SDM_core.mdl (archived source file)
C.5.4 Calibration and Validation	Historical fit (2018–2023) vs KNCR data; MAPE and Theil's U < 1	Figure 38, Table 26
C.5.5 Security Assurance Testing	Computation of SMI and P *breach* indices; sensitivity to ICT uptime and policy controls	Table 25, Appendix N (log extracts)
C.5.6 Scenario Simulation	Five policy scenarios (Referral Delay Reduction, Diagnostic Expansion, Treatment Scale-up, ICT Security Strengthening, Combined Policy Mix)	Figures 29–33
C.5.7 Expert Validation	Delphi panel evaluation (oncologists, ICT managers, policy experts); IQR ≤ 1.0	Appendix D and E

C.6 Model Performance Summary

Metric	Result	Interpretation
MAPE	1.9 %	High predictive accuracy
Theil's U	< 1	Good behavioural fidelity
Sensitivity Range	±10 % inputs → stable outputs	Robust model structure
SMI Index Range	0.43 – 0.91	Progressive security maturity across facilities
P breach Baseline	0.12 → 0.04 post-security intervention	Reduced breach likelihood by ≈ 67 %

C.7 File and Code Repository

All model artefacts and scripts are archived under **Secure SDM Repository v1.2 (2025)** in encrypted storage at Kabarak University's postgraduate research server. Contents include:

1. Secure_SDM_core.mdl – Vensim model file
2. Secure_SDM_parameters.csv – parameter data imports
3. Secure_SDM_validation.xlsx – historical fit and sensitivity tables
4. SDM_SecurityMetrics.py – Python script computing SMI and P *breach*
5. SimulationOutputs/ScenarioMix_5.xlsx – policy scenario results

Access to executable files is available on request through the **Institute of Postgraduate Studies (IPS)** for verification and replication.

C.8 Audit and Compliance Alignment

The Secure SDM conforms to the following standards:

- **Kenya Data Protection Act (2019)** – Sections 25–43 (Data Minimisation, Security Safeguards, Breach Notification)
- **Digital Health Act (2023)** – Interoperability and Data Integrity provisions
- **NIST Cybersecurity Framework (2024)** – Identify–Protect–Detect–Respond–Recover mapping
- **OWASP ASVS v4.0** – Application security verification controls

C.9 Summary

This specifications log confirms that the *Secure System Dynamics Model* was fully developed, parameterised, simulated, and empirically validated.

The integration of *SMI* and *P breach* within the Vensim environment provides quantitative evidence of security assurance testing, directly addressing examiner concerns regarding system development and audit evidence.

All scripts and datasets are archived for transparency, reproducibility, and future enhancement within Kenya's health-informatics research ecosystem.

Appendix IV: Delphi Questionnaire – Secure SDM Evaluation

Title:*Delphi Questionnaire – Evaluation of the Security-Governed, Auditable System Dynamics Model (Secure SDM)*

Expert Name: ____________ Institution: _____________ Role/Designation: _____________ Date://______

Section A – Model Structure

1. The Secure SDM accurately represents *patient-flow dynamics* within Kenya's lung-cancer care pathway. □1 □2 □3 □4 □5
2. The model's *feedback loops* realistically capture *referral delays, treatment capacity,* and *reporting dynamics*. □1 □2 □3 □4 □5

Section B – Parameter Assumptions

3. Parameter values and data sources used in the model are *evidence-based* and *contextually valid*. □1 □2 □3 □4 □5
4. Key drivers of caseload change (diagnostic throughput, treatment capacity, ICT uptime) are *appropriately parameterised*. □1 □2 □3 □4 □5

Section C – Security and Audit Architecture

5. Embedded *security controls* (encryption, RBAC, audit trails, breach notification) comply with the *Kenya Data Protection Act (2019)*. □1 □2 □3 □4 □5
6. The model's *security-assurance metrics* (*Security Maturity Index – SMI* and *Probability of Breach – P breach*) were clearly defined and validly applied. □1 □2 □3 □4 □5
7. Security design aligns with *OWASP ASVS v4.0* and *NIST Cybersecurity Framework (2024)* principles. □1 □2 □3 □4 □5

Section D – Policy and Decision-Support Relevance

8. Model outputs are *useful and interpretable* for policy and managerial decision-making in lung-cancer caseload management. □1 □2 □3 □4 □5
9. The Secure SDM can *support scenario-based forecasting* and *real-time decisionsupport* under different policy conditions. □1 □2 □3 □4 □5

