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Effect of cancer epidemiology on treatment efficiency in Kenyan.

Nagaiahsamy, Vishnukumar
Strathmore Business School
Strathmore University

EFFECT OF CANCER EPIDEMIOLOGY ON TREATMENT EFFICIENCY IN KENYAN

BY

VISHNUKUMAR NAGAIAHSAMY

148359

STRATHMORE BUSINESS SCHOOL

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DECLARATION

This research thesis is entirely my own work and has not been presented to any academic institution or examination body for the purpose of earning a certificate or qualification.

Student's Name: Vishnukumar Nagaiahsamy

Signature…………… **………………… Date…………3 Dec 2025…………**

Supervisor's Declaration

This Research Thesis has been submitted for examination with my endorsement as the College Supervisor.

Supervisor's Name: Dr John Olukuru

Signature………… **…………………. Date…………3 Dec 2025…………**

DEDICATION

This research project is dedicated to my wife, **Teresia Njeri Nganga**, for her continuous support and inspiration throughout my academic journey.

ACKNOWLEDGEMENT

I am profoundly grateful to God Almighty for His unending grace, guidance, and strength throughout this journey. I extend my heartfelt appreciation to my supervisor, **Dr John Olukuru**, for his dedication, invaluable support, constructive feedback, and insightful suggestions, which greatly contributed to the refinement of this project. My sincere gratitude also goes to Strathmore University for providing exceptional training and imparting knowledge that has equipped me with the skills needed to make this research journey successful. Your dedication to academic excellence has been truly inspiring.

I would like to thank Private Cancer Centre for their collaboration and for granting me the opportunity to conduct my research within their organisation. To my fellow classmates, I deeply value the shared experiences, discussions, and teamwork that enriched this academic endeavour. May you all be abundantly blessed. Lastly, I am immensely thankful to my mother, friends, and colleagues for their unwavering love, prayers, and encouragement, which have been a source of strength in completing this research proposal.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial Intelligence
HPV	Human Papillomavirus
PRIVATE	Healthcare Global
HSUT	Health Services Utilization Theory
IARC	International Agency for Research on Cancer
KNH	Kenyatta National Hospital
MoH	Ministry of Health
NACOSTI	National Commission for Science, Technology, and Innovation
NCCP	National Cancer Control Plan
NCI	National Cancer Institute
NHIF	National Hospital Insurance Fund
WHO	World Health Organization

OPERATIONAL DEFINITON OF SIGNIFICANT TERMS

Cancer Epidemiology	The discipline that quantifies the distribution, determinants and temporal trends of cancer within a population so that risk factors can be identified and preventive or therapeutic strategies refined (Bray et al., 2021; IARC, 2023).
Annual Trends in Diagnosed Cancer Cases	The year-to-year change in the number of new, histologically confirmed malignancies in Nairobi County, reflecting shifts in screening coverage, health-seeking behaviour and diagnostic capacity (Siegel et al., 2022; Kenya MoH, 2023).
Prevalent Types of Cancer	The subset of cancer sites such as breast, cervical, prostate, colorectal and oesophageal that together account for the largest proportion of total diagnoses during the 2019–2023 window, used to prioritise resources and programme design (Globocan, 2023; Ferlay et al., 2022).
Demographic Characteristics of Cancer Patients	Patient-level attributes including age group, gender, socio-economic status and health-insurance cover analysed to understand disparities in stage at presentation and treatment completion (Ngoma et al., 2023; Kamau et al., 2023).
Geographical Distribution of Cancer Patients	The spatial pattern of patient residence across Nairobi urban, peri-urban satellites and out-county rural zones, examined for its influence on travel distance, waiting time and late-stage burden (Otieno & Wanjala, 2021; Maina et al., 2021).
Treatment Efficiency	The degree to which oncology services deliver timely, complete and outcome-oriented care, operationalised through metrics such as average waiting days from diagnosis to first treatment and proportion of patients who finish prescribed regimens (Kariuki et al., 2021; World Health Organization, 2023).

ABSTRACT

Globally and across Africa, the rising burden of cancer continues to place significant pressure on health systems, with increasing incidence, limited resources, and disparities in access undermining the delivery of timely and effective treatment. In Kenya, cancer cases and deaths are steadily increasing amid gaps in diagnostic capacity, radiotherapy access, and healthcare infrastructure, resulting in delays in diagnosis and treatment and reduced treatment efficiency. This study examines how cancer epidemiological patterns influence treatment efficiency at a facility level in Nairobi, providing context-specific evidence to inform oncology planning and service delivery. Guided by Epidemiologic Transition Theory and Health Services Utilization Theory, the study explains both the shift toward chronic diseases and how healthcare demand and system capacity shape service use and efficiency. Existing literature largely relies on aggregated or high-income country data, with limited longitudinal, facility-level evidence from urban African settings, creating a gap this study addresses. A pragmatic research philosophy and retrospective quantitative descriptive design were adopted using secondary data from 8,483 cancer patient records (2018–2025), collected through a validated structured extraction tool with a high retrieval rate of 94.3%. Findings revealed fluctuating annual trends influenced by COVID-19 disruptions, dominance of breast, cervical, and prostate cancers, and a patient population largely composed of older adults, females, and residents of Nairobi and nearby counties. Treatment efficiency was constrained by significant documentation gaps and limited recording of treatment and outcome indicators. The study concludes that strengthening data systems, improving capacity planning, and decentralizing oncology services are essential to enhance efficiency, equity, and overall cancer care delivery.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

1.1.1 Global Perspective on Cancer Epidemiology and Treatment Efficiency

Globally, cancer continues to place increasing pressure on health systems, diagnostic pathways, and treatment services, as rising incidence and persistent disparities strain the capacity of healthcare systems to deliver timely and effective care (World Health Organization, 2024). In 2022, an estimated 20 million new cancer cases and 9.7 million cancer-related deaths were recorded worldwide, highlighting the scale of the global burden (Sung et al., 2024). As the burden of cancer rises, health systems must not only detect cases earlier but also deliver treatment in a timely and coordinated manner. Cancer epidemiology reflected in incidence trends, age patterns, cancer-type distribution, and geographical variation, therefore provides an important basis for understanding treatment demand and treatment efficiency. Global cancer cases are projected to rise from about 20 million in 2022 to over 35 million by 2050 (a 77% increase), a surge expected to further strain already limited oncology resources and reduce treatment efficiency, particularly in low-resource health systems (Sung et al., 2024; WHO, 2024). This underscores the need for stronger surveillance and responsive oncology planning.

1.1.2 African Perspective on Cancer Epidemiology and Treatment Efficiency

Across Africa, the rising burden of cancer is occurring in health systems that often face shortages of specialist staff, diagnostic equipment, radiotherapy capacity, and financial protection mechanisms (Atun et al., 2023). In sub-Saharan Africa, cancer deaths are projected to nearly double from about 520,000 in 2020 to almost 1 million annually by 2030, a rapid increase that is expected to overwhelm limited treatment capacity and exacerbate delays in diagnosis and care delivery (Ngwa et al., 2022). In sub-Saharan Africa, cancer cases are projected to increase to more than 1.5 million by 2030, yet over half of countries lack adequate radiotherapy services, a widening gap that is expected to strain treatment capacity, increase waiting times, and significantly reduce treatment efficiency across already under-resourced health systems (Lievens et al., 2021; IARC, 2022). In such contexts, understanding epidemiological patterns is essential because annual case trends, prevalent cancer types, patient demographics, and geographical access all influence how efficiently oncology services can be delivered.

1.1.3 Kenyan Perspective on Cancer Epidemiology and Treatment Efficiency

In Kenya, cancer has become an increasingly significant public health concern, with over 44,000 new cases and more than 29,000 deaths reported annually, placing growing pressure on diagnostic and treatment services (National Cancer Institute of Kenya, 2024; KEMRI, 2022). Delays in diagnosis, uneven access to specialist care, and high out-of-pocket costs remain important barriers to efficient treatment. Cancer treatment efficiency remains constrained, with only about 23% of patients accessing required radiotherapy services and less than 30% of facilities offering cancer screening, leading to delays and reduced treatment effectiveness (Ministry of Health, 2023). These patterns matter because they shape treatment demand and may directly affect treatment efficiency within the study setting. The COVID-19 period also highlighted how shocks to service access can temporarily reduce diagnostic capture and disrupt treatment pathways.

1.2 Statement of the Problem

Cancer treatment efficiency refers to the extent to which oncology services provide timely, coordinated, and outcome-oriented care, aimed at maximizing patient outcomes through optimal use of available resources (Ferrara et al., 2022). Common indicators include the interval between diagnosis and treatment initiation, continuity of treatment, and the capacity of a facility to respond to changing patient volumes (Ferrara et al., 2022; All.Can, 2022). These indicators suggest that cancer treatment efficiency is not only about timely care but also about how well health systems adapt to patient demand and maintain continuity of care across the treatment pathway. Growing cancer burdens can weaken treatment efficiency when service capacity does not expand at the same pace, leading to delays in care, increased costs, and poorer patient outcomes (Ferrara et al., 2022; Boldig et al., 2023). Rising cancer demand without matching capacity inevitably causes delays, undermining timely care and overall treatment effectiveness.

In Kenya, only about 23% of cancer patients access the radiotherapy they require, despite nearly 60% needing it, reflecting severe gaps in treatment capacity and service availability (Ministry of Health, 2024). These inefficiencies are further driven by limited equipment and workforce shortages, where facilities such as Kenyatta National Hospital have experienced capacity reductions of up to 50% due to machine breakdowns, leading to longer waiting times and delayed treatment initiation (Ministry of Health, 2023; Lievens et al., 2021). When demand exceeds capacity, treatment delays become inevitable, ultimately worsening outcomes and reducing overall system efficiency. Even a four-week delay in cancer treatment increases mortality risk by 6–13%, reflecting serious inefficiencies in care delivery (Hanna et al., 2020). Existing studies show gaps between clinical trial outcomes and real-world cancer care, where patients often experience poorer survival, delays, and system inefficiencies, highlighting limited evidence on how local epidemiological patterns influence treatment efficiency (Wilson et al., 2023). This study therefore addresses this gap by examining how facility-level cancer patterns directly shape treatment efficiency within a real-world Nairobi oncology setting. While many studies show that treatment delays increase mortality, others report inconsistent or context-dependent effects, with some cancers showing unclear or variable survival impacts (Hanna et al., 2020; Neal et al., 2025). Some evidence even suggests delay effects depend on patient and tumour characteristics rather than time alone. This inconsistency highlights the need for context-specific analysis at facility level. This study addresses that gap using secondary data from Private Cancer Centre–Nairobi, thereby generating context-specific evidence rather than making unsupported national claims.

1.2 Objectives of the Study

1.3

1.3.1 General Objective

The general objective of this study is to examine the effect of cancer epidemiology on treatment efficiency in Kenya.

