RESEARCH ARTICLE

Editorial Process: Submission:05/03/2025 Acceptance:01/08/2026 Published:01/21/2026

Time-Series Forecasting of Radiotherapy Utilization in Older Adults in Southern Thailand's Largest Quaternary Hospital: A Retrospective Study

Thanarpan Peerawong[1,2], Pasuree Sangsupawanich[1], Sitthichok Chaichulee[3]*

Abstract

Objective: This study aimed to forecast the radiotherapy demand among geriatric patients in Southern Thailand's largest quaternary hospital by 2030 using an Autoregressive Integrated Moving Average (ARIMA) model. **Methods:** This retrospective analysis was conducted using data from January 2004 and December 2022 and comprised patients aged ≥65 years who received radiotherapy. Monthly time-series data were analyzed in two phases. First, descriptive statistics were used to summarize patient demographics, cancer types, and treatment intent over time. Time-series decomposition and automatic machine learning were used to explore these patterns. Stationarity was assessed using the augmented Dickey–Fuller test. The model parameters were selected based on autocorrelation and partial autocorrelation plots and refined through optimization. Model selection was performed based on the Akaike Information Criterion, and forecasting accuracy was measured using the Mean Absolute Percentage Error (MAPE). Residual diagnostics included the Ljung–Box and Jarque–Bera tests as well as the assessment of heteroskedasticity. **Results:** Of the 39,653 patients who underwent radiotherapy, 10,717 (27%) were aged ≥65 years (mean age 71.8; 60% male). The most common cancers were head and neck, lung, colorectal, and breast. Most patients received curative treatment, with increasing trends in radiotherapy utilization, particularly for lung, colorectal, breast, and prostate cancers. The optimal model, ARIMA(3,1,0)(0,0,1,4), incorporating exogenous variables related to the older adult population in Southern Thailand, achieved a MAPE of 0.17 and successfully passed all residual diagnostics. By 2030, the model forecasted approximately 74.7 new monthly cases of geriatric radiotherapy, with a 95% confidence interval of 53.8–95.7. **Conclusion:** The demand for radiotherapy among older adults is projected to increase, underscoring the need for capacity planning. Future studies should explore sophisticated prediction techniques and include more clinical variables to enhance the accuracy of forecasts and aid thorough oncology planning.

Keywords: radiotherapy demand- geriatric oncology- ARIMA model

Asian Pac J Cancer Prev, **27 (1)**, 141-149

Introduction

The global incidence and mortality rates of cancer are increasing, and the aging population has been identified as a major contributing factor. Older adults are disproportionately affected because advancing age correlates with an increased risk for cancer and poor prognosis [1, 2]. According to the GLOBOCAN Cancer Observatory data, the number of new cancer cases is projected to increase from 20 million in 2022 to 33 million by 2045. Similarly, mortality is expected to increase from 9.7 million in 2022 to 16.9 million by 2045. This trend is mirrored in Southeast Asia, including Thailand, where the number of new cases is anticipated to increase from 88.1 thousand in 2022 to 194.1 thousand by 2045. Mortality is expected to increase from 38.1 thousand in 2022 to 158.3 thousand cases by 2045 [3]. This demographic shift presents oncological challenges, particularly concerning treatment tolerance, comorbidity management, and the overall quality of life.

Physical aging predominantly affects cancer treatment and outcomes. Older adults may experience frailty, comorbidities, and cognitive impairments, which impede their ability to tolerate cancer therapies [4]. Additionally, their limited participation in clinical trials restricts the evidence for the treatment of this demographic group. Radiotherapy is a vital therapeutic option for older adults because it avoids systemic toxicity and does not require anesthesia, making it feasible for vulnerable patients [5]. Advances in radiation technology, such as image-

*[1]Department of Clinical Research and Medical Data Science, Faculty of Medicine, Prince of Songkla University, Songkhla, Thailand. [2]Department of Radiology, Faculty of Medicine, Prince of Songkla University, Songkhla, Thailand. [3]Department of Biomedical Sciences and Biomedical Engineering. Faculty of Medicine, Prince of Songkla University, Songkhla, Thailand. *For Correspondence: sitthichok.c@psu.ac.th*

guided radiotherapy, intensity-modulated techniques, and hypofractionation schedules, have improved treatment precision and reduced the overall treatment duration [6]. Despite its importance, the cost of radiotherapy remains high. Radiotherapy resources are scarce in low- and middle-income countries. A report from the International Atomic Energy Agency indicated that the utilization rate of radiotherapy was suboptimal in these regions [7]. As the incidence of cancer in older adults is increasing, it is crucial to predict future radiotherapy requirements, including resource planning, staffing, and infrastructure development.

Data from the Thai Association of Radiation Oncology have indicated a consistent increase in the demand for radiotherapy over the past few decades. The number of cases (20,000 in 2008) was projected to increase to 40,000 by 2018. The annual patient load at radiotherapy centers in Thailand is increasing [8]. In Southern Thailand, Songklanagarind Hospital, the largest quaternary hospital in the region, has been offering radiotherapy services since 1982. The demand at this institution increased from 121 cases in 1982 to over 2,400 cases in 2012, surpassing 2,700 cases in 2020 [9]. This growth has been accompanied by an increase in the number of radiotherapy machines, from an initial single unit to three in recent years [10]. With the aging population, anticipating future workloads is essential for optimizing resource allocation effectively.