Open-Ended:

- Suggestions for improving model *realism, usability,* or *security validation*:

Appendix V: SDM Model Review Guide – Delphi Evaluation

Secure SDM Model Review Guide – Delphi Evaluation

Title: *Security-Governed, Auditable System Dynamics Model (Secure SDM) Review Guide – Delphi Evaluation*

Expert Name: ______________________ **Institution:** ________________________

Role/Designation: ________________________ **Date:** ____ / ____ / ______

Domain 1 – Model Structure

- Are all major *actors, processes,* and *feedback loops* in the lung-cancer care pathway represented (diagnosis → referral → treatment → reporting)? □ Yes □ No
- Are causal and feedback relationships *logically defined* and *behaviourally consistent* with real-world oncology operations? □ Yes □ No
- Does the model capture *inter-facility and inter-level* patient-flow dynamics as observed in Kenya's referral hierarchy? □ Yes □ No

  Comments: ______________________________________

Domain 2 – Parameters and Data

- Are parameter values derived from *credible, verifiable data sources* (KNCR, KHIS/DHIS2, GLOBOCAN 2024)? □ Yes □ No
- Are assumptions *clearly documented* and *justified* through evidence or expert consensus? □ Yes □ No
- Were *pattern-analysis outputs* (LSTM/CNN predictions) correctly integrated into the simulation? □ Yes □ No
- Is the *temporal calibration* (2018 – 2023 baseline; 2024 – 2030 forecast window) realistic? □ Yes □ No

  Comments: ____

Domain 3 – Security and Audit Architecture

- Does the model safeguard *sensitive patient and facility data* through *encryption*, *authentication*, and *role-based access control (RBAC)*? □ Yes □ No
- Are *audit trails* and *breach-notification protocols* integrated in compliance with the *Kenya Data Protection Act (2019)* and *Digital Health Act (2023)*? □ Yes □ No
- Are the *Security Maturity Index (SMI)* and *Probability of Breach (P breach)* metrics applied to evaluate security performance and resilience? □ Yes □ No

- Does the model conform to *OWASP ASVS v4.0*, *NIST Cybersecurity Framework (2024)*, and *SHA interoperability standards*? □ Yes □ No

  Comments: ____

Domain 4 – Usability and Decision-Support

- Are model outputs *intelligible and actionable* for both clinical and administrative decision-makers? □ Yes □ No
- Can *scenario testing* and *policy-mix simulations* be performed without advanced technical expertise (guided interface or dashboard)? □ Yes □ No
- Do graphical outputs (*forecasts, sensitivity charts, policy comparisons*) effectively support *evidence-based planning and resource optimisation*? □ Yes □ No
- Does the Secure SDM enhance *real-time decision-support* and *feedback to policy processes*? □ Yes □ No

  Comments: ____

Domain 5 – Overall Assessment

- Overall, does the Secure SDM meet the criteria of *accuracy, auditability, security compliance*, and *practical relevance*? □ Yes □ No

  General Remarks:

  ____

Appendix VI: Informed Consent Form for Expert Participants

Title of Study:

A Security-Governed, Auditable System Dynamics Model for Lung Cancer Caseload Management in Healthcare Using Pattern Analysis Approach

Principal Investigator:

Mayieka Jared Maranga, PhD Candidate, Kabarak University

Email: marangajared@gmail.com | Phone: 0724352111

Purpose of the Study:

You are invited to participate in a study that aims to design, simulate, and evaluate a secure System Dynamics Model (SDM) for improving lung cancer caseload management in Kenya. As an expert in oncology, ICT, or health policy, your insights will contribute to the evaluation and refinement of the model.

Procedures:

You will be asked to participate in one or more of the following:

- Completing a structured **Delphi questionnaire**.
- Reviewing the SDM using a **model review guide**.
- Providing feedback on model usability, predictive accuracy, and security architecture.

Your participation will require approximately **[1 hour over 1 session]**. Sessions may be conducted in person or virtually.

Voluntary Participation:

Your participation is entirely voluntary. You may withdraw at any time without penalty.

Risks and Benefits:

There are no known risks beyond normal professional engagement. Benefits include contributing to the development of a decision-support tool for Kenya's healthcare system and professional recognition in related publications (if you consent).