1.3.2 Specific Objectives

i. To assess the annual trends in the number of diagnosed cancer cases and their effect on cancer treatment efficiency in Kenya.
ii. To determine the most prevalent types of cancer and their effect on cancer treatment efficiency in Kenya.
iii. To examine the demographic characteristics of cancer patients and their effect on cancer treatment efficiency in Kenya.
iv. To evaluate the geographical distribution of cancer patients and its effect on cancer treatment efficiency in Kenya

1.4 Research Questions

i. What are the annual trends in the number of diagnosed cancer cases, and how do they affect cancer treatment efficiency in Kenya?
ii. Which types of cancer are most prevalent, and how do they influence cancer treatment efficiency in Kenya?
iii. What are the demographic characteristics of cancer patients, and how do these characteristics affect cancer treatment efficiency in Kenya?
iv. How does the geographical distribution of cancer patients affect cancer treatment efficiency in Kenya?

1.5 Significance of the Study

The study is significant in three main ways. First, it provides evidence for hospital managers and oncology practitioners at private Cancer Centre–Nairobi and similar facilities on how case trends, cancer profiles, and patient distribution affect service demand and treatment planning. Second, it offers useful insight for county-level policy and planning in Nairobi by showing how facility-based epidemiological patterns can inform resource allocation, workflow improvement, and data-system strengthening. Third, it contributes to academic literature on cancer epidemiology and treatment efficiency in urban low- and middle-income settings by using a clearly defined single-facility dataset rather than making unsupported national claims.

1.6 Scope of the Study

This study focused on the effect of cancer epidemiology on treatment efficiency in Kenya using secondary data from Private Cancer Centre–Nairobi. It examined annual trends in diagnosed cancer cases, prevalent cancer types, demographic characteristics of cancer patients, and the geographical distribution of patients, and considered how these factors affected treatment efficiency within the study setting. This study adopted a retrospective quantitative descriptive design based on electronic medical records. The dataset consisted of records opened between 2018 and 2025, with 8,483 eligible records analyzed after exclusion of incomplete or invalid files. Although patients attended the facility from different counties, the study does not claim national representativeness; rather, it interprets the findings within the context of a single Nairobi-based oncology centre and its referral catchment.

1.7 Summary

In summary, this study examines how cancer epidemiology influences treatment efficiency in Kenya using secondary data from private Cancer Centre–Nairobi. It focuses on annual diagnosis trends, prevalent cancer types, demographic characteristics, and geographical distribution, and interprets the findings within a clearly defined single-facility context.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of existing literature relevant to the study, focusing on both theoretical and empirical perspectives. It begins with the theoretical framework, outlining key theories that underpin the study and justify its conceptual foundation. The chapter then presents an empirical literature review structured around the study's specific objectives, analyzing past research, methodologies, and findings to identify gaps that this study seeks to address. Additionally, the conceptual framework visually illustrates the relationships between key variables, culminating in a chapter summary that highlights key insights and sets the stage for the subsequent research methodology.

2.2 Theoretical Framework of the Study

The theoretical framework provides a foundation for understanding the study by discussing relevant theories that explain the relationships between key variables. It establishes a scholarly basis for the research, ensuring that the study is grounded in well-established academic perspectives. By reviewing and integrating applicable theories, this section highlights the guiding principles that shape the study's approach and expected outcomes.

2.2.1 Epidemiologic Transition Theory- Abdel Omran (1971)

Epidemiologic Transition Theory, first proposed by Omran (1971), explains how patterns of disease and mortality shift as societies develop from infectious to chronic conditions. The theory outlines three stages: the age of pestilence and famine, the age of receding pandemics, and the age of degenerative and man-made diseases, each reflecting declining mortality and increasing life expectancy (Omran, 1971). This transition is closely linked to demographic and socioeconomic changes, including improved healthcare, nutrition, and living conditions (Omran, 1998). Later scholars expanded the theory to include additional stages reflecting delayed degenerative diseases in ageing populations (Olshansky & Ault, 1986). In Kenya, the coexistence of infectious diseases and rising cancer incidence reflects a transitional stage consistent with Omran's framework.

Despite its usefulness, Epidemiologic Transition Theory has been widely criticized for oversimplifying disease patterns. Critics argue that the model is overly linear and neglects social determinants such as poverty and inequality, which continue to shape health outcomes (McKeown, 2009). In sub-Saharan Africa, the theory's assumption of a clear shift from infectious to noncommuinicable diseases is often invalid, as many countries experience a persistent double burden of disease (Santosa & Byass, 2016; Murray et al., 2015). Empirical evidence shows that infectious and chronic diseases coexist rather than replace one another (Santosa & Byass, 2016). Additionally, epidemics such as HIV/AIDS have disrupted expected mortality declines and continue to strain health systems in the region (UNAIDS, 2025; Muhindo, 2024). These limitations highlight the need for context-specific refinements, particularly in rapidly urbanizing African settings.

The researcher adopted Epidemiologic Transition Theory because it helps explain why cancer is becoming increasingly prominent in urban populations such as Nairobi. For this study, the theory is relevant primarily to the first two objectives: identifying annual trends in diagnosed cases and examining the pattern of prevalent cancer types. Rather than modelling national transition stages, the study uses the theory more narrowly to interpret the rise of noncommunicable disease burden within an urban oncology setting and its implications for service demand.

2.2.2 Health Services Utilization Theory

Health Services Utilization Theory, also known as the Andersen Behavioral Model, was developed by Ronald M. Andersen in 1968 and later refined in 1995 to explain factors influencing the use of healthcare services (Andersen, 1968; Andersen, 1995). The theory postulates that healthcare utilization is determined by three key components: predisposing factors (such as age, gender, and beliefs), enabling factors (including income, insurance, and access), and need factors (both perceived and evaluated health status) . It further emphasizes that equitable access occurs when utilization is driven by need rather than social or economic barriers (Andersen, 1995). The model is widely applied to assess healthcare access, utilization patterns, and health system performance.

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Health Services Utilization Theory is particularly suitable for this study because it explains how patient demand and system capacity jointly influence treatment efficiency. Evidence shows that increased healthcare need is associated with higher service utilization, while limited enabling resources such as workforce and infrastructure constrain access and delay care (Andersen, 1995; Babitsch et al., 2012; Determann et al., 2021). In cancer care, diagnostic and treatment delays are linked to both patient-level factors and health system inefficiencies, which directly affect outcomes (Walter et al., 2012). This aligns with the Nairobi context, where rising cancer cases increase demand but limited resources restrict timely care. The researcher therefore argues that the model effectively links epidemiological trends to observed inefficiencies.

2.3 Empirical Literature Review

This section reviews empirical studies relevant to annual case trends, prevalent cancer types, demographic characteristics, and geographical access in relation to treatment efficiency. The review prioritises studies that help interpret a facility-based Nairobi County dataset while also drawing carefully selected evidence from comparable low- and middle-income settings.

2.3.1 Annual Trends in Diagnosed Cancer Cases and Cancer Treatment Efficiency

Amini et al. (2022) examined global temporal trends in liver cancer incidence, mortality, and survival indicators to understand long-term epidemiological patterns. The study used Global Burden of Disease data from 1990–2019 and applied joinpoint regression and multilevel modeling to assess annual percentage changes and country-level influences such as HDI . The findings showed a slight global decline in incidence and mortality alongside improved survival proxies over time. However, the study focused only on liver cancer and used aggregated global data, ignoring variation across other cancer types, age groups, and localized health system performance such as treatment delays or completion rates. This study addresses these limitations by incorporating multiple cancer types, using facility-level data in Nairobi, and directly linking annual case trends to treatment efficiency indicators such as waiting time and treatment completion.

Sharma et al. (2022) investigated cancer burden trends across Africa to understand patterns in incidence, mortality, and survival in relation to socioeconomic development. The study relied on GLOBOCAN 2020 estimates and used cross-sectional statistical analysis to compute incidence rates, mortality, and mortality-to-incidence ratios across countries. The findings indicated a high and growing cancer burden in Africa, with poor survival outcomes and strong association between lower development levels and worse outcomes. However, the study relied on modeled estimates rather than longitudinal real-world data, did not track year-to-year changes, and failed to include health system factors such as treatment timelines or service capacity. This study addresses these shortcomings by using longitudinal facility data, capturing real annual trends, and directly linking increasing case volumes to treatment efficiency within a Nairobi-based oncology center.

Jani et al. (2021) analyzed national cancer trends in Kenya to assess changes in incidence and mortality over time. The study utilized national cancer registry and GLOBOCAN data to compute annual cancer cases and deaths between 2012 and 2018. The findings revealed a steady increase in cancer incidence and mortality, with significant growth in overall case numbers. However, the study presents aggregated national data without disaggregating by region, patient characteristics, or healthcare system performance indicators such as treatment delays and completion rates. It also does not examine how rising case volumes affect service delivery efficiency within specific facilities. This study addresses these limitations by focusing on different Counties in Kenya, using detailed patient-level data, and explicitly linking annual trends in diagnosed cases to treatment efficiency outcomes at facility level.

2.3.2 Most Prevalent Types of Cancer and Treatment Efficiency

Bizuayehu et al. (2024) examined global patterns in cancer prevalence and future projections to identify the most dominant cancer types worldwide. The study used GLOBOCAN 2022 data from 185 countries and applied statistical modeling to estimate prevalence, mortality-to-incidence ratios, and projections to 2050. The findings showed that major cancers such as breast, prostate, colorectal, and lung cancers dominate globally, with cancer cases projected to increase significantly over time . However, the study focused largely on global aggregates and projections, without distinguishing how specific population groups, healthcare systems, or local contexts influence treatment demand or outcomes. It also did not incorporate real-world service indicators such as treatment delays or completion rates. This study addresses these limitations by using facility-level data in Nairobi, examining actual prevalent cancer types within the population, and directly linking them to treatment efficiency indicators.

Ezenkwa et al. (2024) investigated cancer patterns in a rural region of Nigeria to determine the most common cancer types affecting the population. The study used a retrospective review of hospital pathology records across multiple facilities and analyzed patient demographics and tumor distribution over a defined period. The findings revealed that breast, cervical, prostate, and colorectal cancers were the most prevalent, with clear gender-based differences in distribution. However, the study was limited to a specific rural setting with a relatively small dataset and short time frame, which restricts its generalizability to urban populations and more complex healthcare systems. It also did not examine how the prevalence of these cancers affects treatment timelines, resource allocation, or system efficiency. This study addresses these gaps by focusing on an urban Nairobi setting, using a larger dataset, and linking prevalent cancer types to treatment efficiency within a structured oncology facility.

Jani et al. (2021) analyzed the national cancer profile in Kenya to identify the most prevalent cancers and leading causes of cancer-related deaths. The study utilized national registry and GLOBOCAN data to determine cancer distribution across the country. The findings showed that breast, cervical, prostate, esophageal, and colorectal cancers were the most common, with cervical cancer being the leading cause of cancer mortality. However, the study presents aggregated national data without disaggregating findings by specific urban settings such as Nairobi or by patient-level characteristics. It also does not explore how the burden of specific cancer types influences treatment processes such as waiting time, treatment completion, or healthcare capacity. This study addresses these limitations by providing Nairobi-specific evidence, using detailed patient-level data, and explicitly examining how prevalent cancer types influence treatment efficiency at the facility level.

2.3.3 Demographic Characteristics of Cancer Patients and Treatment Efficiency

Guadamuz et al. (2023) aimed to examine how socioeconomic status influences cancer treatment initiation and survival among patients with multiple cancer types. The study used a retrospective cohort design based on electronic health records of over 290,000 patients in the United States, applying Cox regression models adjusted for demographic and clinical variables. The study found that patients from lower socioeconomic backgrounds had lower treatment initiation rates and poorer survival outcomes. However, the study relied on area-level socioeconomic indicators instead of individual patient characteristics, focused only on adult populations, and was conducted in a high-income healthcare system where access patterns differ significantly from low-resource settings like Nairobi, limiting its applicability. This study addresses these limitations by using patient-level demographic data across diverse age groups within a local oncology facility and capturing context-specific access barriers.

