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ANALYZING COMORBIDITY INDEX FOR CANCER PATIENTS DURING MANAGEMENT USING SEMI MARKOV CHAIN PROCESS

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Abstract: Globally, cancer is a high health burden, as it's the fifth leading cause of death, in the year 2022, a study by the WHO showed there were an estimated 20 million new cases, and the number of deaths totaled 9.7 million. In a group of 5 people, 1 person develops cancer in their lifetime, approximately 1:12 women and 1:9 men die from cancer. The management of cancer patients is complicated by the presence of comorbidities, which can significantly affect transition between time of diagnosis and treatment initiation. The data used in the study was sourced from Cancer regional registry. It entailed the following details of the patients: age, gender, cancer staging, pre-existing and post-existing health condition(s), and cancer subtype. Patients were grouped according to the stage in which they were diagnosed. Stage I and II are the early stages, while Stage III and IV are the late stages. The most prevalent cancer type in males is prostate cancer, while in females it is breast cancer, with hypertension as the commonest comorbid condition. Most of the cancer diagnoses were in late stage, that's stage III and stage IV. This distribution showed that a significant proportion of patients were diagnosed at advanced stages (III and IV), which could affect treatment options and prognosis. Cardiovascular conditions were associated with cancer progression, treatment method, and overall survival. Patients diagnosed at later stages (III-IV) received systemic therapies as their treatment type. There is need to continue the study in the future by prospective researchers in terms of size and variability of the participants investigated at several centers in order to enhance inclusivity. This would be efficient by the use of longitudinal designs so that it monitors disease progression, its response and also model survival rates too.

Keywords: comorbidity; cancer; transition probability; semi Markov; metastasis.

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1. INTRODUCTION

In this study, the participants were patients suffering from cancer as either their primary or secondary disease. Comorbidity is a condition where disorders coexist with the primary disease of interest [1]. In a cancer it relates to health-related conditions alongside cancer. Comorbidity prevalence varies from one patient to another as they all have different extents of immunity [2]. Comorbidity increases frailty in cancer patients [3]. There is a low rate of survival for patients with comorbidity [4], but the underlying conditions remain unclear to study their survival rate. To study their survival rate, it requires one to conduct a study of the disease prognosis. In recent decades, the survival rate for cancer patients without comorbidity has improved [5], in contrast, it has decreased for communicants. There has been significant improvement in the health sector across all continents of the globe. This has been steered ahead by measures like vaccination to control the spread of infectious diseases. In the year 2022, a study by the W.H.O. shows there were an estimated 20 million new cases, and the number of deaths totaled 9.7 million [6].

In a group of 5 people, 1 person develops cancer in their lifetime, and approximately 1:12 women and 1:9 men succumb to the disease. Of the different types of cancer, the dominant ones are: lung cancer, breast cancer, cervical cancer, colorectal cancer, prostate cancer, and stomach cancer [7]. In Africa, cancer incidences and mortality are significantly increasing, with some 1.1 million new cases and 0.7 million mortalities [8]. The main cancer groups are prostate, breast, colorectal and cervical. In Kenya, Cancer is one of the leading killer diseases, and the burden of mortality is expected to increase by at least 60% in the forthcoming two decades. The high cause of death has been accelerated by inaccessibility to treatment programs, which are inefficient as well as inequitable. Most of these cases can be prevented or treated through early detection by screening or treatment programs. It's a heterogeneous disease that exists in different subtypes[9]. It varies from the infection area and rate of spread. Cancer patients are classified as either high-risk or low-risk, and this categorizes each person in their respective cancer stage [10].

This analysis incorporates clinical data on cancer-comorbidities patients, tracking their gender, age, co-existing conditions, cancer stages, and treatment interventions, enabling to check on cancer prevalence. According to [11], comorbid conditions significantly influence cancer prognosis, treatment decisions, and patient outcomes [12]. Understanding the prevalence of these conditions can aid in optimizing management strategies.

2. PRELIMINARIES

2.1 Study Setting

The data used in the study was sourced from Cancer regional registry. It entailed the following details of the patients: age, gender, cancer staging, pre-existing and post-existing health condition(s), and cancer subtype. The patients fit in as a study sample were ailing from cancer and had other underlying health conditions. The data structure was in tabular form, entailing rows and columns indicating the various patient variables. Key variables considered are age, gender, underlying condition(s), diagnosis stage, and treatment stage.

2.2 Ethical Consideration

The Chuka University Institutional Ethics Review Committee granted ethical approval, with reference number NACOSTI/NBC/AC-0812. Under the ORCID ID: 0009-0000-4484-8335, also got the NACOSTI research permit to conduct this study, License No: NACOSTI/P/25/418258.