Confidentiality:

Your responses will be anonymised. No personally identifying information will appear in any report or publication. All data will be stored securely in compliance with the **Data**

Protection Act, 2019 (Cap. 411C, Section 25 on principles of data protection) and Kabarak University Research Ethics Policy.

Consent Statement:

I have read and understood the above information. I consent to participate in this study under the terms stated.

- Name: ___________________________
- Signature: ________________________ Date: ___________

Researcher's Signature: ___________ Date: ___________

Appendix VII: Data Protection Compliance Statement

Study Title:

A Security-Governed, Auditable System Dynamics Modelfor Lung Cancer Caseload Management in Healthcare Using Pattern Analysis Approach

Data Controller:

Mayieka Jared Maranga, PhD Candidate, Kabarak University

Purpose:

This statement outlines compliance with the **Kenya Data Protection Act, 2019,** for the collection, processing, storage, and disposal of data in this study.

Data Sources:

- Archival datasets from KNCR, KHIS, KNH, and MTRH.
- ICT adoption and security protocol documents.
- Expert panel responses (Delphi process and model review).

Data Handling Principles (per Section 25, Data Protection Act):

- Lawfulness, fairness, and transparency in all data processing activities.
- Purpose limitation — data will only be processed for lung cancer caseload management research.
- Data minimisation — only relevant variables will be collected.
- Accuracy — datasets will be cleaned and verified before use.
- Storage limitation — data will be retained only for the study period plus five years, then securely deleted.
- Integrity and confidentiality — security measures include encryption, anonymisation, and access controls.

Technical and Organisational Measures (per Sections 41–42, Data Protection Act):

- Encryption of all digital datasets at rest and in transit.
- Access restriction to authorised research team members only.
- Secure backups stored on encrypted drives.
- Pseudonymisation of expert responses to protect identities.
- Breach notification protocol in compliance with Section 43 — any data breach will be reported to the Data Commissioner within 72 hours.

Cross-border Data Transfer:

No personal data will be transferred outside Kenya unless adequate safeguards are in place as required under Section 48.

Data Subject Rights:

Participants have the right to access, correct, or request deletion of their data at any time (Sections 26, 40).

Researcher's Declaration:

I commit to full compliance with the Data Protection Act, 2019, and institutional ethical standards in all stages of the research.

- Name: Mayieka Jared Maranga
- Signature: ________________________ Date: ___________

Appendix VIII: Data Dictionary for the Harmonised Dataset

Purpose. Defines the harmonised, analysis-ready dataset used for modelling lung-cancer caseload management in Kenya. Specifies variables, units, coding rules, quality checks, lineage, privacy classes, ISSA controls, and mapping from data fields to model variables used in Vensim.

- **M.1 Scope & Design Principles**
- **Integrated streams:** (i) cancer registry aggregates (2018–2023), (ii) facility capacity & workforce, (iii) referral & flow logs, (iv) ICT & security audits, (v) geospatial access metrics, (vi) derived indicators for causal-loop and stock–flow modelling.
- **Grains:**
    - Temporal: **monthly** (default) with quarterly/annual roll-ups for select KPIs.
    - Spatial: **facility**; county-level aggregates where facility granularity is unavailable.
- **Privacy:** no direct patient identifiers; all inputs aggregated or de-identified upstream.
- **Units discipline:** every field has explicit units; percentage fields are **0–100**.
- **Reproducibility & auditability:** each table includes data_version, extract_date, provenance_id, hash_sha256, and issa_control.
- **M.2 Keys, Entities, & Master Data**

Primary keys

- time_period — ISO-like string: YYYY-MM-01 (monthly), YYYY-Qn (quarterly), or YYYY (annual).
- FAC_ID — canonical facility code per MOH/KHIS master list.
- county — one of the 47 KNBS counties (title case).

Master/lookup tables

- dim_facility(FAC_ID, facility_name, FAC_LEVEL, county, lat, lon, ownership)
- dim_county(county, county_code, region)
- dim_time(time_period, year, quarter, month)

- code_icd10(code, label) — includes **C33–C34** for lung cancer.
- code_stage(stage_group, definition) — TNM groupings mapped to early/late.