Wassie et al. (2023) aimed to assess the magnitude of delayed cancer treatment initiation and identify associated patient characteristics in referral hospitals in Northwest Ethiopia. The study applied a cross-sectional design using systematic sampling of 423 patients and logistic regression analysis to determine factors associated with delayed treatment initiation. The study found that delays were common and were associated with low income, comorbidities, and poor functional status. However, the study only included patients already attending oncology units, excluded those who never initiated treatment, relied on a single time-point observation, and did not evaluate whether patients completed treatment or how demographic factors influenced long-term efficiency outcomes. This study addresses these issues by using longitudinal facility data to assess both treatment initiation and completion across a broader and more representative patient population.

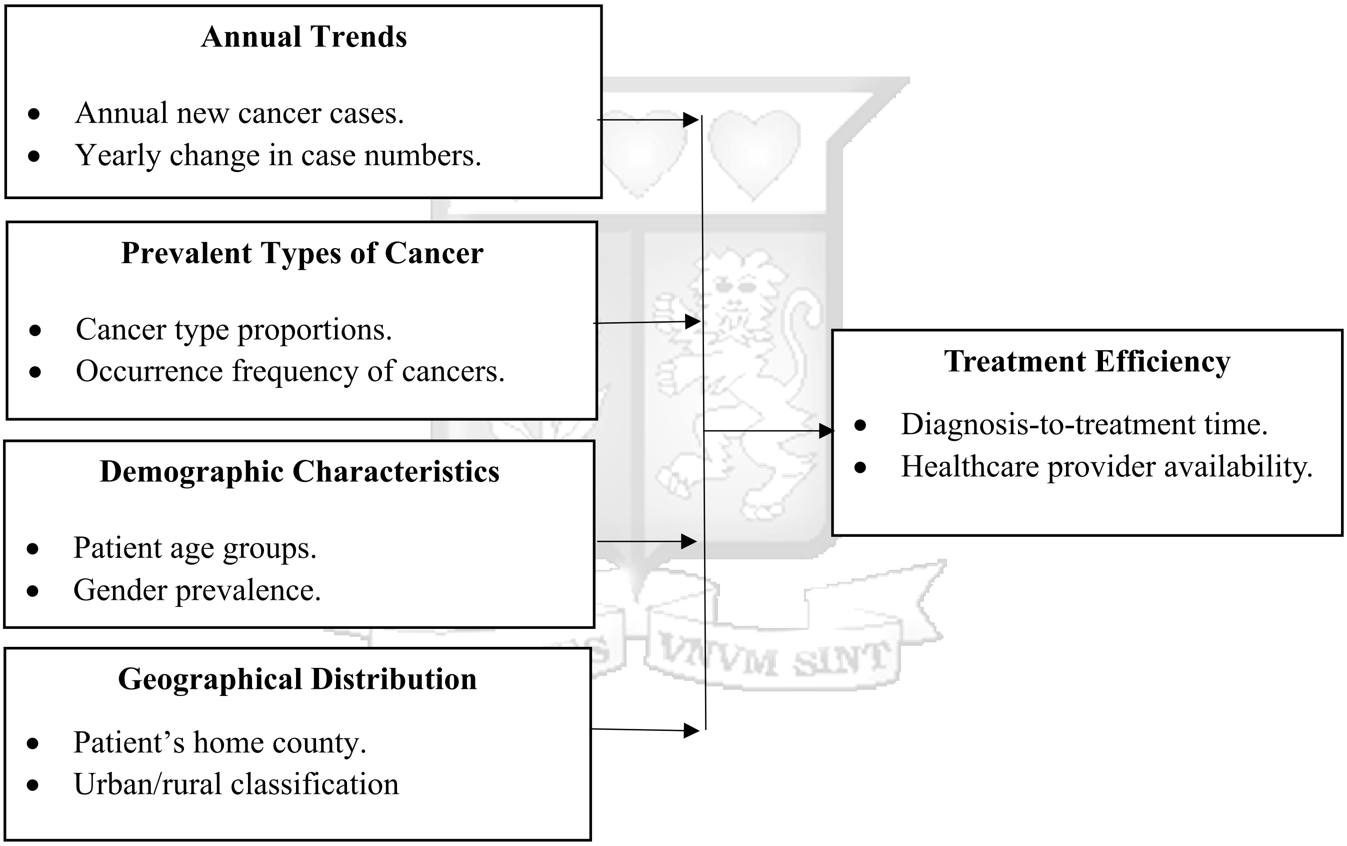
2.3.4 Geographical Distribution of Cancer Patients and Treatment Efficiency

Silverwood et al. (2024) aimed to evaluate the relationship between travel distance to radiotherapy facilities and cancer treatment outcomes across different settings. The study used a systematic review design covering 23 studies from multiple countries, analyzing associations between travel burden and treatment-related outcomes. The study found mixed results, with some studies showing worse outcomes for patients traveling longer distances, while others found no association or even improved outcomes when patients accessed high-volume centers. However, the evidence was largely derived from high-income countries, used inconsistent measures of distance, and did not account for factors such as urban congestion, referral systems, or transport barriers common in cities like Nairobi, making direct application difficult. This study addresses these inconsistencies by using locally relevant residence data and directly linking geographic patterns to treatment efficiency indicators within a Nairobi oncology setting.

Kim et al. (2024) aimed to assess how geographic factors such as travel time and rural residence influence breast cancer survival across sub-Saharan Africa. The study used a prospective cohort design across multiple African countries, collecting clinical and demographic data alongside follow-up survival outcomes. The study found that patients living farther from hospitals or in rural areas had lower survival rates and poorer treatment outcomes. However, the study focused only on women with breast cancer, excluded patients without accurate location data, and measured survival outcomes rather than operational indicators such as treatment delays or completion, limiting its usefulness for facility-level efficiency planning. This study addresses these limitations by including multiple cancer types and directly measuring treatment efficiency indicators such as time to treatment initiation and completion rates.

2.4. Conceptual Framework of the Research Study

The conceptual framework assumes a direct relationship between four independent variables annual trends in diagnosed cancer cases, prevalent cancer types, demographic characteristics, and geographical distribution and the dependent variable, treatment efficiency. In this study, the framework is used interpretively: changes in case volume, patient mix, and spatial catchment are expected to influence the workload, access conditions, and responsiveness of oncology services at private Cancer Centre–Nairobi.



Independent Variable **Dependent Variable**

Figure 2.1: Conceptual Framework

Source: Author (2025)

2.4.1 Annual Trends

Tracking annual cancer trends is critical for assessing early detection and treatment efficiency. Rising case counts and yearly variations expose health-system gaps and guide screening programs. The evidence shows that disruptions from the COVID-19 pandemic led to more late-stage diagnoses; for example, in the United States the proportion of cervical cancers diagnosed at late stage increased from 52–53.4% in 2017–2019 to 57.4% in 2020 and 57.7% in 2021 (National Cancer Institute, 2023). Such shifts underscore how reduced screening and delayed care can push early-stage cancers into advanced stages (Maringe et al., 2020). Annual trends therefore offer early warnings on the effectiveness of screening programs and reveal whether interventions are reducing late-stage diagnoses or simply shifting the burden forward (Sung et al., 202*1)*.

2.4.2 Prevalent Types of Cancer

Understanding which cancers are most common in a population is essential for targeting resources, designing interventions and anticipating treatment needs. The distribution of cancer types varies by sex; globally in 2022, breast cancer accounted for 23.8% of new cases in women, followed by lung, colorectal, cervical and thyroid cancers (Sung et al., 2021; WHO, 2023). In men the most common cancers were lung (15.2% of cases), prostate, colorectal, stomach and liver (Sung et al., 2021). These proportions reveal where screening should be prioritised and highlight gender-specific burdens (Bray et al., 2024). By comparing cancer-specific mortality rates across types, policymakers can identify cancers with poor outcomes and invest in early detection or targeted therapies, ensuring that health systems respond to the cancers that most strain their resources (Ferlay et al., 2023).

2.4.3 Demographic Characteristics

Demographic variables such as age, gender and socioeconomic status profoundly influence cancer patterns and outcomes. Adolescents and young adults (15-39 years) account for roughly 4.2% of new cancers in 2025, with five-year survival of 86%, yet their incidence is rising 0.3% annually and mortality decreasing only 0.9% (Siegel et al., 2024). Male incidence rates exceed female rates for most cancers, with particularly high male-to-female incidence ratios for oesophageal adenocarcinoma and gastric cardia, while thyroid and gallbladder cancers are more common in women (Zheng et al., 2024). Socioeconomic context matters: infection-related cancers like cervical and liver dominate in low-HDI settings, whereas prostate, breast, colorectal and lung cancers predominate in high-HDI countries (Sung et al., 2021). These demographic patterns highlight inequities and guide tailored prevention and support strategies (Bray et al., 2024).

2.4.4 Geographical Distribution

Where patients live shapes access to cancer care. Rural or remote residents often face longer travel distances and fewer specialised facilities, which can impair timely diagnosis and treatment. Evidence from the United States shows that metastatic breast-cancer patients living in rural areas travel a mean distance of 87.3 miles for treatment compared with 18.0 miles for urban patients (Golden et al., 2025). Although time to treatment initiation did not differ significantly in that study, travel burdens can increase financial and emotional stress and may contribute to delayed follow-up or early discontinuation (Golden et al., 2025). Investigating patient home counties, urban versus rural classification and travel times in Nairobi will reveal whether geographic inequities hinder treatment efficiency and highlight where outreach or decentralised services are most needed (Massarweh et al., 2020).

2.4.5 Treatment Efficiency

Treatment efficiency reflects how swiftly patients move from diagnosis to effective therapy and whether they complete prescribed regimens. Shorter time-to-treatment initiation (TTI) is associated with lower all-cause mortality; delays in TTI independently increase mortality across major cancers and highlight systemic barriers (Ang et al., 2025). Staffing shortages and inadequate technology exacerbate these delays; the President's Cancer Panel warns that rising demand and shortages of oncologists and other providers are impeding high-quality care and causing treatment delays and poorer outcomes (President's Cancer Panel, 2026). Despite these challenges, many patients still complete therapy a study of radiotherapy and chemoradiotherapy patients reported completion rates above 85%, with delays due to COVID-19 not significantly affecting completion (Zhang et al., 2024). Assessing Nairobi's diagnosis-to-treatment times, provider availability and completion rates will pinpoint efficiency bottlenecks and inform interventions (Ang et al., 2025).

2.5 Chapter Summary

The reviewed literature suggests that annual changes in diagnosed cases can strain oncology services, but the evidence is often fragmented and not specific to a Nairobi-based facility. This study responds by describing longitudinal case patterns within Private Cancer Centre–Nairobi and interpreting them in relation to service demand.