2.3 Data Management and Analysis

Patients were grouped according to the stage in which they were diagnosed. Stages I and II are the early stages, while Stages III and IV are the late stages. There were four state spaces $\{S_1, S_2, S_3, S_4\}$. The demographics of patients were described by measure of frequency and percentage. To get probability per every state, it was computed as follows: Patients per stage/ Total number of patients that were diagnosed from in that stage.

The embedded transition matrix was P_{ij}, where;

$$P_{ij} = [i = current\ state, j = next\ state]$$

The sojourn time distribution for each transition is independent and varies from the current state to the next state. It's defined by

$$F_{ij}(t) = P(sojourn\ time \leq t)$$

For the mean of time spent during states transitions, it was computed as follows

$$m_{ij} = E[sojourn | i \rightarrow j]$$

$$m_i = \sum_i P_{ij}\, m_{ij} \tag{1}$$

Semi Markov chain is dependent and makes transitions from state to state like a Markov process, the amount of time spent in each state before a transition to the next state occurs is an arbitrary random variable that depends on the next state the process will enter. It is defined as

$$Q_{ij}(t) = P(X_{n+1} = j, T_{n+1} - T_n \leq t | X_n = i) = p_{ij} . F_{ij}(t) \quad (2)$$

$$F_{ij}(t) = Holding\ time\ matrix$$

$$p_{ij} = states\ transition\ matrix$$

To compute state transition:

$$P_{ij} = \frac{N_{ij}}{\sum_j N_{ij}} \quad (3)$$

For instance,

$$S_{11} = \frac{patients\ at\ stage\ one}{total\ no.\ of\ patients\ from\ stage\ 1\ and\ transitted\ to\ stage\ 4.}$$

$$S_{22} = \frac{patients\ at\ stage\ two}{total\ no.\ of\ patients\ from\ stage\ 2\ and\ transitted\ to\ stage\ 4.}$$

$$S_{33} = \frac{patients\ at\ stage\ three}{total\ no.\ of\ patients\ from\ stage\ 3and\ transitted\ to\ stage\ 4.}$$

$$S_{44} = \frac{patients\ at\ stage\ four}{total\ no.\ of\ patients\ from\ stage\ four\ and\ transitted\ to\ stage\ 4.}$$

S_{11} is cancer stage 1 at state one

S_{22} is cancer stage 2 at state two

S_{33} is cancer stage 3 at state three

S_{44} is cancer stage 4 at state four

In a general case for the other cases its S_{ij}; i is the current state and j is the future state.

Below is a general case matrix,

$$P_{ij} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & S_{14} \\ S_{21} & S_{22} & S_{23} & S_{24} \\ S_{31} & S_{32} & S_{33} & S_{34} \\ S_{41} & S_{42} & S_{43} & S_{44} \end{bmatrix}$$

The matrix in figure x of order 4x4 is defined as P_{ij}, it's the transition matrix for the cancer probabilities. Where i is the current state and j is the future state. This is a discrete-time stochastic process that has 4 state spaces, $\{S_1, S_2, S_3, S_4\}$.

Let

$$P\{X_k = i | X_{k-1} = j, X_{k-2}, X_{k-3}, \ldots\ldots X_k\} = P\{X_k = i | X_{k-1} = j\} \quad (4)$$

This is a Markov property that illustrates that future state(s) depend on the current state. The future state j depends on i, such that, $\{X_k = i|X_{k-1} = j, X_{k-2}, X_{k-3}, \dots \dots X_k\}$. Transition steps of $P_{ij}$is the probability from state i to j in a single step. For movement in more than one step, it can be demonstrated as;

$P(X_2 = j/\ \ X_0 = i)$

Two-step transition probabilities are given by a matrix P^2

$P(X2 = j/\ \ X0 = i) = \ \ P(X_{k+2} = j/\ X_k\ = i)\ \ =\ \ (P^2)ij^n$

Now for a general case;

$P(X_K = j|X_0 = i) = \ P(X_{k+2} = j|\ X_k\ = i) = (P^t)ij^n$

$$P_{ij} = P(X_{n+1}) = j/P(X_n) = \text{i} \tag{5}$$

Where i is the current state and j is the future state.

The future state depends on the current state.