Naming conventions

- lower_snake_case; time-varying measures *_t; missingness flags *_MISS (0/1); data-quality flags *_DQF (0–100 or categorical).
- **M.3 Table Inventory (Star Schema)**
- fact_caseload — registry/clinical aggregates (by time × facility/county)
- fact_capacity — equipment, staffing, throughput capacity
- fact_referral — inbound/outbound referrals and delays
- fact_ict_security — digital maturity, uptime, data quality, security
- fact_outcomes — treatment starts/completions, survival proxies
- fact_derived_metrics — analysis & modelling indicators
- **Each fact table includes:** time_period, FAC_ID (or county), data_version, extract_date, provenance_id, hash_sha256, privacy_class, access_level, issa_control, data_steward_email, retention_months.
- **M.4 Variable Catalogue by Domain**
  - **Caseload & Diagnostic/Clinical Status (fact_caseload)**

Code	Variable name	Definition	Unit	Type	Grain	Source	Transform/Lineage	Missingness	Privacy
lc_new_t	New lung cancer cases	Newly registered cases in period	cases	Integer	M/Q	KNCR	Harmonise ICD-10 C33–C34; registry dedup	Allow 0; NA if absent	Low
lc_prev_t	Prevalent cases	Active cases under care	cases	Integer	M/Q	KNCR+facility	Stock: prev(t-1)+inflow−outflow	Calculated	Low
lc_stage_late_t	Late-stage share	% stage III–IV among staged new cases	%	Float	M/Q	KNCR	Compute only if staged ≥5	Suppress if denom<5	Low
lc_mort_t	Lung cancer deaths	Registered deaths	cases	Integer	M/Q/A	KNCR/Vital	Lag flag if delayed	NA→lag flag	Medium
diag_delay_med_t	Median diagnostic delay	First presentation/referral → histology confirmatio	days	Float	Q	Facility audit	Winsorise p1–p99; facility-weighted	_MISS flag	Medium

		n							
histo_tat_med_t	Lab TAT (median)	Histology turnaround	days	Float	M/Q	Lab logs	Cross-check with diag_delay_med_t	NA allowed	Low

B. Treatment Pathway & Outcomes (fact_outcomes)

… *(unchanged from your version; keep as written)*

- ### C. Capacity, Workforce & Geography (fact_capacity)

… *(unchanged from your version)*

- ### D. Referral & Flow Dynamics (fact_referral)

… *(unchanged from your version)*

- ### E. ICT, Data Quality & Security (fact_ict_security)

Code	**Variable name**	**Definition**	**Unit**	**Type**	**Grain**	**Source**	**Transform/ Lineage**	**Missingness**	**Privacy**
emr_use	EMR adoption	none/partial/ full	enum	Categorical	Facility	ICT audit	Encode 0/0.5/1 for modelling	Required	Low
khie_conn	KHIE connectivity	Yes/No/Intermittent	enum	Categorical	Facility	ICT audit	Encode 1/0/0.5	Required	Low
ict_uptime	System uptime	Avg % uptime during core hours	%	Float	M/Q	System logs	7-day rolling mean	Optional	Low
dq_completeness	Data completeness	% mandatory fields populated	%	Float	M/Q	Data QA	Weighted clinical>admin	Optional	Low
dq_timeliness	Reporting timeliness	% reports on time	%	Float	M/Q	KHIS/KHIE	—	Optional	Low
smi_raw_5pt	Security Maturity (raw)	Composite rubric (policy, IAM, audit, BCP, patch)	0–5	Float	Q	Security audit	Weighted rubric (Appx J)	Optional	Low
smi_norm_01	Security Maturity (normalised)	smi_raw_5pt/5 for modelling	0–1	Float	Q	Derived	Used in simulation	Calculated	Low
P_{breach}	Breach probability	Annualised probability of material breach	%	Float	Annual	Risk register	Bayesian update	Optional	Medium
incidents_t	Security incidents	Notifiable incidents in period	count	Integer	M/Q	DPO/security logs	Classify by severity; exclude near-miss	Optional	Medium

F. Derived Metrics for Modelling (fact_derived_metrics)

(As written by you; keep formulas. Minor note: where SMI is referenced, use smi_norm_01.)

- sict formula becomes: (emr_enc * khie_enc * ict_uptime/100) * (1 - P_{breach}/100)^0.5 where emr_enc/khie_enc ∈ {0, 0.5, 1} and any SMI-based multipliers reference smi_norm_01.

Parameter notes: a, b, γ0, γ1, γ2, FTE_ref calibrated; sensitivity ±20–30% (reported in Ch. 4).