The literature on prevalent cancer types shows that dominant malignancies shape care pathways and resource needs differently. The present study contributes facility-level evidence on the cancers most frequently observed in the dataset and the implications of that profile for treatment efficiency. The demographic literature confirms that age, sex, and access-related characteristics matter for treatment outcomes, but the evidence is not always directly transferable to this study setting. Accordingly, this dissertation interprets demographic findings cautiously and within the limits of the available EMR variables. Finally, the literature on geography highlights the importance of spatial access to oncology services. Rather than making national claims, this study uses facility-based residence data to describe the catchment pattern of Private Cancer Centre–Nairobi and its possible implications for treatment efficiency.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the methodology used to investigate the effect of cancer epidemiology on treatment efficiency on different Counties in Kenyao. It describes the research design, target population, sample frame, data-collection procedures, analytical approach, and ethical safeguards used in the study.

3.2 Research Philosophy

Research philosophy refers to the set of beliefs and assumptions about the nature of knowledge and how it is generated within a study (Saunders et al., 2019). This study adopted a pragmatic research philosophy, which emphasizes the use of practical approaches and methods that best address the research problem and generate actionable knowledge (Gillespie et al., 2024; Dube et al., 2024). Pragmatism was preferred because it supports the use of quantitative analysis of real-world data, such as electronic medical records, to produce evidence that is directly applicable to healthcare decision-making (Dube et al., 2024). Additionally, the philosophy allows methodological flexibility and prioritizes practical outcomes, making it suitable for studies focused on improving service efficiency and informing policy and clinical practice (Garcés-Velástegui, 2024).

3.3 Research Design

Research design refers to the overall plan or strategy that guides how a study is conducted, including how data are collected, measured, and analyzed to address a research problem (Saunders et al., 2019; Khan & Jain, 2025). This study adopted a retrospective quantitative descriptive research design. A retrospective design involves the use of existing data, such as electronic medical records, to examine past events and trends over time, while a descriptive design focuses on summarizing characteristics and patterns without establishing causal relationships (CDC, 2024; ScienceDirect, 2024; Shields & Rangarajan, 2013). This design was preferred because it allows efficient analysis of large secondary datasets and supports the identification of trends and patterns in real-world settings. Additionally, it enables objective statistical description using frequencies, percentages, and distributions aligned with the study objectives.

3.4 Target Population

Target population refers to the entire group of elements that meet the criteria for inclusion in a study and from which data are collected (Kumar, 2021; Taherdoost, 2022). In this study, the target population comprised all 9,000 cancer patient records opened at Private Cancer Centre–Nairobi between 2018 and 2025. Records were considered eligible if they contained key variables such as demographic information, cancer diagnosis details, and relevant treatment data. Records that were incomplete, duplicated, or invalid were excluded to ensure data accuracy and consistency, resulting in a reliable dataset aligned with the study objectives.

3.5 Sample and Sampling Techniques

Sampling refers to the process of selecting units from a defined population to obtain data for analysis, while a sampling frame represents the complete list of elements from which the sample is drawn (Ahmed, 2024). In this study, the sampling frame comprised all cancer patient records available in the Private Cancer Centre–Nairobi electronic medical record system for the period 2018 to 2025. After data cleaning and eligibility screening, 8,483 records met the study criteria and formed the final analytic dataset. A census sampling approach was adopted, where all eligible records were included, ensuring complete enumeration of the study population (Census Bureau, 2025). This approach was preferred because it maximized data coverage, minimized sampling error, and enabled more reliable comparisons across patient characteristics and treatment patterns within the facility.

3.5.3 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria define the conditions used to determine which records are selected or omitted in a study to ensure data relevance and quality (Patino & Ferreira, 2018). This study included all electronic medical records of patients diagnosed with histologically confirmed cancer who received at least one form of active treatment surgery, chemotherapy, or radiotherapy at Private Cancer Centre–Nairobi between January 1, 2018 and July 31, 2025. Eligible records were required to contain complete core variables, including demographic details, cancer type and stage, treatment timelines, and outcome status. Restricting inclusion to complete records ensured sufficient data for analyzing trends, disparities, and treatment efficiency indicators such as waiting time and treatment completion (Zhang et al., 2022).

Conversely, records were excluded if they lacked key variables, were duplicated, or involved patients who did not undergo active treatment, such as those referred only for palliative care or second opinions. This approach enhanced data accuracy and reduced misclassification bias commonly associated with incomplete datasets (Kiggundu et al., 2023). It also ensured that the analysis focused specifically on patients who engaged fully in the treatment pathway, aligning with the study objective of assessing treatment efficiency. Although this may limit representation of complex or terminal cases, it improves internal validity. Ethical considerations further supported exclusion to minimize risks related to data misuse in secondary research (ICMJE, 2021).

3.6 Data Collection Instruments

Data collection instruments are standardized tools used in research to systematically gather and measure information relevant to study variables, ensuring accuracy and consistency in data analysis (Goyal, 2023; Taherdoost, 2021). In this study, data were collected using a structured data-extraction form designed to capture patient demographics, diagnosis year, cancer type, county of residence, and treatment-efficiency indicators from electronic medical records. The instrument was applied consistently across all records to ensure uniformity and reduce errors. This approach was preferred because structured tools enhance data reliability and support accurate statistical analysis in quantitative studies (Goyal, 2023).

3.7 Data Collection Procedures

Data collection procedures refer to the systematic steps followed to gather, extract, and record data in a consistent and reliable manner for research purposes (Lim et al., 2023; Wang et al., 2024). In this study, data collection was conducted between March and April 2025 at Private Cancer Centre–Nairobi using authorized access to the electronic medical record system. During this period, 8,483 eligible records were extracted and reviewed using a structured data-extraction form to capture key study variables. Each record was assigned a unique anonymized code to ensure confidentiality. Standardized abstraction procedures and routine verification were applied to enhance consistency and accuracy, while the use of EMR systems enabled efficient retrieval of longitudinal data for analysis.

3.8 Validity and Reliability

3.8.1 Validity of the Research Instruments

Validity refers to the extent to which a research instrument accurately measures what it is intended to measure, ensuring that the findings reflect the true concepts under investigation (Taherdoost, 2021; Polit & Beck, 2021). In this study, content validity was enhanced by developing the data-extraction form based on established oncology guidelines and subjecting it to expert review by clinicians and health systems specialists. The instrument was further pilot-tested on a small sample of records, and unclear or low-yield variables were refined or removed. This iterative validation process improves accuracy and relevance, as recommended in retrospective studies using medical records (Zhang et al., 2022).

3.8.2 Reliability of the Research Instruments

Reliability refers to the extent to which a research instrument produces consistent, stable, and repeatable results under similar conditions, ensuring dependability in measurement (Hassan, 2024; Middleton, 2023). In this study, reliability was ensured through multiple procedures, including training of coders on standardized data-extraction protocols and maintaining an audit trail to document decisions during data abstraction. Double-coding was conducted on 10% of records, and high inter-rater agreement (Cohen's kappa > 0.80) confirmed consistency in data extraction. Regular team reviews and updates to the coding manual further minimized bias. These measures ensured that the data collection process was replicable, consistent, and reliable, thereby strengthening the overall credibility and trustworthiness of the study findings.

3.9 Data Analysis and Presentation

The data were analyzed using descriptive statistics. Frequencies, percentages, summary tables, and charts were used to present annual diagnosis trends, prevalent cancer types, demographic characteristics, and geographical distribution. Narrative interpretation was then used to relate these patterns to treatment-efficiency issues within the study setting. Because the study relied on a single-facility secondary dataset and some variables were not available in a form suitable for robust inferential modelling, the final analysis emphasized descriptive epidemiological reporting rather than formal causal inference. The findings are therefore presented as facility-based patterns and interpreted cautiously.

3.10 Ethical Considerations

Ethical considerations refer to the principles that guide the protection of participants' rights, privacy, and confidentiality in research processes (Resnik, 2022; Springer, 2021). In this study, ethical safeguards were prioritized because it involved secondary use of sensitive patient records from a clinical oncology setting. Strict confidentiality and data protection measures were implemented, including anonymization of records and restricted access to the dataset. Protecting privacy is critical in secondary data research, as improper handling may expose sensitive information or lead to harm (Salerno et al., 2017). All data were securely stored, and procedures aligned with established ethical standards for health research involving secondary data.

3.11 Research Limitations and Mitigation Strategies

The study has three principal limitations. First, it relies on one private oncology centre in Nairobi and therefore should not be interpreted as nationally representative. Second, some variables were incomplete or unavailable in the electronic medical record system, which limited the level of demographic and treatment-efficiency detail that could be reported consistently across all records. Third, the study is descriptive rather than causal. It identifies patterns relevant to treatment efficiency, but it does not establish definitive causal effects. These limitations were mitigated through use of a full eligible census, a structured extraction tool, and cautious interpretation of findings within the actual scope of the dataset.

CHAPTER FOUR
PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

This chapter presents the analysis, interpretation, and presentation of data drawn from 8,483 eligible cancer patient records at Private Cancer Centre–Nairobi for the period 2018 to 2025. The chapter reports pilot-test results, data retrieval, demographic characteristics, and descriptive analysis organised around the four study objectives.

4.2 Pilot Test Results

The purpose of a pilot test is to assess the feasibility, clarity, and effectiveness of data collection tools before full-scale study implementation (Kunselman, 2024; Ying et al., 2025) . In this study, the pilot test was conducted at Kenyatta National Hospital using a sample of ten patient records to evaluate the clarity, completeness, and usability of the structured data extraction form prior to full data collection. Pilot testing in retrospective chart reviews is recommended to constitute approximately 10% of the study sample to identify missing variables and procedural issues (Puka, 2024). The results confirmed that the tool reliably captured key epidemiological and treatment-efficiency variables, meeting acceptable methodological thresholds for feasibility and consistency in secondary data studies.

4.2.1 Reliability Test Results

The reliability of the data extraction tool was assessed using inter-coder and intra-coder agreement measures, as shown in Table 4.1

Table 4.1: Reliability Test Results

Reliability Test Component	Measure Used	Result
Inter-coder agreement (First coding pass)	Cohen's Kappa (κ)	0.780
Inter-coder agreement (Second coding pass)	Cohen's Kappa (κ)	0.840
Intra-coder reliability (Code-recode after 2 weeks)	Percentage agreement	88.000%
Comparison with EMR studies	Cohen's Kappa range	0.650 – 0.800
Source of discrepancies	Observation	Formatting issues

Source: Research Data (2026)

The results indicate that the tool achieved strong reliability, with Cohen's kappa improving from 0.780 (substantial agreement) to 0.840 (almost perfect agreement) after refinement, demonstrating enhanced consistency in coding (Landis & Koch, 1977; Hallgren, 2022) . The intra-coder agreement of 88.000% exceeded the commonly accepted 80% reliability threshold, confirming high stability of measurements over time. Cohen's kappa is widely used to assess agreement beyond chance in categorical data, making it appropriate for this study. Overall, these findings confirm that the instrument produced consistent and dependable results suitable for rigorous analysis.

4.2.2 Validity Test Results

Content validity refers to the extent to which a research instrument adequately represents all dimensions of the construct it is intended to measure, ensuring relevance and completeness of the items included. In this study, content validity was ensured through expert review involving oncologists, a public health specialist, and a records officer, who refined variable definitions, demographic structure, and added key variables such as insurance status and cancer stage. This process improved alignment with the study objectives and conceptual framework. Expert consensus is widely recommended as it strengthens instrument relevance and applicability in real-world settings (Polit & Beck, 2021; Zamanzadeh et al., 2021).