Semi Markov is defined by,

$$Q_{ij}(t) = P(X_{n+1} = j, T_{n+1} - \ T_n \leq \frac{t}{X_n} = i \tag{6}$$

X_n is the state of the n^{th} transition, and T_n is the time for the n^{th} transition.

$$\lim_{t\to\infty} Q_{ij}(t) = P(X_{n+1} = j\ , X_n = i) \tag{7}$$

Where

$$F_{ij}(t) = 1 - \ e^{-t/m_{ij}}, rate = \ 1/m_{ij} \tag{8}$$

For each transition from $i \to j$, we collected the observed sojourn time $S_{ij}(t)$ to estimate $F_{ij}(t)$

2.4 Cancer Comorbidity Prevalence per Stage

From the data obtained, proportions were derived in each stage so that they can be used to assess the prevalence of cancer in each stage during the diagnosis and treatment stages. Proportions in each stage should add up to one. A retrospective analysis was conducted to assess the prevalence of cancer comorbidities among cancer patients. Data was collected on various conditions, including hypertension, diabetes, retroviral disease, and chronic kidney disease. Descriptive statistical methods were used to present the distribution of these comorbidities.

3. MAIN RESULTS

3.1 Distribution of Cancer per Gender

From the sample size of 176 patients, 79 were females while 97 were males, with a percentage distribution of 44.9%, and 55.9%, respectively. The age range of the patients was between 18 years and 94 years. The youngest was a male while the oldest was a female; the median age was 67 years; mean age was 65.85 years. Figure 1shows the age distribution according to gender. The range of age for females and males was between 36-94 years and 18- 90 years, respectively. The mean age for females was 63 years while that for males was 70 years.

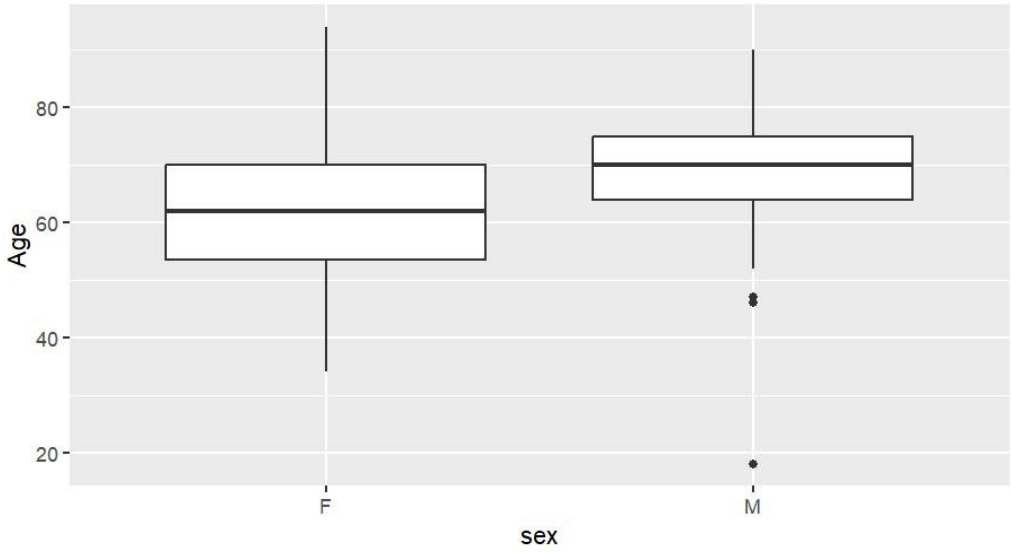

Figure 1: Age Distribution per Gender

3.2 Cancer Diagnosis Stage

Cancer is grouped into four stages: Stage I, Stage II, Stage III, and Stage IV. Table 1 gives the proportions of patients in each stage. Table 1 shows the distribution of cancer types.

Table 1 : Cancer Stage at Diagnosis

Cancer Stage	Count	Percentage
Stage I	6	3.41%
Stage II	41	23.3%
Stage III	41	23.3%
Stage IV	88	50%

Patients were grouped according to the stage in which they were diagnosed. Stage I and II are the early stages, while Stage III and IV are the late stages. Stage IV had the greatest number of patients, whose count was 88 out of 176, stage II and Stage III had an equal number of patients, 41 each while Stage I had only 6 patients.

3.3 Age Distribution Per Cancer Stage

The dataset in Figure 2 was divided into two sets: females (F) on the left and males (M) on the right, with each data point representing an individual case. The x-axis in represents different cancer stages (stage I, II, III, IV), while the y-axis represents age at diagnosis.