We aim to address this gap using an Autoregressive Integrated Moving Average (ARIMA) model on historical radiotherapy data. By forecasting the demand for radiotherapy among older adults by 2030, this study provides a data-driven foundation for strategic planning and capacity development for cancer care.

Materials and Methods

Patients and study design

A retrospective analysis was conducted at the Radiation Oncology Unit of Songklanagarind Hospital (PSURO). This study included patients aged ≥65 years who underwent radiotherapy between January 2004 and December 2022. The data for this analysis were retrieved from the hospital information system. The workflow of this study is illustrated in Figure 1.

Sample size

A minimum of 50 data points is recommended for applying the ARIMA model to time-series forecasting [11]. To achieve reliable and precise outcomes, using a dataset with over 100 data points is recommended because a larger dataset improves the ability of the model to accurately identify and forecast trends and patterns associated with radiotherapy patient volume.

Statistical analyses

The statistical analyses conducted in this study comprised two primary components.

1. Descriptive statistics

The initial phase involved summarizing and examining the dataset to establish a foundational understanding of the data characteristics and distribution.

2. Time-series forecasting

The ARIMA model was used, and its three principal components (autoregressive (AR), integrated (I), and moving average (MA)) were analyzed to achieve a comprehensive understanding of the model. ARIMA modeling assumes that the data are stationary and that the residuals exhibit white-noise characteristics. First, the data were decomposed and analyzed for patterns using automatic machine learning with the PyCaret library [12]. Subsequently, the stationarity of the dataset was evaluated using the augmented Dickey–Fuller (ADF) test, with significance achieved to confirm stationarity. The AR (p) component of time-series models captures the relationship between an observation and its preceding values, whereas the MA (q) component incorporates the error terms from previous observations into the model. To formulate the ARIMA model, the Akaike Information Criterion (AIC) and the Mean Absolute Percentage Error (MAPE) were used for evaluation, with lower AIC and MAPE values indicating better model performance and higher accuracy, respectively.

Following the application of conventional statistical techniques, PyCaret was used to autonomously optimize the various model parameters. This step aims to identify models that surpass the performance of a manually configured ARIMA model. Each ARIMA model was assessed by analyzing the residuals. The Ljung–Box test

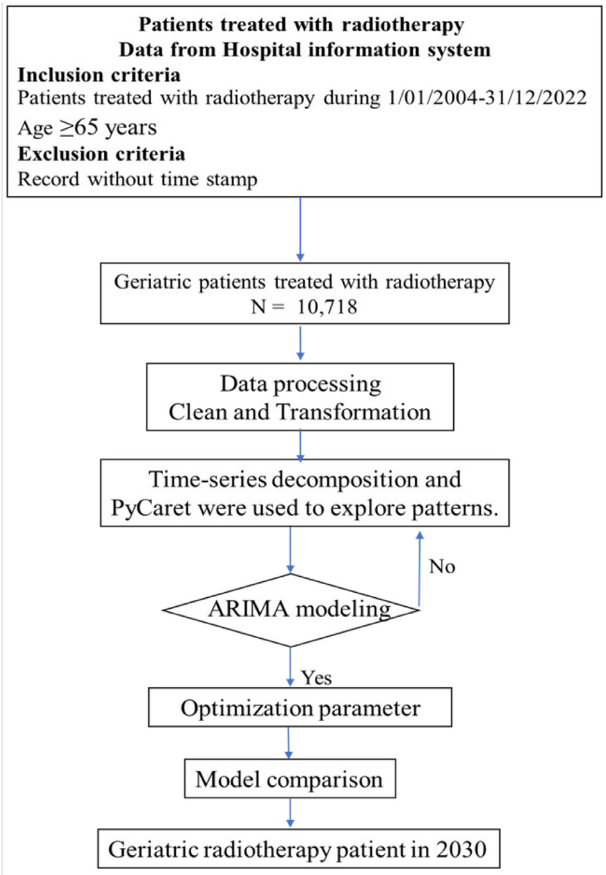

Figure 1. Study Flow Diagram. A schematic overview of the study design, data source, inclusion criteria, data processing steps, and modeling framework.

was used to evaluate the autocorrelation residuals. A significant outcome from this test may indicate that the model does not adequately capture the inherent structure of the time-series data. The Jarque–Bera test was used to examine the normality of the distribution of the residuals, with a significant result suggesting a deviation from the assumption of a normal distribution. In addition, heteroskedasticity tests were conducted to determine whether the residuals exhibited unequal variances, which could undermine the reliability of the model. A significance threshold of $p < 0.05$ was used for all tests.

This research received approval from the Institutional Review Board of the Faculty of Medicine at Prince of Songkla University, with the approval number REC.65-409-7-1.