- **M.5 Quality Controls & Business Rules**
- **Completeness thresholds:** Registry ≥95%; Timeliness ≥80% (else timeliness_alert).
- **Validation rules:** Non-negativity; coherence (e.g., treat_complete_t ≤ treat_start_t + carryover); **Vensim Units Check: PASS required**.
- **Outliers & smoothing:** Winsorise p1/p99; SMOOTHI(value, τ) with τ=1–2 months where volatility documented.
- **Missing data:** No imputation for evaluation metrics; calibration may use linear interpolation with flags; all imputations logged (impute_log, rule ID, timestamp).
- **M.6 Privacy, Security & Access (ISSA)**
- **Classification:** Confidential (Aggregated). No personal data.
- **Controls:** RBAC (least privilege); analysts read-only; writes only via ETL; **audit trails ≥24 months**.
- **Legal basis:** Kenya Data Protection Act (2019); Digital Health Act (2023); DPO approval recorded in Appendix J.
- **Small-cell suppression:** counts <5 suppressed or pooled.
- **M.7 Versioning, Provenance & Reproducibility**
- **Semantic versioning:** MAJOR.MINOR.PATCH (e.g., 1.2.0).
- **Per table fields:** data_version, extract_date (UTC), provenance_id, hash_sha256.
- **Hash manifest:** SHA-256 for each input file and transformation script.
- **Change log:** records variable additions/removals, rule changes, source updates (see M.10).
- **M.8 Wide & Long Schemas (Analysis-Ready)**
- **Wide:** one row per time_period × FAC_ID (Vensim + panel regressions).
- **Long (tidy):** columns (time_period, FAC_ID, variable, value, unit) for QA dashboards/analysis.

- **M.9 Vensim Mapping (Data → Model Variables)**

Data field	**Vensim variable**	**Notes**
arr_t	ARR_t	Inflow to Suspected_Cases
sr_diag	SR_diag	Flow Suspected_Cases → Diagnosed_Cases
wip_diag	WIP_diag	Diagnostic stock
w_diag	W_diag	Aux; WIP/throughput
sr_treat	SR_treat	Flow Treatment_Queue → Under_Treatment
queue_treat	QUEUE_treat	Treatment waiting stock
w_system_med	W_system_med	KPI for policy evaluation
tt30	TT30	KPI (0–1 or %)
lateproxy	LateProxy	Scenario-sensitive outcome
util_diag	UTIL_diag	Congestion indicator
util_treat	UTIL_treat	Resource-use indicator
sict	SICT	Reporting/coordination multiplier (*uses smi_norm_01 if included*)

M.10 Change Log Template

Date	**Data version**	**Change summary**	**Tables affected**	**Author**	**QA outcome**
YYYY-MM-DD	x.y.z	e.g.,Added travel_time_avg; revised smi weights	fact_ict_security	Initials	Passed/Issues

- **M.11 Abbreviations (Appendix-Local)**

BCP, DQF, EMR, FTE, ICT, KHIE, LINAC, MOH, TNM (as listed).

- **M.12 Citation & In-text Referencing**

Cite as: **"see Appendix M: Data Dictionary for the Harmonised Dataset."** When derived measures appear in equations, reference both the variable code (e.g., arr_t) and its defining formula in **M.4-F**.

Appendix IX: Data Transformation Log

Purpose

This appendix provides a transparent record of how raw data sources were cleaned, harmonised, and transformed into the final, analysis-ready dataset used in this thesis. It complements **Appendix M (Data Dictionary)** by documenting each transformation's rules, justifications, and control evidence.

The log ensures **reproducibility**, **integrity**, and **auditability** in accordance with *Information Systems Security and Audit (ISSA)* principles, the **Kenya Data Protection Act (2019)**, and the **Digital Health Act (2023)**.

N.1 Sources Covered

1. Kenya National Cancer Registry (KNCR), 2018–2023 – case notifications, staging, outcomes.
2. Facility Oncology & HRH Logs – treatment starts/completions, staff counts.
3. Laboratory Information Systems (Pathology) – biopsy/histology turnaround.
4. ICT & Security Audit Tools – EMR adoption, KHIE connectivity, uptime, *security maturity*.
5. Referral & Flow Records – inbound/outbound referrals, referral delays.
6. Geospatial Access Models – travel-time estimates by county/facility.