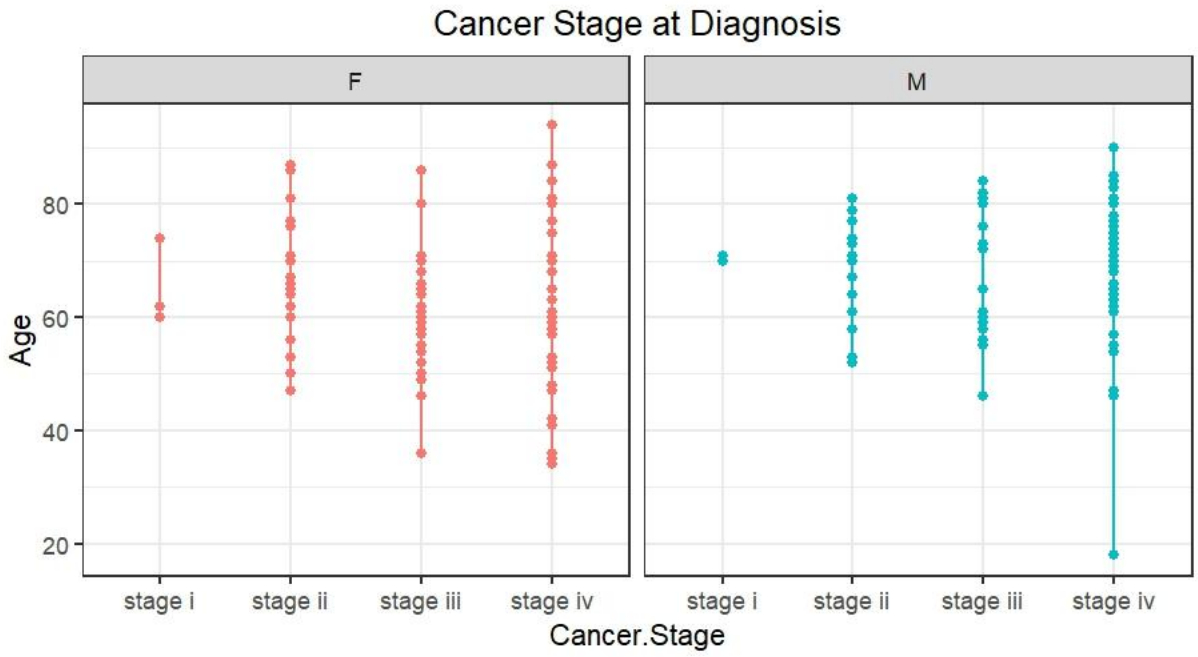

Figure 2: Age distribution of Cancer Stage at diagnosis

There was a disparity in cancer staging as per one's gender as follows. In both genders**,** stage I had fewer data points, which was a clear indication that fewer people were diagnosed at the early stage. The ages of diagnosis were widely spread across stages II, III, and IV. For females, most cases clustered between 40 to 80 years old, with some variance. For males, the spread appeared broader, especially at stage IV, with the youngest and oldest diagnosed individuals.

3.4 Cancer Type

Figure 3 illustrates the distribution of various cancer types, represented as a percentage of the total cases analyzed, from the most prevalent to the least prevalent. In this study, 30 different cancer types were recorded.