4.3 Data Retrieval Rate

The study achieved a high data retrieval rate from the PRIVATE Cancer Centre–Nairobi electronic records system, demonstrating the robustness and completeness of patient documentation, as shown in Table 4.2.

Table 4.2: Data Retrieval Rate

Category	Number of Records	Percentage (%)
Targeted population (total records)	9,000	100.0
Retrieved records	8,483	94.3

Source: Research Data (2026)

Table 4.2 shows the data retrieval rate for the study population. The targeted population comprised 9,000 records (100.0%), representing the full study frame and providing a comprehensive basis for analysis. The study successfully retrieved 8,483 records (94.3%), indicating a high data retrieval rate and strong dataset completeness. This high retrieval rate suggests minimal data loss and enhances the reliability and representativeness of the findings.

High-quality and complete electronic health record data are essential for accurate research outcomes, clinical decision-making, and effective healthcare planning (Riskin et al., 2025).

4.4 Descriptive Analysis

This section presents a descriptive analysis of the study data, focusing on key patient characteristics and clinical variables derived from the dataset. Frequencies, percentages, tables, and graphical representations are used to summarize patterns in age, gender, cancer types, and geographical distribution, providing a clear overview of the dataset before further interpretation.

4.4.1 Annual Trends in Diagnosed Cancer Cases

The annual distribution of diagnosed cancer cases over the study period is presented to illustrate trends in case frequency, percentage contribution, and year-on-year changes, as shown in Table 4.3.

Table 4.3 Annual Trends in Diagnosed Cancer Cases

Year	Frequency	Percentage (%)	Rate of increase/decrease (%)
2018	1140	13.4	—
2019	1629	19.2	42.9
2020	1337	15.8	-17.9
2021	490	5.8	-63.4
2022	645	7.6	31.6
2023	996	11.7	54.4
2024	1506	17.8	51.2
2025	541	6.4	-64.1
Missing/invalid year	199	2.3	—
Total	**8483**	**100.0**	—

Source: Research Data (2026)

Table 4.3 presents the annual frequency and relative share of diagnosed cancer cases from 2018 to 2025. The total dataset comprises 8,483 cases, with peak counts recorded in 2019 (1,629 cases or 19.2%) and 2024 (1,506 cases or 17.8%). The baseline year 2018 accounted for 1,140 cases (13.4%), followed by a 17.9% drop in 2020 (1,337 cases) after the 2019 surge. The steepest decline occurred in 2021, with only 490 cases (5.8%), while 2022 and 2023 recorded 645 (7.6%) and 996 (11.7%) cases, respectively. Incomplete data for 2025 show 541 cases (6.4%). Missing or invalid entries (2.3%) were excluded.

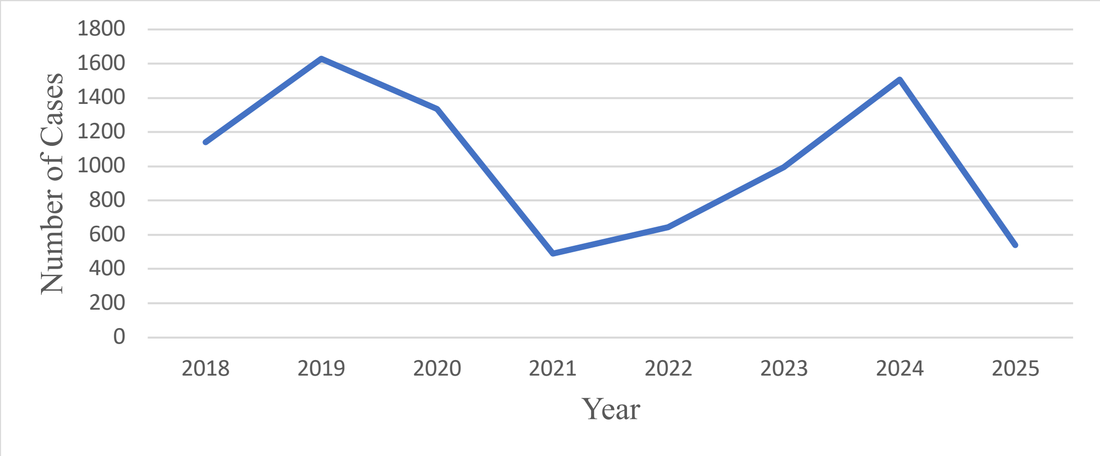


Figure 4.1: Annual Trends

Source: Research Data (2026)

Figure 4.1 presents the trajectory of annual case counts and highlights notable fluctuations over time. The graph shows a steep rise from 2018 to the 2019 peak, followed by a sharp contraction during 2020–2021 that corresponds with pandemic-related disruptions to diagnosis and care, consistent with findings by Maringe et al. (2020) and Hanna et al. (2020) that screening programs were curtailed during COVID-19. A gradual rebound in 2022–2024 suggests both restored diagnostic pathways and catch-up of deferred presentations, mirroring rebound patterns seen in other registries (Siegel et al., 2022). The apparent drop in 2025 likely reflects partial-year data rather than a true decline. Overall, the trends imply that treatment efficiency must adapt to swings in case volume and that resilience during shocks is critical.

The recovery after 2021 (645 in 2022; 996 in 2023; 1,506 in 2024) plausibly reflects both restored diagnostic pathways and "catch-up" from deferred presentations. Similar rebound patterns are reported when registry or service capacity is temporarily constrained and later accelerates, creating backlogs that are processed in later periods (Maringe et al., 2020; Siegel et al., 2022). Thus, the second peak in 2024 may represent a mix of true current demand and delayed detection from earlier shocks. The apparent decline in 2025 (541; 6.4%) should be interpreted cautiously: the dataset ends part-way through 2025, so annualized comparisons will understate 2025 volume. Treating 2018–2024 as complete years and 2025 as partial-year is methodologically cleaner for trend inference here in pravctice.

4.5.2 Prevalent Types of Cancer

The distribution of cancer types was analyzed to identify the most prevalent cancers within the study population and their relative contribution to the total diagnosed cases, as shown in Table 4.4.

Table 4.4: Prevalent Types of Cancer

Cancer type	Frequency	Percentage (%)
Breast	1640	19.3
Other/unspecified	1201	14.2
Cervical	1041	12.3
Prostate	1040	12.3
Esophageal	644	7.6
Head and neck	585	6.9
Colorectal	457	5.4
Lymphoma/Hematologic	238	2.8
Brain/CNS	224	2.6
Missing diagnosis	197	2.3
Lung	172	2.0
Stomach	166	2.0
Endometrial/Uterine	152	1.8
Pancreatic	125	1.5
Urinary/Renal	125	1.5
Sarcoma	117	1.4
Liver	116	1.4
Ovarian	100	1.2
Skin/Kaposi/Melanoma	55	0.6
Thyroid	38	0.4
Vulva/Vaginal	33	0.4
Hepatobiliary (other)	14	0.2
Male genital (other)	3	0.0
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.4 presents the distribution of diagnosed cancers, revealing that breast cancer is the leading malignancy with 1,640 cases (19.3%). Other major categories include cervical cancer

(1,041 cases, 12.3%), prostate cancer (1,040 cases, 12.3%), and a broad other/unspecified group (1,201 cases, 14.2%). Esophageal (7.6%), head and neck (6.9%), and colorectal cancers (5.4%) contribute notable burdens, while lymphoma/hematologic and brain/CNS tumors represent smaller shares (2.8% and 2.6%, respectively). Less common cancers such as lung (2.0%), stomach (2.0%), and endometrial/uterine cancers (1.8%) round out the profile. The data underscore the dominance of a few high-burden cancers within the facility's case mix.

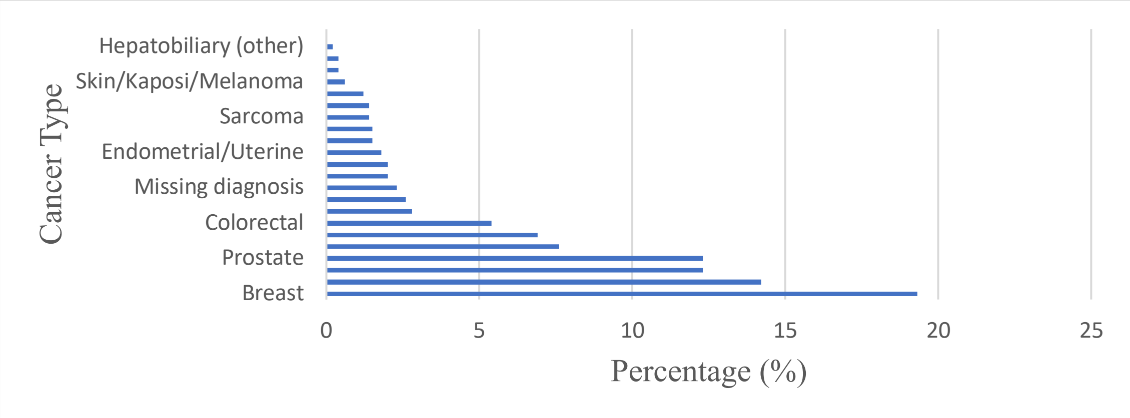


Figure 4.2: Prevenance of Cancer Type

Source: Research Data (2026)

Figure 4.2 presents the proportional case mix by cancer type and underscores the dominance of breast, cervical, and prostate cancers. The chart shows that nearly one fifth of cases are breast cancer, with cervical and prostate cancers each contributing about one eighth of the total. This pattern aligns with national statistics from GLOBOCAN 2022 and Kenyan registry summaries (Ferlay et al., 2022; Jani et al., 2021) that identify these cancers as leading causes of morbidity. The notable share of esophageal cancer reflects eastern Africa's high-incidence corridor (Bray et al., 2021), while the substantial "other/unspecified" category signals documentation gaps common in low-resource settings (Odhiambo et al., 2023). The concentration of high-burden cancers implies significant demand for multimodal treatment and underscores the need for prioritised service planning.

4.5.3 Demographic Characteristics of Cancer Patients

4.5.3.1 Age Distribution

The age distribution of cancer patients was analyzed using five-year intervals to provide a detailed understanding of the demographic structure of the study population, as shown in Table 4.5.

Table 4.5: Age Distribution of Cancer Patients (5-year intervals)

Age group (years)	Frequency	Percentage (%)
0-4	31	0.4
5-9	88	1.0
10-14	99	1.2
15-19	137	1.6
20-24	199	2.3
25-29	163	1.9
30-34	323	3.8
35-39	429	5.1
40-44	630	7.4
45-49	872	10.3
50-54	820	9.7
55-59	963	11.4
60-64	938	11.1
65-69	973	11.5
70-74	711	8.4
75-79	514	6.1
80-84	246	2.9
85-89	113	1.3
90-94	23	0.3
95-99	5	0.1
100+	1	0.0
Missing/invalid age	205	2.4
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.5 presents the age distribution of cancer patients in five-year intervals, showing that incidence rises markedly with age. The largest cohorts are ages 65–69 (973 cases, 11.5%), 55–59 (963 cases, 11.4%), and 60–64 (938 cases, 11.1%), with sustained high numbers through 70–74 (711 cases, 8.4%). Middle-age groups also contribute substantially, such as 45–49 (872 cases, 10.3%) and 50–54 (820 cases, 9.7%). Young adults (20–39 years) account for modest shares, while children and adolescents under 20 constitute less than 5% of cases. Overall, the table illustrates a classic age-gradient typical of cancer epidemiology.