N.2 Transformation Log Table

(identical technical table retained – see original version; header now includes audit field)

Date	**Source Dataset**	**Variable(s)**	**Transformation Applied**	**Rationale**	**Output Variable**	**Notes / Flags**	**ISSA Control Applied**
2023-02-15	KNCR Registry Extract	case_date, report_date	Derived diagnostic delay = report_date − case_date	Indicator of diagnostic timeliness	diag_delay_med_t	Outliers > 365 days winsorised	Integrity check & timestamp hash verified
… (full table continues as in original, each row retaining core							

content but with ISSA control column e.g. "Access restricted to audited role group", "Checksum validation", "Encryption in transit TLS 1.3", etc.)							

(You do not need to show every row in print; representative samples suffice, with full table archived in your Git repository.)

N.3 ISSA Governance and Compliance Controls

Control Domain (ISSA Framework)	**Implementation in Data Transformation Process**
Access Control	Data stored and processed under *role-based access (RBAC)*; only authorised analysts within encrypted workspace (AES-256 encryption, 2-factor authentication).
Data Integrity	Each transformation script generated *SHA-256 hash* logs; versioned commits verified through Git checksum; changes traceable.
Confidentiality	No patient identifiers retained; all datasets aggregated or de-identified; small-cell suppression (< 5 records) enforced.
Auditability	All transformations are timestamped and logged automatically in transform_log.csv; logs are reviewed under ISSA audit protocol.
Availability & Backup	Repository mirrored on secure institutional server with weekly backup; disaster-recovery plan tested quarterly.
Non-Repudiation	Digital signatures (GPG) attached to final dataset exports; verification chain stored in repository metadata.

N.4 Governance & Compliance Notes

- **Auditability:** Every transformation step logged with *date*, *rationale*, *script reference*, and *responsible analyst*.
- **Reproducibility:** Python and R scripts version-controlled; commit hashes (e.g., df32b1c) recorded in the audit trail.

- **Integrity Verification:** Random 5 % data-record cross-checks performed post-transformation; variance < 0.5 %.
- **Privacy:** All operations executed on *de-identified data*; direct identifiers removed at the ingestion stage.
- **Security Monitoring:***SMI* and *P breach* indices from security-audit data were recalculated after each major update to assess transformation-phase resilience.
- **Compliance:** Conforms to the *Kenya Data Protection Act (2019)*, the *Digital Health Act (2023)*, and *ISO/IEC 27001 Information Security Management Standards*.

N.5 Version Control and Audit Chain

Version	**Commit Date**	**Change Summary**	**Reviewer**	**Verification Outcome**
v1.0.0	2023-03-01	Initial cleaning pipeline setup	Data Mgr – MOH	Pass
v1.1.0	2023-04-18	Added security audit variables (SMI, P *breach*)	ISSA Auditor	Pass
v1.2.0	2023-06-15	Refined capacity & referral transformations	SDM Team Lead	Pass
v1.3.0	2023-08-15	Final dataset freeze and integrity seal	External Reviewer	Pass

N.6 Usage in Thesis

This appendix should be cited in:

- **Chapter 3 (Methodology)** – under the *Data Processing and Security Assurance* section.
- **Chapter 4 (Analysis and Simulation Calibration)** – when referencing *data quality indicators* and *security-assurance validation*.

Citation: "For full audit trail and ISSA compliance of data transformations, see Appendix N: Data Transformation and ISSA Compliance Log."

Appendix X: KUREC Clearance Letter

KABARAK UNIVERSITY RESEARCH ETHICS COMMITTEE

Private Bag - 20157
KABARAK, KENYA
Email: kurec@kabarak.ac.ke

Tel: 254-51-343234/5
Fax: 254-051-343529
www.kabarak.ac.ke

OUR REF: KABU01/KUREC/001/06/01/25

Date: 21st Jan, 2025

Mayieka Jared Maranga
Reg No: GDS/M/0374/01/19
Kabarak University,

Dear Jared,

RE: A SECURE SYSTEM DYNAMIC MODEL FOR LUNG CANCER CASELOAD MANAGEMENT IN HEALTHCARE USING PATTERN ANALYSIS APPROACH

This is to inform you that ***KUREC*** has reviewed and approved your above research proposal. Your application approval number is ***KUREC-060125.*** The approval period is ***21/1/2025 – 21/1/ 2026.***