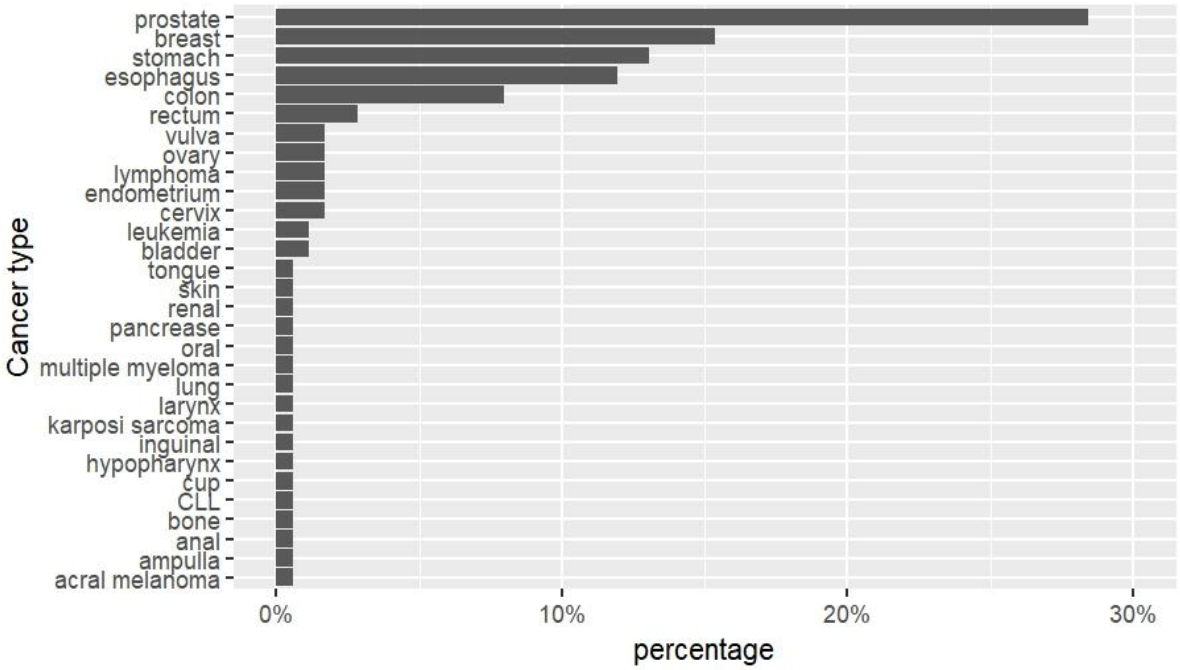

Figure 3: Cancer Types

The most common cancer type was prostate cancer, which accounted for 28% of all cases. Breast cancer followed closely, and contributed to 25% of cases. Stomach cancer and esophageal cancer represented 15% and 12%, respectively. Colorectal cancers, including colon (8%) and rectum (5%), formed a significant portion of cases. Other notable cancer types were vulva (4%), ovary (3%), and lymphoma (3%). Several less common cancers, such as leukemia (2%), bladder (2%), tongue (1.5%), and skin (1.5%), exhibited lower incidence rates. Rare cancer types such as pancreatic, oral, multiple myeloma, lung, larynx, Kaposi sarcoma, inguinal, hypopharynx, CUP (cancer of unknown primary), CLL (chronic lymphocytic leukemia), bone, anal, ampulla, and accrual melanoma contributed to less than 1% each.

3.5 Co-Existing Conditions

There was a cross-examination of the prevalence of common comorbid conditions among cancer patients and this highlighted the potential implications for clinical management. Figure *4*Figure *4* presents the distribution of comorbid conditions within the study.

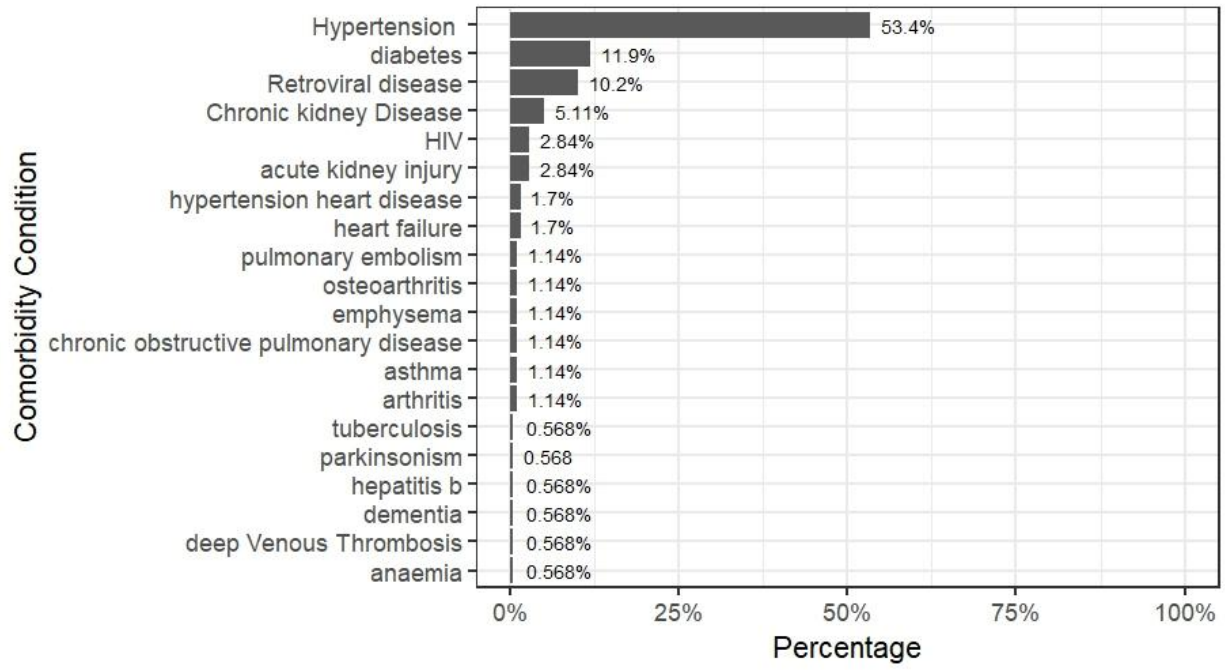

Figure 4: Co-existing conditions

Hypertension was the most prevalent comorbidity, affecting 53.4% of patients, followed by diabetes (11.9%) and retroviral disease (10.2%)**.** Other notable comorbid conditions included chronic kidney disease (5.11%)**,** HIV (2.84%)**,** and acute kidney injury (2.84%)**.** Less common conditions, each with a prevalence of ≤2%, included heart failure (1.7%), chronic obstructive pulmonary disease (1.14%), asthma (1.14%), tuberculosis (1.14%), dementia (0.568%), and deep venous thrombosis (0.568%).