Results

The general characteristics of the study population

Over 19 years, 39,653 patients received radiotherapy at Songklanagarind Hospital. Of these, 27% (10,718 patients) were aged ≥65 years and were included in this study. To minimize the confounding effects of the coronavirus disease 2019 pandemic on service utilization patterns, patients treated between 2021 and 2022 were excluded from the time-series analysis and forecasting.

Among the 10,718 older patients, 60% (6,425) were male, and 58.7% (6,295) received curative-intent radiotherapy (Table 1). The mean age was 71.8 (range: 68.2–76.6) years. The age distribution revealed that 38.1% were aged 65–69 years (n = 4,087), 29.2% were 70–74 years old (n = 3,125), and 32.7% were aged ≥75 years (n = 3,506). The most common cancer types were the head and neck (25.9%), lung (16.1%), colorectal (9.0%), cervical (8.3%), and esophageal (7.3%) cancers. In total, 277,753 treatment fractions were identified.

During this timeframe, a total of 227,063 treatment fractions were delivered, with older adults undergoing a median of 46 daily sessions, ranging from 38 to 53. The facility utilized radiotherapy machines, including two cobalt-based units: Cobalt1 (Theratron 780C, MDS Canada Inc., Canada) and Cobalt2 (Theratron Phoenix, Best Theratronics, Canada), which had median daily usage interquartile ranges of 3 (2–4) and 15 (11–19) fractions per day, respectively. The single energy linear accelerators, Linac-6EX (Varian Medical Systems, USA) and Unique (Varian Medical Systems, USA), had median daily usages of 8 (3–14) and 18 (13–23) fractions, respectively. The dual energy linear accelerators, Linac IX and Clinac 2100C (Varian Medical Systems, USA), were used more frequently, each with a median of 21 daily fractions, with ranges of 18–25 and 17–26, respectively. The Truebeam STX, intended for advanced therapies, had a median daily usage of 7 (3–13) sessions. The timeline of installation and end of use was reported elsewhere [9, 10].

Between 2004 and 2020, the annual number of older patients receiving radiotherapy increased from 476 to 698; however, there was a temporary decline around 2012 owing to equipment replacement (Figure 2A). The 65–69-year age group consistently represented the largest cohort, with an increase from 205 patients in 2004 to 298 patients in 2020. Notably, post-2014, the number of patients aged ≥75 years exceeded that in the 70–74-year age group (Figure 2B). During the study, the curative intent was predominant, and the number of curative cases increased from 222 in 2004 to 422 in 2020. The curative-to-palliative ratio increased from 1.13 to 1.53 over the same period (Figure 2C).

The analysis of cancer-specific trends revealed evolving treatment patterns (Figure 2D). Although head and neck cancers remained the most prevalent, their incidence decreased after 2016. Conversely, lung, colorectal, breast, and prostate cancers exhibited consistent upward trends. Notably, the incidence of colorectal and breast cancers increased significantly after 2014. The rates of cervical and esophageal cancers remained relatively stable. The composition of the top five treated cancers shifted post-2014, with colorectal, breast, and prostate cancers replacing cervical and esophageal cancers.

Time-series analysis and forecasting

Time-series data were organized in monthly intervals between 2004 and 2020 (Figure 3A). Visual examination indicated a gradual upward trend in radiotherapy volume (Figure 3C). Using PyCaret, a significant and multiplicative seasonal component was identified, recurring every four-time units, which corresponds to a 4-month lag time unit seasonality (Figure 3B). First-order non-seasonal differencing (d = 1) was sufficient to achieve stationarity, as confirmed by the ADF test (pre-differencing, p = 0.09;

Table 1. Patient Characteristics Across the Study Period (2004–2020)

Characteristics	2004–2013	2014–2022	Overall
Total cancer cases	5,231	5,487	10,718
Sex (M/F)	3,187/2,044 (61/39)	3,238/2,249 (59/41)	6,425/4,293 (60/40)
Age	72.0 (68.4,76.4)	71.8 (68.0,76.8)	71.8 (68.2,76.6)
Age distribution			
65–69 years	1,910 (36.5)	2,177 (39.7)	4,087 (38.1)
70–74 years	1,615 (30.9)	1,510 (27.5)	3,125 (29.2)
> 75 years	1,706 (32.6)	1,800 (32.8)	3,506 (32.7)
Aim			
Curative	3,005(57.4)	3,290 (60.0)	6,295 (58.7)
Palliative	2,226(42.6)	2,197 (40.0)	4,423 (41.3)