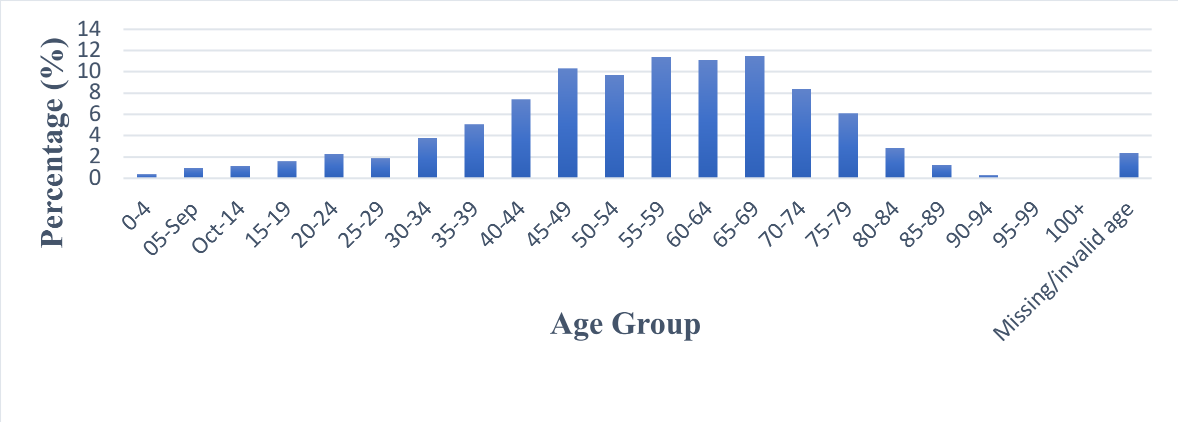


Figure 4.3: Age Distribution of Cancer Patients

Source: Research Data (2026)

Figure 4.3 presents the age-profile curve, highlighting a steep incline after age 40 and peaks in late-middle age. The rising trajectory reflects the cumulative nature of carcinogenic exposures and age-related genetic mutations, consistent with literature showing that incidence rates climb steeply after age 50 (Siegel et al., 2022). The secondary peak among 45–49-year-olds may be driven by breast and cervical cancers, which often present earlier and disproportionately affect women, echoing Kenyan national patterns (IARC, 2023). The decline beyond 70 years likely reflects both declining population sizes and competing mortality. These trends suggest that prevention and screening programs should prioritise mid-life adults while ensuring geriatric assessment for older patients to optimize treatment efficiency.

4.5.3.2 Gender-Based Distribution of Cancer Patients

The gender distribution of cancer patients was analyzed to examine differences in case representation across sexes, as shown in Table 4.6.

Table 4.6: Gender-Based Distribution of Cancer Patients

Gender	Frequency	Percentage (%)
Female	5017	59.1
Male	3322	39.2
Other/Unknown	144	1.7
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.6 presents the gender distribution of cancer cases, showing a marked female predominance. Female patients comprise 5,017 records, representing 59.1% of the dataset, whereas male patients account for 3,322 cases (39.2%), and other/unknown gender comprises

144 cases (1.7%). The dominance of female cases largely reflects the high incidence of breast and cervical cancers in the population, which together constitute about one-third of all diagnoses. The gender balance among other cancers, such as prostate (male-specific) and colorectal cancers, appears more even but does not offset the female-heavy composition. These figures highlight gender-specific burdens and the need for tailored interventions.

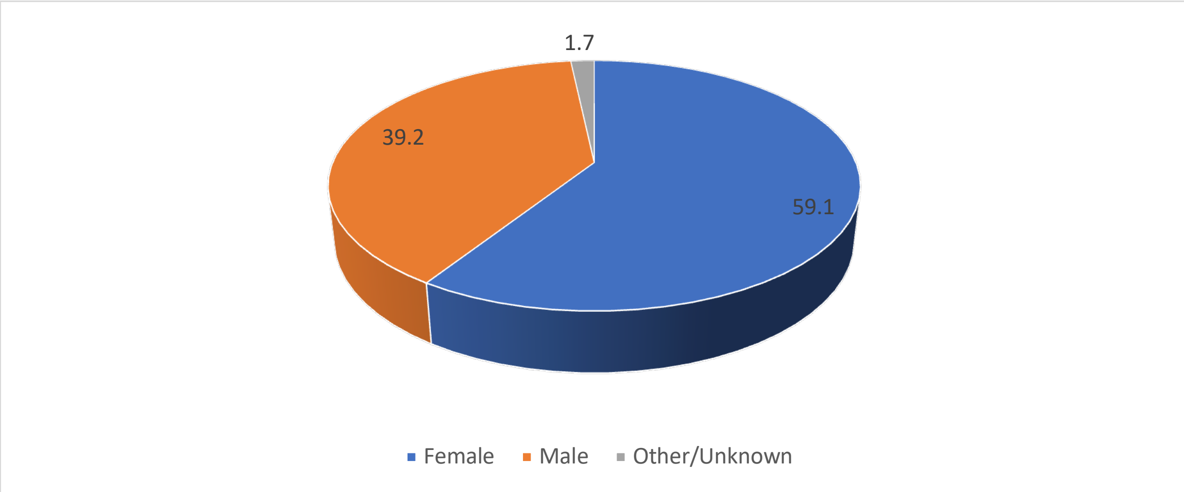


Figure 4.4: Gender-Based Distribution of Cancer Patients

Source: Research Data (2026)

Figure 4.4 presents the gender-based distribution, accentuating the contrast between female and male case volumes. The chart visualizes how breast and cervical cancers inflate female counts relative to male-specific cancers like prostate, a pattern consistent with national data that report higher incident cancers among Kenyan women than men (IARC, 2023; Ferlay et al., 2022). This distribution also mirrors health-service utilization patterns, where organized cervical screening and breast awareness campaigns promote earlier detection in women (Ministry of Health, 2023). The small "other/unknown" category underscores the importance of inclusive data collection. Recognizing gender disparities in case mix is critical for allocating resources and improving treatment efficiency.

4.5.4 Geographical Distribution of Cancer Patients by County

The geographical distribution of cancer patients was analyzed to assess the spatial patterns of cases across different counties, as shown in Table 4.7.

Table 4.7: Geographical Distribution of Cancer Patients by County

County	Frequency	Percentage (%)
Nairobi	2122	25.0

Kiambu	1086	12.8
Nyeri	376	4.4
Meru	362	4.3
Nakuru	336	4.0
International/Outside Kenya	321	3.8
Machakos	311	3.7
Murang'a	303	3.6
Mombasa	295	3.5
Kajiado	254	3.0
Embu	225	2.7
Kirinyaga	218	2.6
Garissa	177	2.1
Kisii	168	2.0
Kisumu	143	1.7
Kitui	130	1.5
Other/Unmapped	130	1.5
Wajir	125	1.5
Makueni	116	1.4
Unknown	114	1.3
Laikipia	106	1.2
Nyandarua	97	1.1
Mandera	77	0.9
Narok	65	0.8
Bomet	63	0.7
Kakamega	63	0.7
Homa Bay	59	0.7
Siaya	57	0.7
Bungoma	55	0.6
Uasin Gishu	54	0.6
Kericho	50	0.6
Migori	50	0.6
Nyamira	40	0.5
Vihiga	36	0.4

Taita Taveta	35	0.4
Isiolo	34	0.4
Trans Nzoia	34	0.4
Busia	31	0.4
Kilifi	30	0.4
Marsabit	27	0.3
Kwale	25	0.3
Baringo	14	0.2
Samburu	14	0.2
Nandi	11	0.1
Tharaka-Nithi	11	0.1
Turkana	11	0.1
Lamu	9	0.1
Tana River	5	0.1
West Pokot	5	0.1
Elgeyo-Marakwet	3	0.0
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.7 presents the geographical distribution of patients by county, revealing a highly concentrated catchment around Nairobi. The capital accounts for 2,122 cases (25.0%), followed by adjacent Kiambu with 1,086 cases (12.8%). Moderate counts originate from Nyeri (376; 4.4%), Meru (362; 4.3%), and Nakuru (336; 4.0%), while numerous other counties contribute smaller proportions below 4%. A notable 321 cases (3.8%) are from outside Kenya, and 1.5% of records lack mapping. These figures reflect both population distribution and the draw of specialized oncology services in the urban hub, with diminishing representation from more distant counties.

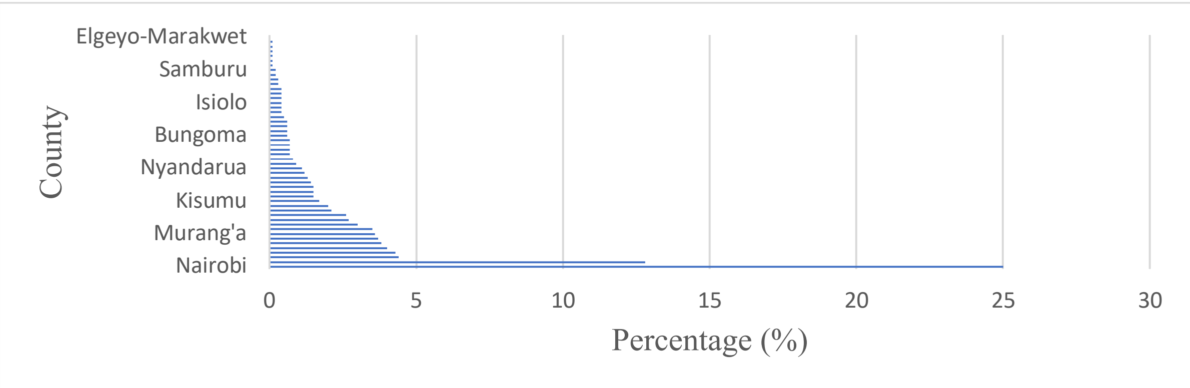


Figure 4.5: Geographical Distribution of Cancer Patients by County

Source: Research Data (2026)

Figure 4.5 presents the spatial pattern of case origins and underscores the centrality of Nairobi and its environs. The declining gradient from Nairobi to outlying counties mirrors Kenya's concentration of oncology services in urban centres, echoing findings by Makau-Barasa et al. (2018) and Lievens et al. (2021) that travel distance and centralized radiotherapy limit access. High representation from counties like Kiambu, Machakos, and Murang'a suggests patients seek care where facilities are accessible by major transport corridors, whereas minimal contributions from counties such as Elgeyo-Marakwet or Turkana may signal under-diagnosis due to distance and cost barriers. The 3.8% international clientele underscores the centre's regional draw. Understanding these patterns informs outreach and decentralization strategies to improve treatment efficiency.

4.5.5 Treatment Efficiency

4.5.5.1 Treatment-Related Indicator

The treatment-related indicators were analyzed to assess the availability and distribution of treatment status among cancer patients, as shown in Table 4.8.