3.6 Cancer Type and Co-Existing Condition

From the data obtained, the cancer patients had cancer and other underlying medical conditions. Table 2 shows the different cancer types and the co-existing condition per cancer type.

Table 2: Cancer type and co-existing condition

Cancer Type	Co-Existing condition	n	Cancer Type	Co-Existing condition	n
prostate	Hypertension	30	hypopharynx	Retroviral disease	1
Breast	Hypertension	20	inguinal	Hypertension	1
Stomach	Hypertension	13	Kaposi sarcoma	Hypertension	1
Colon	Hypertension	9	larynx	tuberculosis	1
Esophagus	Hypertension	6	leukemia	acute kidney injury	1
Prostate	Chronic kidney disease	6	leukemia	hypertension heart disease	1
prostate	diabetes	6	lung	Hypertension	1
esophagus	Retroviral disease	5	lymphoma	Hypertension	1
breast	diabetes	3	lymphoma	Retroviral disease	1
endometrium	Hypertension	3	lymphoma	acute kidney injury	1
stomach	Retroviral disease	3	multiple myeloma	Hypertension	1
stomach	diabetes	3	oral	Hypertension	1
breast	Retroviral disease	2	ovary	Chronic kidney Disease	1
cervix	Retroviral disease	2	ovary	Hypertension	1
colon	heart failure	2	ovary	diabetes	1
esophagus	arthritis	2	pancreas	diabetes	1
esophagus	diabetes	2	prostate	HIV	1
prostate	asthma	2	prostate	acute kidney injury	1
rectum	Hypertension	2	prostate	chronic obstructive pulmonary disease	1
rectum	diabetes	2	prostate	emphysema	1
CLL	hypertension heart disease	1	prostate	heart failure	1
acral melanoma	Hypertension	1	prostate	osteoarthritis	1
ampulla	Hypertension	1	rectum	Retroviral disease	1
anal	HIV	1	renal	diabetes	1
bladder	Hypertension	1	skin	diabetes	1
bladder	Retroviral disease	1	stomach	HIV	1
bone	hepatitis b	1	stomach	acute kidney injury	1
breast	HIV	1	stomach	dementia	1
breast	hypertension heart disease	1	stomach	pulmonary embolism	1
cervix	diabetes	1	tongue	Chronic kidney Disease	1
colon	deep Venous Thrombosis	1	vulva	HIV	1
colon	parkinsonism	1	vulva	Hypertension	1
colon	pulmonary embolism	1	vulva	Retroviral disease	1
cup	Retroviral disease	1	esophagus	anemia	1
esophagus	Chronic kidney Disease	1	esophagus	chronic obstructive pulmonary disease	1
esophagus	acute kidney injury	1	esophagus	emphysema	1
esophagus	osteoarthritis	1			

Hypertension is the most common co-existing condition, particularly in patients with prostate cancer (30 cases), breast cancer (20 cases), and stomach cancer (13 cases). Diabetes and retroviral disease (HIV-related conditions) are also frequently reported across multiple cancer types. Certain rare conditions, such as tuberculosis, deep venous thrombosis, and parkinsonism, appear in only one or two cases. Some cancer types, like prostate cancer, have multiple co-existing conditions, including chronic kidney disease, asthma, emphysema, and heart failure.

3.7 Treatment type

Patients sought various treatment types as a way of managing cancer. There were various treatment types and one could use the convenient one after they were diagnosed. Table 3 shows the common treatment types.

Table 3: Common Treatment types

Treatment Type	Yes	No
Surgery	24.4%	75.6%
Chemotherapy	37.5%	62.5%
Hormonal therapy	32%	62%

There distribution of different cancer treatment types included surgery, chemotherapy, and hormonal therapy, among the study population. The percentages indicated the proportion of patients who received ("Yes") or did not receive ("No") for each treatment type. Only 24.4% of patients underwent surgery**,** while 75.6% did not receive surgical treatment. 37.5% of patients received chemotherapy**,** whereas 62.5% didn’t. 32% of patients received hormonal therapy**,** while 62% did not.

3.8 Transition Probability between Diagnosis and treatment initiation

Cancer is grouped into four stages, and the frequency per stage was used to account for the percentage contribution of patients per every stage.

Table 4 shows the movement of patients between diagnosis time and the treatment time.