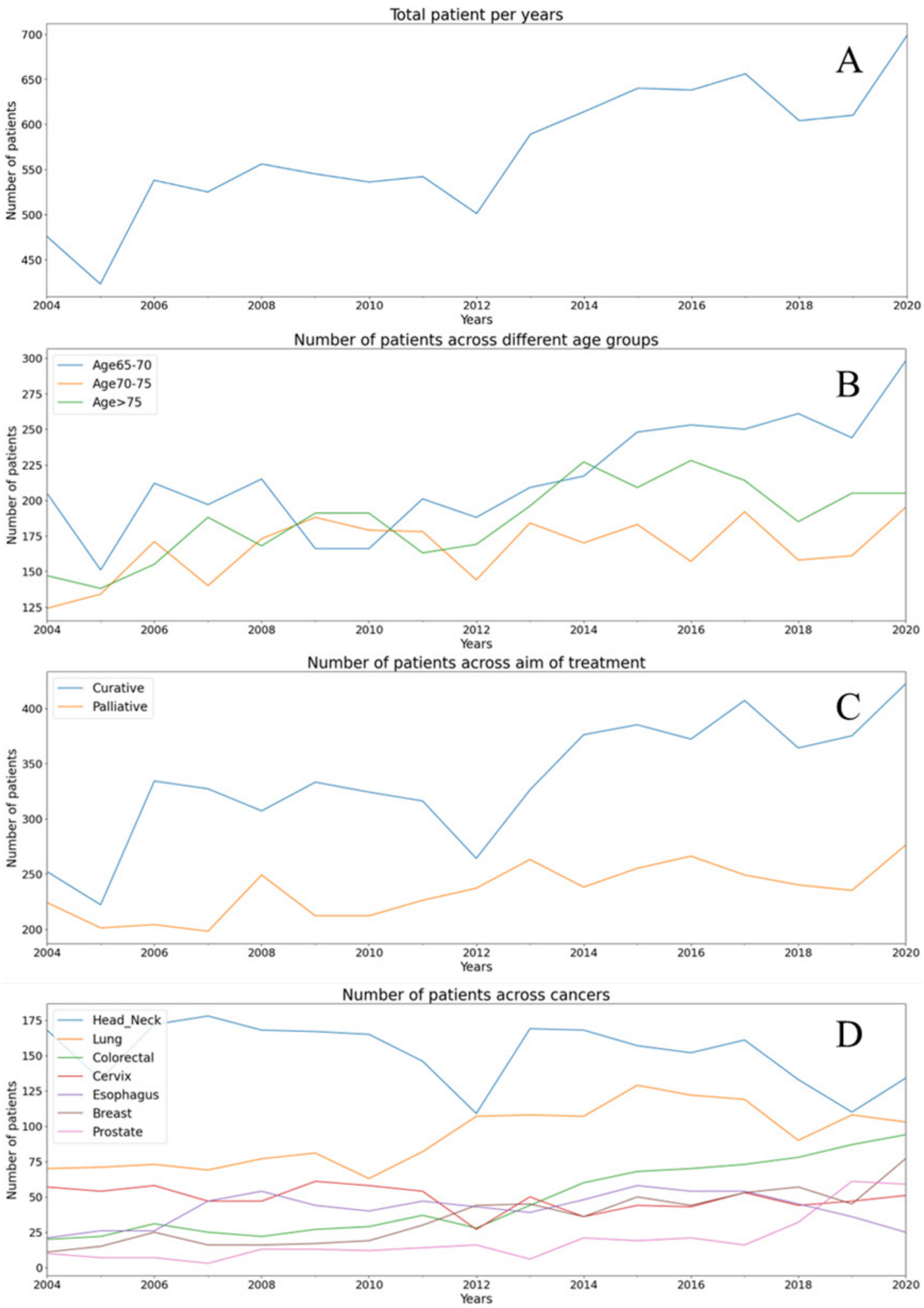

Figure 2. Patients with Geriatric Cancer Over Time (2004–2020). A) Total number of patients per year, B) number of patients across different age groups, C) number of patients across the aim of treatment, D) number of patients across different cancers.

post-differencing, $p < 0.001$). Seasonal differences were considered unnecessary (D=0).

Initial classical modeling indicated ARIMA(3,1,3) as a viable candidate, with an AIC of 1131 and a MAPE of 0.17 for the in-sample and out-of-sample data. The conventional optimization resulted in ARIMA(0,1,1)(0,0,1,4), which achieved a lower AIC of 1128 while maintaining similar MAPE values. Further refinement led to ARIMA(2,1,3)(0,1,14), which produced the lowest AIC of 1112 and a MAPE of 0.19 for the in-sample and 0.17 for the out-of-sample data. A summary of these models and their performances is provided in Table 2.

An exogenous variable representing the older population in Southern Thailand provided by the Ministry of Health [13] was incorporated to enhance model performance. The initial dataset encompasses the 2006–2023 period. Subsequently, the researcher performed forward and backward forecasting of the aging population in Southern Thailand, using the annual percent change (Figure 4A). Next, an aging dataset for 2004–2030 was developed and used as an exogenous variable.