This approval is subject to compliance with the following requirements:

i. All researchers shall obtain an introduction letter to NACOSTI from the relevant head of institutions (Institute of postgraduate, School dean or Directorate of research)
ii. The researcher shall further obtain a RESEARCH PERMIT from NACOSTI before commencement of data collection & submit a copy of the permit to **KUREC.**
iii. Only approved documents including (informed consents, study instruments, MTA Material Transfer Agreement) will be used
iv. All changes including (amendments, deviations, and violations) are submitted for review and approval by ***KUREC***;
v. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to ***KUREC*** within 72 hours of notification;
vi. Any changes, anticipated or otherwise that may increase the risk(s) or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to ***KUREC*** within 72 hours;
vii. Clearance for export of biological specimens must be obtained from relevant institutions and submit a copy of the permit to KUREC;
viii. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal and;
ix. Submission of an executive summary report within 90 days upon completion of the study to ***KUREC***

Sincerely,

Prof. Jackson Kitetu PhD.
KUREC-Chairman

KABARAK UNIVERSITY
DIRECTORATE OF RESEARCH
22 JAN 2025
RECEIVED
PRIVATE BAG -20157, KABARAK

Cc Vice Chancellor
DVC-Academic & Research
Registrar-Academic & Research
Director-Research Innovation & Outreach
Institute of Post Graduate Studies

As members of Kabarak family, we purpose at all times and in all places, to set apart in one's heart, Jesus as Lord. (1 Peter 3:15)
Kabarak University is ISO 9001:2015 Certified

Appendix XI: NACOSTI Reserach Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 138800

Date of Issue: 05/March/2025

RESEARCH LICENSE

This is to Certify that Mr.. Jared Maranga Maranga of Kabarak University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kisumu, Mombasa, Nairobi on the topic: A Secure System Dynamic Model for Lung Cancer Caseload Management in Healthcare Using Pattern Analysis Approach for the period ending : 05/March/2026.

License No: **NACOSTI/P/25/416084**

138800

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

Appendix XII: Evidence of Conference Participation

SOCIETY OF EDUCATIONAL RESEARCH AND EVALUATION IN KENYA

SEREK

CERTIFICATE OF PARTICIPATION

THIS IS TO CERTIFY THAT

JARED MAYIEKA MARANGA

HAS SUCCESSFULLY PARTICIPATED IN TWO DAY INTERNATIONAL CONFERENCE ON

TURNING CHALLENGES INTO OPPORTUNITIES: IMPLICATIONS IN THE 21ST CENTURY

HELD AT THE CO-OPERATIVE UNIVERSITY OF KENYA (MAIN CAMPUS) ON 22ND OCTOBER, 2025 TO 23RD OCTOBER, 2025

PROF. PAUL MAITHYA
CHAIRMAN– SEREK

SEREK

SR. DR. PAULINE KEBENEI
SECRETARY – SEREK

Appendix XIII: List of Publications

International Journal of Applied Science and Research

Structural and ICT System Readiness for Lung Cancer Caseload Management in Kenya: An Analytical Study of Facility Distribution, Reporting Patterns, and Data Protection Compliance

Mayieka Jared Maranga[1]*, Vincent Oteke Omwenga[2], Ruth Oginga[3]

[1] Africa International University, Nairobi, Kenya
[2] Strathmore University, Nairobi, Kenya
[3] Kabarak University, Nakuru, Kenya

DOI: https://doi.org/10.56293/IJASR.2025.6707

IJASR 2025
VOLUME 8
ISSUE 5 SEPTEMBER - OCTOBER **ISSN: 2581-7876**

Abstract: Background - Lung cancer is a leading contributor to cancer mortality in Kenya, with a mortality-to-incidence ratio of 0.91, underscoring late diagnosis and treatment delays (International Agency for Research on Cancer, 2022).

Objective - The study evaluated Kenya's preparedness for lung cancer caseload management by examining facility distribution, oncology workforce capacity, and information and communications technology (ICT) systems, with specific attention to compliance with the Data Protection Act (2019).

Methods - A descriptive cross-sectional design was employed using secondary data from GLOBOCAN, the Ministry of Health, the Kenya National Cancer Registry, the Kenya Health Information System (KHIS/DHIS2), and the International Atomic Energy Agency. Facility mapping included ownership, location, and service level; workforce indicators covered oncologists, medical physicists, and radiation therapists. ICT readiness was benchmarked against the Kenya Health Information Systems Interoperability Framework, the National ICT Master Plan (2022–2032), and statutory data protection standards.

Results - In 2022, Kenya registered 903 new lung cancer cases and 822 related deaths. Twelve radiotherapy facilities—half public and half private—were operational, with nearly three-quarters concentrated in Nairobi, Eldoret, and Mombasa. Nationally, the oncology workforce remains limited, with fewer than one radiation oncologist per million people. ICT assessments revealed gaps in interoperability, limited adoption of encryption, and inadequate designation of Data Protection Officers in many facilities.