Table 4 Time taken before treatment after diagnosis

Cancer stage at diagnosis	Cancer stage at treatment	Count (n)
Stage I	Stage I	6
Stage II	Stage II	40
Stage II	Stage III	1
Stage III	Stage III	40
Stage III	Stage IV	1
Stage IV	Stage IV	88

Table 5 is a matrix representation of the movement of the patient in different stages

	Stage I	Stage II	Stage III	Stage IV
Stage I	6	0	0	0
Stage II	0	40	1	0
Stage III	0	0	40	1
Stage IV	0	0	0	88

Table 5 Transition Matrix

The transitions above were later recomputed as into percentage to come up with a Markov transition probability matrix.

$$P_{ij} = \begin{bmatrix} 1.000 & 0 & 0 & 0 \\ 0 & 0.9756 & 0.0244 & 0 \\ 0 & 0 & 0.9756 & 0.0244 \\ 0 & 0 & 0 & 1.000 \end{bmatrix}$$

3.9 Holding time between diagnosis and treatment

Table 6 Average Holding times

	Stage I	Stage II	Stage III	Stage IV
Stage I	1.17	0	0	0
Stage II	0	2.28	4	0
Stage III	0	0	2.75	7
Stage IV	0	0	0	2.60

Table 6 shows the average time a patient spent in every stage before they initiated their treatment process after being diagnosed with cancer. In stage I, the average time was 1.17 months, stage II was 2.28 months, stage II to stage III was 4 months, stage III was 2.75 months, stage III to stage IV was 7 months, and stage IV was 2.60 months. The holding time per stage was standardized and used to compute the time transition matrix represented by $F_{ij}(t)$. Where i is the current time state and j is the future time state whereas t is the holding time in the month. Holding times are exponentially distributed.

$$F_{ij} = \begin{bmatrix} 1.17 & 0 & 0 & 0 \\ 0 & 2.28 & 4 & 0 \\ 0 & 0 & 2.75 & 7.0 \\ 0 & 0 & 0 & 2.60 \end{bmatrix}$$

The CDF of $F_{ij}(t)$ is given by

$$F_{ij}(t) = 1 - e^{-\lambda ij^t} \tag{10}$$

$$\lambda ij = 1/T$$

$$T = \text{time in the holding time matrix}$$

In Stage I, a time of 1.17 was recorded, with no time spent in other stages at this point. Moving to Stage II, the time spent increased to 2.28**,** with a recording of 4 months in Stage II, and III, suggesting a transition from Stage II to Stage III. In Stage III, time spent was 2.75 months, recorded in this stage, and a further **7** in Stages III, and IV, indicating progression. Finally, in Stage IV, time spent was 2.60, with no additional time recorded in previous stages. After normalizing the time,

$$F_{ij}(t) = 1 - e^{-\lambda ij^t}$$

$$F_{11}(1) = exp(-\frac{1}{1.17}) = 0.5745896$$

$$F_{22}(1) = exp(-\frac{1}{2.28}) = 0.355059$$

$$F_{23}(1) = exp(-\frac{1}{4}) = 0.2211992$$

$$F_{33}(1) = exp(-\frac{1}{2.75}) = 0.3048561$$

$$F_{34}(1) = \exp\left(-\frac{1}{7}\right) = 0.1331221$$

$$F_{44}(1) = exp(-\frac{1}{2.60}) = 0.3192876$$

$$F_{ij} = \begin{bmatrix} 0.5745896 & 0 & 0 & 0 \\ 0 & 0.355059 & 0.2211992 & 0 \\ 0 & 0 & 0.3048561 & 0.1331221 \\ 0 & 0 & 0 & 0.3192876 \end{bmatrix}$$

the above matrix is for the normalized holding time matrix.

3.10 Obtaining the Semi-Markov chain transition matrix

A Semi-Markov chain is composed of an embedded first-order Markov chain representing the transition between distinct states and discrete state occupancy distributions representing sojourn times in non-absorbing states [13]. To compute the semi-Markov chain model, there need to be

integration of the Markov chain matrix and the holding time matrix, and the matrix formed is demote as $Q_{ij}(t)$.

$$Q_{ij}(t) = P_{ij} * F_{ij}(t) \tag{11}$$

P_{ij}= Markov chain matrix

$f_{ij}(t)$= Holding time matrix

$$Q_{ij}(t) = \begin{bmatrix} 1.000 & 0 & 0 & 0 \\ 0 & 0.9756 & 0.0244 & 0 \\ 0 & 0 & 0.9756 & 0.0244 \\ 0 & 0 & 0 & 1.000 \end{bmatrix} * \begin{bmatrix} 0.5745896 & 0 & 0 & 0 \\ 0 & 0.355059 & 0.2211992 & 0 \\ 0 & 0 & 0.3048561 & 0.1331221 \\ 0 & 0 & 0 & 0.3192876 \end{bmatrix}$$

$$Q_{ij}(t) = \begin{bmatrix} 0.5745896 & 0 & 0 & 0 \\ 0 & 0.3379435 & 0.0001316932 & 0 \\ 0 & 0 & 0.2901605944 & 7.925557e05 \\ 0 & 0 & 0 & 3.192876e01 \end{bmatrix}$$