The final model selected ARIMA(3,1,0)(0,0,1,4)

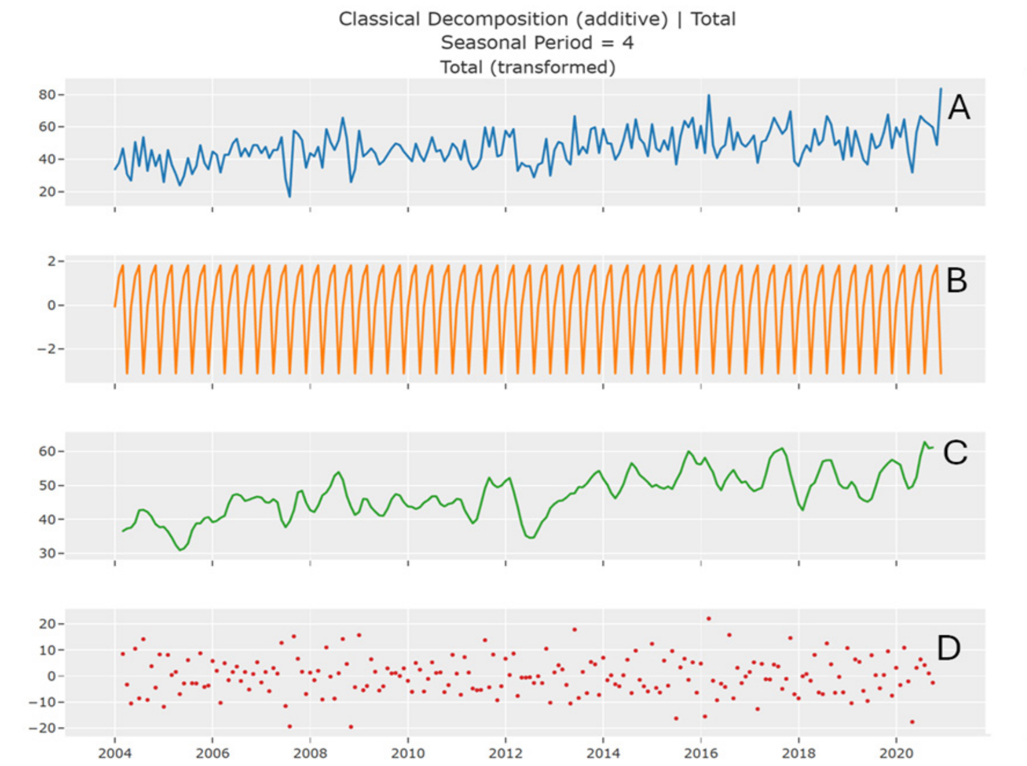

Figure 3. Time-Series Decomposition of Monthly New Patients with Geriatric Cancer Undergoing Radiotherapy. A 4-month lag time unit is evident and informed model parameterization: A) actual value, B) seasonal, C) trend, D) residual, that illustrates the trend, seasonal, and residual components.

with exogenous input, achieving an AIC of 1132, with a MAPE of 0.17 for the in-sample data and 0.18 for the out-of-sample data. The residual diagnostics, as presented in Table 2, confirmed the adequacy of the model. The coefficient for the exogenous variable ($\beta = 4.668\times10^{-5}$, $p = 0.014$) was statistically significant, indicating a positive correlation between the increase in the older population and the demand for radiotherapy. Strong autoregressive effects were observed with AR(1), AR(2), and AR(3) coefficients of –0.9826, –0.9765, and –0.9229, respectively (all $p < 0.001$), suggesting robust temporal dependence. A seasonal moving average term at lag 4 was also significant (–0.8502, $p < 0.001$), confirming a 4-month cyclicality. The estimated residual variance ($\sigma^2 = 91.12$, standard error = 13.04) was within acceptable limits. Based on the final model, the monthly number of new geriatric radiotherapy cases is projected to increase steadily, reaching 74.7 new patients per month, with a 95% confidence interval of 53.8–95.7 by the end of 2030 (Figure 4B).

Discussion

The demand for radiotherapy can be forecast using

Table 2. Model Comparison Table

Model	AIC	MAPE In sample	MAPE Out sample	Ljung–Box (p-value)	Jarque–Bera (p-value)	Heteroskedasticity (p-value)
ARIMA(3,1,3)	1131	0.17	0.17	0.02	0.28	1.06
				-0.87	-0.87	-0.84
ARIMA(2,1,3)(0,1,1,4)	1112	0.19	0.17	0.02	1.83	0.99
				-0.9	-0.4	-0.98
ARIMA(0,1,1)(0,0,1,4)	1128	0.17	0.17	0.01	0.31	1.11
				-0.92	-0.86	-0.7
ARIMA(1,0,0)(0,1,0,4)	1176	0.23	0.2	0	0.56	1.3
AutoML-arima				-0.96	-0.76	-0.36
ARIMA(3,1,0)(0,0,1,4)	1134	0.18	0.16	0.02	0.35	1.15
(AutoML Autoarima)				-0.9	-0.84	-0.62
ARIMA(3,1,0)(0,0,1,4)	1132	0.17	0.18	0.17	0.64	1.1
With exogenous variable				-0.68	-0.73	-0.73