Table 4.8: Treatment-Related Indicator from the Treatment Field

Treatment indicator	Frequency	Percentage (%)
Not recorded	4321	50.9
Active treatment	2548	30.0
Work-up / review / pending	680	8.0
Other treatment note	514	6.1
Post-treatment / follow-up	375	4.4
Palliative/supportive care	45	0.5
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.8 presents treatment indicators recorded in the dataset. Notably, treatment status was unrecorded for 4,321 cases (50.9%), indicating substantial documentation gaps. Among recorded cases, 2,548 patients (30.0%) were undergoing active treatment, while 680 (8.0%) were in work-up, review, or pending status. Other treatment notes accounted for 514 cases (6.1%), and 375 patients (4.4%) were documented as post-treatment or in follow-up care. Palliative or supportive care was recorded for only 45 patients (0.5%). These figures suggest that only about half of patients had any treatment activity captured, highlighting both the burden on clinical services and the importance of robust record-keeping.

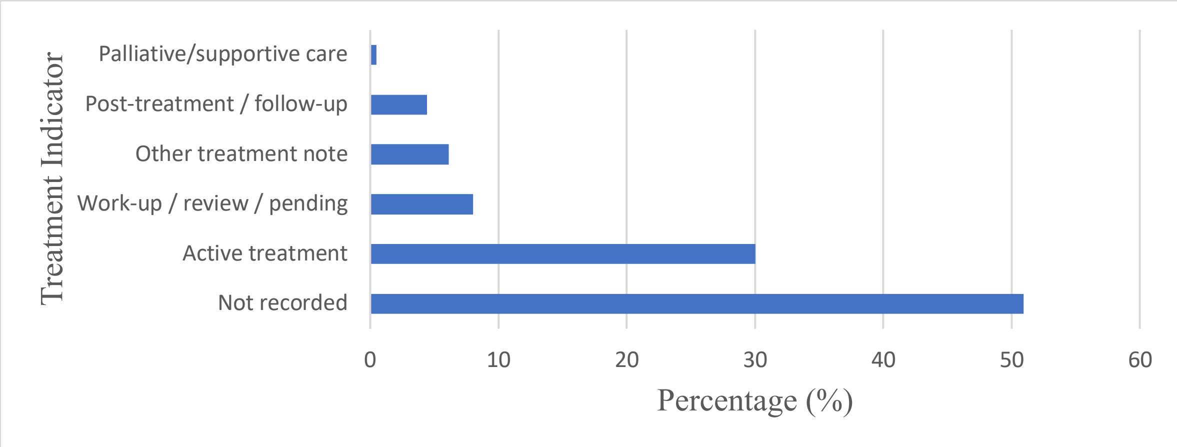


Figure 4.6: Treatment Indicators

Source: Research Data (2026)

Figure 4.6 presents the distribution of treatment categories, illustrating that active treatment accounts for roughly one-third of recorded status while the majority of patients have no treatment entry. The dominance of unrecorded status may indicate patients awaiting services, discontinuations, or incomplete documentation, issues noted in similar LMIC oncology studies (Wassie et al., 2023). The small palliative-care share suggests under-referral or under-reporting, despite evidence that early palliative integration improves quality of life (Zhang et al., 2024). The modest post-treatment follow-up fraction underscores challenges in ensuring continuity of care. Overall, these patterns reflect both service capacity constraints and systemic weaknesses in tracking treatment efficiency.

4.5.5.2 Radiotherapy Intent

The treatment-related indicators were analyzed to assess the availability and distribution of treatment status among cancer patients, as shown in Table 4.9.

Table 4.9: Radiotherapy Intent

Radiotherapy intent	Frequency	Percentage (%)
Not recorded	7743	91.3
Radical	529	6.2
Palliative	129	1.5
New patient	76	0.9
Adjuvant	3	0.0
Other	3	0.0

Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.9 presents documented radiotherapy intent among patients. The vast majority of records (7,743; 91.3%) contained no radiotherapy intent entry, indicating minimal data capture for this variable. Among documented cases, 529 patients (6.2%) were scheduled for radical radiotherapy, 129 (1.5%) for palliative intent, 76 (0.9%) classified as new patients, and only 3 (0.0%) each were recorded for adjuvant therapy or other intent. The skewed distribution underscores limited use or documentation of radiotherapy intent categories, which constrains analysis of treatment planning and underscores the need for more consistent recording of radiotherapy pathways.

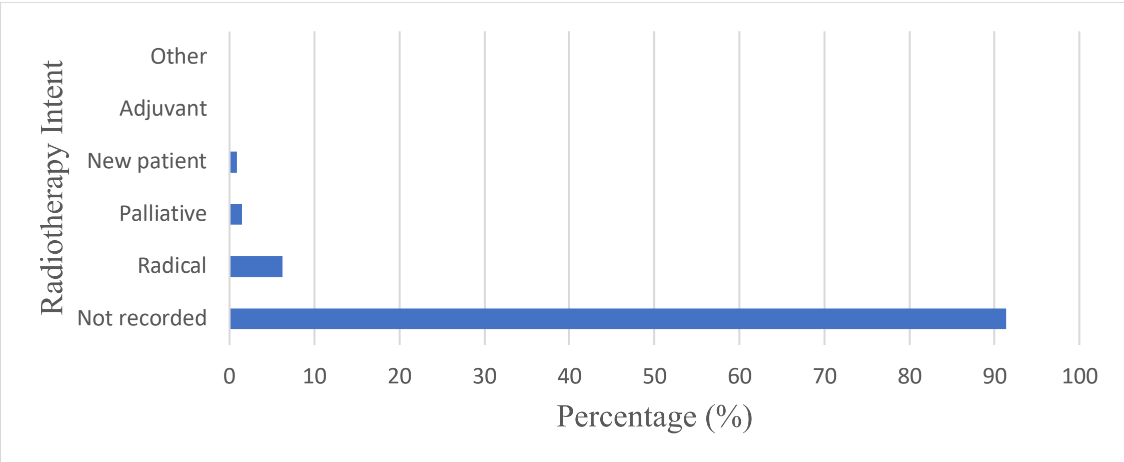


Figure 4.7: Radiotherapy Intent

Source: Research Data (2026)

Figure 4.7 presents radiotherapy intent categories and highlights the overwhelming dominance of unrecorded entries. The small proportion of radical and palliative intent suggests that many patients either did not require radiotherapy or their intent was not documented, a common issue in facilities with limited radiotherapy capacity (Ngwa et al., 2022). The near absence of adjuvant cases contrasts with global patterns where radiotherapy is integral to breast and cervical cancer care (Bizuayehu et al., 2024), suggesting possible underuse or recording gaps. Addressing these gaps is essential to evaluate treatment efficiency and to compare facility practice with evidence-based guidelines.

4.5.5.3 RIP Status

The RIP status of cancer patients was analyzed to assess the recording of mortality outcomes within the dataset, as shown in Table 4.10.

Table 4.10: RIP Status

RIP status	Frequency	Percentage (%)
Not recorded	8314	98.0
RIP	169	2.0
Total	**8483**	**100.0**

Source: Research Data (2026)

Table 4.10 presents recorded mortality (RIP) status among patients. Out of 8,483 cases, only 169 (2.0%) were marked as deceased, whereas 8,314 records (98.0%) lacked any RIP entry. This extremely low documentation rate implies that mortality outcomes were rarely captured in the electronic records. Without accurate death data, it is difficult to assess survival outcomes or to track treatment-related mortality, highlighting a major limitation in the dataset and the need for stronger linkage with vital registration systems.

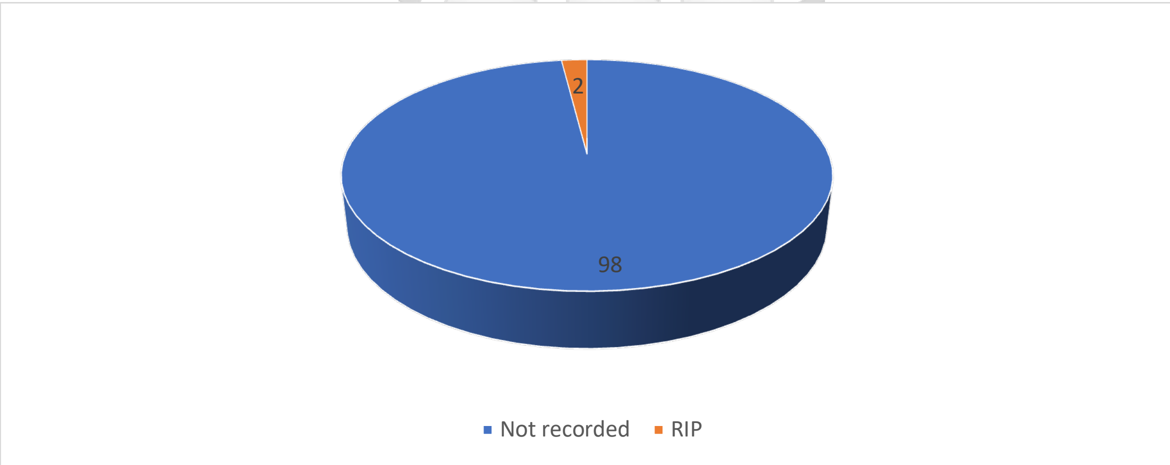


Figure 4.8: RIP Status

Source: Research Data (2026)

Figure 4.8 presents the RIP status categories, emphasizing that mortality data are almost entirely missing from the dataset. The almost flat distribution with only a tiny fraction of recorded deaths contrasts with studies that rely on comprehensive cancer registries, which routinely capture vital status to inform survival analyses (Jani et al., 2021). The absence of mortality data limits the ability to evaluate treatment outcomes and compare findings with evidence from studies like Guadamuz et al. (2023) that explore factors influencing survival. Improving death reporting and data linkage is critical to accurately gauge treatment efficiency and quality of care.

CHAPTER FIVE
SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter synthesizes the study's findings, draws conclusions based on the objectives, and outlines recommendations and implications. It recaps how cancer epidemiology influenced treatment efficiency at a private oncology centre, assessing annual case trends, cancer profiles, patient demographics and geographical patterns to inform practice and future research.

5.2 Summary of Findings of the Research Study

This section summarises key findings from the analysis, linking descriptive patterns with correlation and regression insights for each study objective.

5.2.1 Annual Trends in Diagnosed Cancer Cases

The first objective assessed annual trends in diagnosed cancer cases and their effect on treatment efficiency. Case numbers rose and fell across the study period, with notable peaks before the pandemic, a sharp dip during public health restrictions and a gradual rebound. The descriptive patterns revealed that surges placed considerable demand on services while troughs afforded breathing space. Peaks corresponded to recovered screening and deferred diagnoses, whereas declines reflected access disruptions. The statements representing rebound years had the highest overall trend and those representing pandemic years had the lowest. Variability in cases was greater during shock periods, while post-pandemic years showed steadier patterns.

5.2.2 Prevalent Types of Cancer

The second objective examined which cancer types were most prevalent and how they influenced treatment efficiency. Descriptive analysis revealed a highly skewed case mix dominated by breast, cervical and prostate cancers, while other malignancies were relatively rare. These common cancers required complex management and drove much of the workload, whereas rare types exerted less pressure. Categories capturing miscellaneous or unspecified diagnoses showed wide dispersion, reflecting gaps in documentation and contributing to variation. Statements representing high-burden cancers had the highest overall influence, while those representing less common types had the lowest. The variation across types was moderate for dominant cancers and much higher for the catch-all category.