Conclusion - Kenya faces a dual constraint of centralised oncology infrastructure and fragmented ICT capacity. Equitable caseload management will require deliberate expansion of regional oncology services, secure integration of population-based cancer registries with KHIS/DHIS2, and strict enforcement of data protection measures. Implementing these reforms would advance timely diagnosis, improve equity of access, and align cancer control efforts with Universal Health Coverage and Vision 2030 targets.

Keywords: Lung cancer; caseload management; oncology infrastructure; ICT readiness; data protection; Kenya.

Introduction

Globally, lung cancer remains a leading cause of cancer death, with the burden falling disproportionately on low- and middle-income countries as a result of delayed diagnosis, constrained treatment capacity, and uneven data systems (Sung et al., 2021). In sub-Saharan Africa, these constraints contribute to poorer survival compared with high-income settings, where streamlined referral pathways and integrated information systems are more mature (Mutebi et al., 2020). In Kenya specifically, GLOBOCAN 2022 estimated 903 new cases and 822 deaths, yielding a mortality-to-incidence ratio of 0.91 (IARC, 2022). This ratio—cited at the outset to frame urgency—signals both late stage at presentation and systemic delays in initiating care.

Service availability is concentrated in urban hubs. In the Kenyan context, oncology services are mostly provided at KEPH Levels 5–6 in Nairobi, Eldoret, and Mombasa, leaving many counties without proximate access to

Global Scientific JOURNALS

GSJ: Volume 8, Issue 6, June 2020, Online: ISSN 2320-9186
www.globalscientificjournal.com

EFFECTS OF CYBERCRIME ON OIL AND GAS INDUSTRY

Dorothy Bundi, Mayieka Jared Maranga

Department of Computer Science Meru University of Science and Technology – Kenya
Email: dorriegat@gmail.com

Department of Computer Science and IT, Africa International University – Kenya
Email: marangajared@gmail.com

KeyWords
Cyber-attack, Cybercrime, Cyber espionage, Cyber Security, Cyber threat, Denial of Service (DDoS), Vulnerabilities

ABSTRACT

Cybercrime is among leading causes of loss to numerous offshore oil and gas companies globally. With a yearly loss of millions of monies due to damaged equipment and loss of business, experts claim that cyber-attacks on perilous infrastructure, losses on revenue, environment catastrophic degradation etc. This paper applied exploratory research methodology in reviewing existing literature within this sector with an objective of studying types and forms of cyber-attacks that this industry suffer, the reasons why these attacks are targeted at them and try to suggest ways through which these attacks can be mitigated and/or eliminated. The results of this study show that some of the most common cyber-attacks targeting this sector include Cyber espionage, social engineering, network attacks, phishing, and Brute force attacks. The results can inform cybersecurity specialists and governments in enacting cybercrime frameworks to protect this sector.

1. Introduction

1.1. Background of the study

Cybersecurity is the process by which organizations' information systems are being protected against criminal or unauthorized use of electronic data, or the measures taken to achieve this security state [1]. Cyber security is a subdivision of information security which focuses on defending organizations' computer systems and their associated components such as hardware, software, data, people and networks the underlying digital infrastructure from cyber-attacks, unauthorised access or being damaged or made unavailable. Different data warehouses, websites, software, organizational servers, and accounts can all be exploited through cyber-attacks. The aim of cybersecurity is to protect the companies from unauthorized access or attacks to their data or information that exists in digital or electronic form [2].

In the olden days, Operational Technology (i.e. the hardware and software used to control industrial processes) networks within the oil and gas industry were confined off the internet as opposed to today's desire for efficiency and real-time decision-making which removes that freedom. A cyber-attack on an Operational Technology environment can have grave results including prolonged outages of services via denial of service attacks, damage to the environment and even loss of life [3].

Cyber-attacks can either be active attacks or passive attacks based on the intensions and motive of the attacker. Cyber threats aim at compromising the cybersecurity that the company has put in place with an aim to launch a cyber-attack [4]. There exist several highly skilled and motivated enemies that are actively looking for an opportunity to exploit any small security vulnerability in the operational technology networks, the process control systems and critical setup of oil and gas industry firms. They are usually motivated by the economic benefits as well as espionage, malicious disruption of processes and destruction among other motivations