Abbreviation: MAPE, Mean Absolute Percentage Error

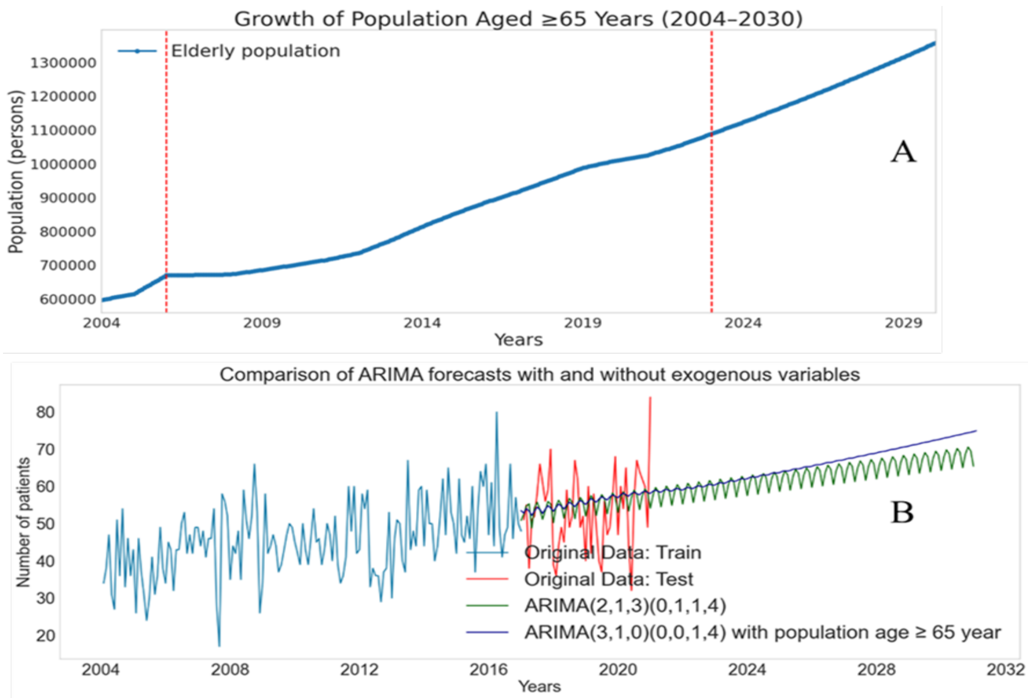

Figure 4. Forecasting Patient Numbers Using Autoregressive Integrated Moving Average (ARIMA) Models. A) Older adult population growth between 2004 and 2030, B) forecasting patient numbers using Autoregressive Integrated Moving Average (ARIMA) models with and without the older adult population as an exogenous variable.

various methodologies, depending on the perspectives and objectives of the stakeholders involved. Each methodology relies on distinct data types and fulfills specific interpretive requirements [14]. In our study, we used a time-series analysis, specifically the ARIMA model, because of its suitability for managing less complex datasets and ease of interpretation at the hospital level. While previous studies have considered historical activity data or focused on trend analysis [15-17], our approach is distinguished by the application of ARIMA forecasting, specifically for patients with geriatric cancer undergoing radiotherapy. This method demonstrated the potential for demand prediction in this patient population.

Over time, the focus of cancer treatment in geriatric oncology has shifted towards colorectal, breast, and prostate malignancies, replacing cervical and esophageal cancers. According to ARIMA-based forecasting, the demand for radiotherapy is projected to increase to approximately 74.7 new cases per month among older adults by 2030. This trend may indicate enhanced clinical confidence in administering definitive radiotherapy to older adults, facilitated by the implementation of geriatric risk-adapted protocols and improved tools for evaluating performance status and comorbidities.

The increasing prevalence of radiotherapy among older adults can be attributed to the aging global population [18] and the growing demand for nonsurgical cancer treatments. Radiotherapy is particularly beneficial for older adults because it is target-specific, minimizing the systemic side effects. Technological advancements and the adoption of hypofractionated regimens have enhanced their feasibility by decreasing treatment burden and improving tolerability. The treatment of older adults with cancer is decided by the healthcare providers [19]. The use of radiotherapy usually decreases with age among patients with geriatric cancer [20]. This may be due to age-related treatment bias [21]. However, there is no data for Southeast Asia, including Thailand. Our data showed a steady increase in utilization; however, our projections may underestimate the future demand, as access to advanced radiotherapy technologies continues to expand and barriers to treatment are diminishing.

There is a scarcity of comparable data on the use of radiotherapy among older adults, and only a few studies have documented long-term trends for this demographic. In 2022, a report from the Netherlands highlighted the trend in radiotherapy usage for non-metastatic prostate cancer from 2008 to 2019. The study observed an increasing trend in radiotherapy for intermediate-risk and high-risk localized prostate cancer, as well as for locally advanced conditions. However, it noted a decline in the use of Brachy-monotherapy [22]. In 2023, a report from Korea examined the trend of radiotherapy in older adults with hepatocellular carcinoma, revealing an upward trend between 2002 and 2017 [23]. There is currently no forecasting research available in the field of geriatric radiotherapy. This information might indicate a trend in the use of radiotherapy among older adults.