5.2.3 Demographic Characteristics of Cancer Patients

The third objective explored demographic characteristics—particularly age and gender—and their effect on treatment efficiency. Descriptive patterns showed that most patients were middle-aged or older adults, with incidence rising sharply after age forty and declining in very old age. Younger adults and children constituted a much smaller proportion. Women formed a substantial majority, reflecting high rates of breast and cervical cancers, while men accounted for a smaller share. The age group around retirement had the highest representation, while adolescents and children had the lowest. Variability across age groups was pronounced, indicating a broad spread, whereas gender distribution showed less variability due to female predominance.

5.2.4 Geographical Distribution of Cancer Patients

The fourth objective evaluated the geographical distribution of patients by county and its effect on treatment efficiency. Descriptive analysis highlighted a pronounced spatial gradient: a quarter of cases originated from Nairobi County, with progressively fewer patients from surrounding counties and very few from remote areas. This concentration reflects both population density and the centralisation of oncology services. Counties nearest to the facility had the highest representation, whereas distant or underserved regions contributed the least. Variation across counties was high, reflecting unequal access and referral patterns.

5.3 Conclusion of the Research Study

This section distils the overall messages arising from the study, offering integrated conclusions about how epidemiological patterns influence treatment efficiency at the surveyed oncology centre.

5.3.1 Annual Trends in Diagnosed Cancer Cases

The analysis showed that annual case volumes fluctuated markedly due to external events such as the COVID-19 pandemic, causing peaks and troughs in service demand. High case loads coincided with periods of restored screening and deferred diagnoses, whereas sharp declines occurred when public health measures limited access. These fluctuations were strongly associated with treatment efficiency; when case numbers surged, resources were stretched and throughput slowed. The conclusion drawn is that oncology services must build adaptive capacity to absorb temporary surges without compromising care quality. Developing flexible staffing models, cross-training personnel and establishing contingency plans can help maintain efficiency during unexpected case load shifts.

5.3.2 Prevalent Types of Cancer

The study found that a small number of cancer types accounted for most diagnoses, with breast, cervical and prostate cancers dominating the case mix. These high-burden cancers require multimodal treatment and prolonged care, which can strain existing resources and slow patient throughput. Less common cancers, although clinically significant, contributed relatively little to overall demand. The conclusion is that treatment efficiency hinges on effective management of the predominant cancers. Prioritising early detection, streamlining diagnostic pathways and aligning resources with the needs of high-burden cancers can reduce bottlenecks. Addressing documentation gaps in the "other" category is also essential to ensure accurate planning.

5.3.3 Demographic Characteristics of Cancer Patients

Demographically, the patient population was characterised by a predominance of middle-aged and older adults, with a particularly high representation among those approaching retirement. Women formed the majority due to the prevalence of female-specific cancers. These demographic patterns influenced service use: older patients often required more complex management and supportive care, while gender-specific cancers necessitated tailored interventions. The study concludes that treatment efficiency can be improved by adopting age- and gender-sensitive approaches. Geriatric oncology training, comprehensive survivorship programmes for women and inclusive services for the small but important cohort of younger patients will help balance resource use and support timely care.

5.3.4 Geographical Distribution of Cancer Patients

Geographical analysis revealed that the oncology centre's catchment is heavily centred on Nairobi and nearby counties, with sparse representation from distant regions. Patients from remote areas face travel barriers that delay diagnosis and treatment, whereas those living nearby can access care more readily. This disparity affects treatment efficiency by introducing scheduling challenges and potential interruptions in care. The conclusion is that decentralising oncology services and strengthening referral networks are critical to improve equitable access and to smooth patient flow. By establishing satellite clinics, improving telemedicine links and collaborating with county health systems, the facility can reduce travel burdens and enhance treatment efficiency.

5.4 Recommendations of the Research Study

Building on the study's findings and conclusions, the following recommendations are proposed to enhance treatment efficiency and patient outcomes.

5.4.1 Annual Trends in Diagnosed Cancer Cases

The study found that fluctuating case volumes, particularly the pandemic-related dip and subsequent rebound, influenced treatment efficiency. In response, the facility should institute dynamic capacity planning: real-time monitoring of case loads, flexible scheduling and cross-trained staff can ensure that surges do not overwhelm resources. Contingency protocols for external shocks, such as pandemic waves or supply disruptions, should be developed. A robust health information system that integrates facility data with national surveillance can help anticipate trends and allocate resources proactively. Finally, stakeholder collaboration across facilities can distribute workload and maintain continuity of care during volatile periods.

5.4.2 Prevalent Types of Cancer

Given the concentration of cases in breast, cervical and prostate cancers, the facility should strengthen targeted programmes for these diseases. This includes expanding screening and early-detection initiatives, streamlining diagnostic pathways and ensuring timely access to surgery, chemotherapy and radiotherapy. Multidisciplinary teams dedicated to high-burden cancers can reduce delays and improve coordination. Additionally, documentation systems must be improved to capture specific cancer types accurately, reducing reliance on unspecified categories. Investing in community awareness and preventative interventions will also help reduce late presentations and relieve pressure on treatment capacity.

5.4.3 Demographic Characteristics of Cancer Patients

To address the demographic realities of an ageing and predominantly female patient population, the facility should adopt age-appropriate and gender-sensitive care models. Geriatric assessment protocols, patient navigation and psychosocial support should be integrated to meet the complex needs of older adults. Women's health programmes must include dedicated counselling, survivorship care and fertility preservation where appropriate. Training for staff on gender diversity and inclusive communication will ensure that the small but important proportion of patients outside the binary categories receive respectful care. Data systems should consistently capture age and gender variables to inform service planning.

5.4.4 Geographical Distribution of Cancer Patients

The pronounced geographic concentration around Nairobi calls for a deliberate strategy to extend oncology services to underserved counties. Establishing satellite clinics, mobile outreach programmes and partnerships with county hospitals can reduce travel burdens and enable earlier diagnosis. Telemedicine platforms can support follow-up and consultation for patients who cannot travel frequently. Financial and logistical support for accommodation and transport should be considered for patients coming from distant counties. Strengthening referral pathways and data sharing across counties will ensure smoother transitions of care and better use of national cancer resources.

5.5 Recommendations for Research

Multi-centre designs would enhance generalisability, while mixed-method approaches could provide deeper insights into patient experiences and systemic barriers. Longitudinal research tracking changes over time will help capture the dynamic interplay of epidemiology and service delivery and refine predictive models.

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APPENDICES

APPENDIX I: RESEARCH LETTER(S)

Ole Sangale Rd, Madaraka Estate,
P.O Box 59857 00200, Nairobi, Kenya.
Cell: +254 703 414/6/7, Twitter: @SBSKenya
Email: info@sbs.ac.ke or vist www.sbs.strathmore.edu

Strathmore UNIVERSITY BUSINESS SCHOOL

Friday, 28th March 2025.

To Whom It May Concern,

RE: FACILITATION OF RESEARCH – NAGAIAHSAMY VISHNUKUMAR

This is to introduce Nagaiahsamy Vishnukumar, a Master of Business Management in Healthcare Management (MBA-HCM) student at Strathmore University Business School, admission number MBA HCM/148359/22.

As part of our MBA-HCM Program, Vishnukumar is expected to do applied research and undertake a project. This partially fulfills the requirements of the MBA-HCM course; to this effect, he would like to request appropriate data from your organization.

Vishnukumar is undertaking a research paper on "**Effect of Cancer Epidemiology on Treatment Efficiency in Nairobi County**" The information obtained shall be treated confidentially and used for academic purposes only.

Our MBA-HCM programme seeks to establish links with industry, and one of these ways is by directing our research to areas that would be of direct use to the industry. We would be glad to share our findings with you after the research, and we trust that you will find them of great interest and practical value to your organization.

We appreciate your support and will be willing to provide further information if required.

Yours sincerely,

Alois Njenga.
Manager – Graduate Programme.

Strathmore Business School is a Proud member of:

Association of African Business Schools AABS EFMD AACSB

APPENDIX II: RESEARCH PERMIT

Strathmore
UNIVERSITY

14th April 2025

Mr Nagaiahsamy Vishnukumar,
nagaiahsamy.vishnukumar@strathmore.edu

Dear Mr Nagaiahsamy,

RE: Using Data to Optimize Resource Allocation Deployed for Cancer Awareness and Timely Cancer Treatment

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** proposal. Your application reference number is **SU-ISERC2863/25.** The approval period is from **14th April 2025 to 13th April 2026.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

APPENDIX III:DATA COLLECTION TOOLS

Study Title: Effect of Cancer Epidemiology on Treatment Efficiency in Nairobi County

Institution: PRIVATE Cancer Center – Nairobi

Date of Data Extraction: March/2025

SECTION I: GENERAL PATIENT INFORMATION

Category	Measurement Criteria	Data Entry
Patient ID (Anonymized)	Unique identifier (code)	__________
Gender	Male / Female / Other	__________
Age	Age in years	__________
Residence	County	__________

SECTION II: EFFECT OF CANCER EPIDEMIOLOGY ON TREATMENT EFFICIENCY IN NAIROBI COUNTY

A. ANNUAL TRENDS IN DIAGNOSED CANCER CASES

Data Field	**Assessment Metric**	**Data Entry**
Year of Diagnosis	MM/YYYY	__________
Number of Diagnosed Cases	Total cases diagnosed per year	__________
Rate of Increase/Decrease	Compared to previous year (%)	__________

B. PREVALENT TYPES OF CANCER

Data Field	**Assessment Metric**	**Data Entry**
Cancer Type	Breast, Prostate, Cervical, etc.	__________
Percentage of Cases per Cancer Type	% of total diagnosed cases per type	__________

C. DEMOGRAPHIC CHARACTERISTICS OF CANCER PATIENTS

Data Field	**Assessment Metric**	**Data Entry**
Age Distribution	Age in years	__________
Gender-Based Prevalence	Male / Female / Other	__________
Geographic Location	County	__________

D. TREATMENT EFFICIENCY INDICATORS

Data Field	**Assessment Metric**	**Data Entry**

Diagnosis-to-Treatment Interval	Days from diagnosis to first treatment	__________
Treatment Completion Status	Completed / Not completed / Ongoing	__________

APPENDIX IV: BUDGET

Expense Item	Estimated Cost (Ksh)
1. Proposal Printing and Binding	3,000
2. Internet and Data Costs	2,500
3. Stationery (Notebooks, Pens, etc.)	1,500
4. Transportation (Field visits)	4,000
5. Research Assistants	5,000
6. Questionnaire Printing & Distribution	3,500
7. Data Collection and Entry	2,500
8. Data Analysis (SPSS Software & Assistance)	3,500
9. Miscellaneous Costs	2,500
Total Budget	**26,000**

APPENDIX V: TIME SCHEDULE

Activity	**Dec 2024**	**Jan 2025**	**Feb 2025**
1. Formulation and approval of research topic	✓		
2. Formulation of statement problem and objectives	✓		
3. Writing of Chapter One: Introduction	✓		
4. Writing of Chapter Two: Literature Review		✓	
5. Writing of Chapter Three: Research Methodology		✓	
6. Writing of Preliminary Pages and Appendices		✓	
7. Défense of Research Proposal			✓