$Q_{ij}(t)$provides the semi-Markov matrix, for the matrix, the probabilities of the rows must sum up to 1, thus there is a need to normalize the matrix, and to normalize it,

$$Q_{ij}(t) = \frac{Q_{ij}(t)}{\sum Q_{ij}(t)} \tag{12}$$

Normalized $Q_{ij}(t) = \begin{bmatrix} 1.0 & 0 & 0 & 0 \\ 0 & 0.9846578 & 0.01534216 & 0 \\ 0 & 0 & 0.98919671 & 0.01080329 \\ 0 & 0 & 0 & 1.0 \end{bmatrix}$

3.11 Discussion

This study documented cancer patients' statistics with other co-existing conditions in the central region of Kenya. The findings showed how cancer is prevalent in different cancer types, cancer stages, treatment types, age, and gender of patients, as well as the co-existing medical conditions. The age in comparison to cancer comorbidity prevalence for both groups varied significantly, males had a higher number compared to females. This is similar to the case of [14] for the age between 35 and 74 years, where there were 31 cancer types, 9 in women and 22 in men. Additionally, there was an outlier in the male category, particularly at the lower end of the age range, which indicated that some younger individuals deviate significantly from the overall distribution**.** The most prevalent cancer type in the dataset is prostate cancer, accounting for the largest proportion, followed by breast cancer, which is consistent with the research done by [4].

Other notable cancer types with significant representation include stomach, esophagus, colon, and rectum cancers. The results indicated that Stage IV had the most cases and accounted for 50% of the cancer comorbidity cases. Stages II and III were equally represented, each accounting for 23.3% of participants. Stage I cancer was the least common, with only 3.41% of the case which was consistent to a study done by [15] where stage I was the least prevalent. The presence of comorbidity increased the rate of detecting distant metastases in these cases, early detection did not happen more frequently[16]. There was a high prevalence of hypertension and diabetes, which increased the burden of cardiovascular and metabolic disorders among cancer patients, this was also observed by [17]. In cases of co-existing conditions, hypertension had the most cases of 94 patients, making it the most prevalent comorbid condition with 53.4%, followed by diabetes with 21 patients, tallying to 11.9%, then there were retroviral diseases with 18 patients, 10.2%. other conditions, such as Chronic Kidney disease, HIV, acute kidney injury, hypertension, heart disease, heart failure, pulmonary embolism, osteoarthritis, emphysema, chronic obstructive pulmonary disease, asthma, tuberculosis, Parkinsonism, hepatitis b, dementia, deep venous thrombosis, and anemia, all had less than 10 cases. In a research conducted by [18], participants with hypertension experienced a higher mortality rate compared to non-hypertensive.

CONCLUSION

There was a low percentage of Stage I diagnoses, highlighting the potential challenges in early detection, which is crucial for cancer care. This distribution showed that a significant proportion of patients were diagnosed at advanced stages (III and IV), which could have implications for treatment options and prognosis. Cardiovascular conditions were associated with cancer progression, treatment method, and overall survival**.** The presence of retroviral disease and HIV highlighted the need for immune function monitoring and infection control strategies**,** particularly in immunocompromised cancer patients. Patients diagnosed at later stages (III-IV) received systemic therapies as their treatment type. Advanced patients' age, poor overall health, or other health complications led to non-surgical treatment decisions. The patient's comorbidity greatly impacted the stage of cancer at diagnosis. yet, the effect on patients is not the same for all types of cancer, depending on their other conditions and the total comorbidity in their case. These results sensitized the need for multidisciplinary approaches to cancer management to optimize patient outcomes.

The study recommended the urgent need for early detection and immediate intervention, as these measures can enhance treatment effectiveness while reducing the risk of progression. A primary focus should be on early diagnosis and timely intervention to improve patient outcomes based on observations of cancer stage progression. Medical organizations must enhance their screening procedures, particularly for cancers that predominantly affect one gender, such as prostate cancer in men and breast cancer in women. The healthcare system must invest in making diagnostic tools readily available and initiate educational campaigns along with regular screenings to identify conditions before they escalate. Stages III and IV demonstrated need for improved oncology care systems and better resource allocation due to the extended waiting periods and treatment delays. Implementing more effective palliative care systems, along with streamlined early diagnosis referral processes and prompt therapeutic interventions, will help mitigate late-stage issues for patients.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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