Focus on distribution of cancer sites and patient characteristics, Patient profiles among older adults undergoing radiotherapy demonstrate considerable variability across regional centers, highlighting disparities in demographics, disease patterns, and healthcare infrastructure. In an Indian study, the mean age of older patients undergoing radiotherapy was approximately 70 years, with a male-to-female ratio of 66–34%. The most frequently treated cancers include the head and neck, lung, cervical, and esophageal types [24]. Conversely, a study in Iraq reported a higher mean age of 77 years (with the inclusion criteria of >70 years), with males dominating the population (75%). The predominant cancer types in Iraq are lung, head and neck, breast, and prostate cancers [25]. Based on hospital data, a report from Northeast Thailand indicated that older adults constituted 31.6% of all cancer cases registered over 20 years. Notably, the number of cancer cases in patients aged ≥80 years doubled between the first and second decades of the study. Among males, the most common cancer types were liver and bile duct, lung, and colorectal cancers, whereas in females, liver and bile duct, oral cavity, and cervical cancers predominated [26]. Our study reported a mean age of 71.8 years, with a male-to-female ratio of 60:40. The most commonly treated cancers were the head and neck, lung, colorectal, and breast types. Notably, the data from Northeast Thailand do not exclusively pertain to radiotherapy, which is less commonly indicated for liver and bile duct cancers. Therefore, understanding local disease patterns is crucial for optimizing clinical strategies.

The definition of “geriatric” in oncology remains inconsistent. The identified variations in the institutional thresholds were age-based treatment decisions. A recent Delphi consensus emphasized the significance of prioritizing physiological age over chronological age, a perspective supported by formal geriatric assessment tools [27]. Per the international guidelines of the American Society of Clinical Oncology and National Comprehensive Cancer Network, our study considered age ≥65 years as the inclusion criterion, aligning with that of national cancer registries and public health [4]. These frameworks advocate geriatric screening, particularly when concurrent chemoradiation is considered.

The anticipated increase to 74.7 new older patients per month by the end of 2030 necessitates modifications to the clinical workflow and infrastructure. The integration of comprehensive geriatric assessments and nutritional evaluations is essential to enhance treatment safety and efficacy [28]. However, geriatric assessments are time-consuming and require at least 30 min per case [29]. According to our forecast, approximately four new patients with geriatric cancer will be scheduled for screening daily. Patients may experience a decline in their daily functioning during radiotherapy [30]. Geriatric conditions are associated with radiation-induced toxicity [31]. Nevertheless, data on the frequency of these assessments is lacking. Notably, 24% of older adults with cancer experience falls. The side effects of cancer treatment, such as neuropathy, muscle weakness, and fatigue, increase fall risk [32]. Other practical considerations, including fall risk, transfer requirements, and wheelchair accessibility, should be incorporated into strategic planning.

Moreover, the detection of a seasonal pattern with a 4-month lag in radiotherapy volume suggests recurring peaks in service demand. Although this is an unusual phenomenon, it has operational implications because staffing and scheduling should be aligned with the anticipated patient influx to minimize waiting times and optimize machine utilization.

This study had certain limitations. Reliance on billing records may result in an underestimation of the actual demand for radiotherapy because these records may not account for patients who were referred but did not commence or complete treatment. Furthermore, administrative health data usually lack detailed information on intra-month waiting times and treatment delays. While the facility delivers a wide range of radiotherapy procedures, including conventional external beam and advanced stereotactic techniques, the accuracy of treatment modality data in the hospital registry is limited due to a lack of granularity in reimbursement coding rules, as the codes prioritize reimbursement over clinical detail. The exact counts for specific modalities, such as volumetric modulated radiotherapy, stereotactic body radiotherapy, and stereotactic radiosurgery, could not be determined. Similarly, although the ARIMA model offers reliable baseline forecasts, its linear structure restricts its capacity to capture complex nonlinear patterns in healthcare demand. The consistency of the MAPE values across in-sample and out-of-sample predictions underscores the robustness and reliability of the ARIMA model. Despite its simplicity, this model delivers stable forecasts, making it a practical tool for healthcare planners, particularly when interpretability is prioritized.

Future research should consider advanced time-series models such as the Bayesian structural time-series and machine learning types, which incorporate multiple predictors and capture dynamic nonlinear relationships [33-36]. However, these methods present challenges concerning interpretability. A hybrid approach that balances the transparency of traditional models with the predictive strength of machine learning may offer the most practical and scalable solution for radiotherapy forecasting in clinical settings.

We forecast the radiotherapy demand among older adults using ARIMA modeling with exogenous variables. The inclusion of older population data enhanced the accuracy of the model, underscoring its influence on service demand. These findings highlight the need for workforce planning, infrastructure development, and geriatric protocols. Future research should consider advanced forecasting methods and incorporate various clinical variables to refine the projections and support comprehensive oncology planning.

Author Contribution Statement

Conceptualization, Thanarpan P, Pasuree S. Investigation and methodology, Thanarpan P, Pasuree S., Sitthichok Ch. Supervision, Pasuree S., Sitthichok Ch. Writing of the original draft, Thanarpan P. Writing of the review and editing, Pasuree S., Sitthichok Ch. Validation, Sitthichok Ch. Formal analysis and visualization, Thanarpan P. All the authors have proofread the final version.

Acknowledgements

General

We express our appreciation to the Division of Digital Innovation and Data Analytics at the Faculty of Medicine, Prince of Songkla University, for supplying data from the radiotherapy unit. We also extend our gratitude to the Office of International Affairs, Faculty of Medicine, Prince of Songkla University, for facilitating English editing services through Editage. We also thank the radiotherapy team for its unwavering commitment to assisting patients with cancer in Southern Thailand.

Approval

This study forms part of Thanarpan Peerawong's doctoral dissertation in Health Science and Medical Research.

Ethical Declaration

The Institutional Review Board of the Faculty of Medicine at Prince of Songkla University approved this study (approval number REC.65-409-7-1).

Conflict of Interest

I have nothing to declare.

References

1. Cheng YX, Liu XY, Kang B, Tao W, Wei ZQ, Peng D. Comparison of surgical and oncologic outcomes in very elderly patients (≥80 years old) and elderly (65-79 years old) colorectal cancer patients: A propensity score matching. BMC Gastroenterol. 2022;22(1):205. https://doi.org/10.1186/s12876-022-02277-y.
2. Bray F, Laversanne M, Sung H, Ferlay J, Siegel RL, Soerjomataram I, et al. Global cancer statistics 2022: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians. 2024;74(3):229-63. https://doi.org/10.3322/caac.21834.
3. Ferlay J, Laversanne M, Ervik M, Lam F, Colombet M, Mery L, et al. Global Cancer Observatory: Cancer Tomorrow (version 1.1) [Internet]. Lyon, France: International Agency for Research on Cancer; 2024 [cited 2025 May 1]. Available from: https://gco.iarc.who.int/tomorrow
4. Goede V. Frailty and cancer: Current perspectives on assessment and monitoring. Clin Interv Aging. 2023;18:505-21. https://doi.org/10.2147/cia.S365494.
5. Roeder F, Jensen AD, Lindel K, Mattke M, Wolf F, Gerum S. Geriatric radiation oncology: What we know and what can we do better? Clin Interv Aging. 2023;18:689-711. https://doi.org/10.2147/cia.S365495.
6. Amini A, Morris L, Ludmir EB, Movsas B, Jagsi R, VanderWalde NA. Radiation therapy in older adults with cancer: A critical modality in geriatric oncology. J Clin Oncol. 2022;40(16):1806-11. https://doi.org/10.1200/jco.21.02656.
7. Rosenblatt E, Fidarova E, Zubizarreta EH, Barton MB, Jones GW, Mackillop WJ, et al. Radiotherapy utilization in developing countries: An iaea study. Radiother Oncol. 2018;128(3):400-5. https://doi.org/10.1016/j.radonc.2018.05.014.
8. Thai Association of Radiation Oncology. Statistics in radiation oncology [Internet]. Bangkok (Thailand): Thai Association of Radiation Oncology; [cited 2025 Apr 25]. Available from: https://www.thastro.org/Statistics-Online.php
9. Phungrassami T, Funsian A, Sriplung H. 30 years of radiotherapy service in southern thailand: Workload vs resources. Asian Pac J Cancer Prev. 2013;14:7743-8. https://doi.org/10.7314/APJCP.2013.14.12.7743.
10. Peerawong T, Chaichulee C, Sangsupawanich P. Forecasting daily radiotherapy patient volumes in a tertiary hospital using autoregressive integrated moving average (arima) models. Cureus. 2024;16(10):e72752. https://doi.org/10.7759/cureus.72752.
11. Peixeiro M. Time series forecasting in Python. Shelter Island (NY): Manning Publications Co.; 2022.
12. Ali M. PyCaret: an open-source, low-code machine learning library in Python [Internet]. Version 1.0.0. 2020 Apr [cited 2024 Apr 11]. Available from: https://www.pycaret.org
13. Division of Strategy and Planning, Office of the Permanent Secretary, Ministry of Public Health. Public health statistics [Internet]. Nonthaburi (Thailand): Ministry of Public Health; [cited 2025 Apr 4]. Available from: https://spd.moph.go.th/public-health-statistics/
14. Delaney GP, Barton MB. Evidence-based estimates of the demand for radiotherapy. Clin Oncol (R Coll Radiol). 2015;27(2):70-6. https://doi.org/10.1016/j.clon.2014.10.005.
15. Sathian B, Sreedharan J, Sharan K, Baboo S, Chawla R, Nishida C, et al. Statistical modelling technique in forecasting of palliative oncotherapy load in hospitals. Nepal J Epidemiol. 2010;1. https://doi.org/10.3126/nje.v1i1.4111.
16. Sathian B, Sreedharan J, Sharan K, Suresh BN, Ninan J, Joy T, et al. Forecasting breast cancer cases requiring radiotherapy at a teaching hospital in nepal. J Clin Diagn Res. 2010;4:2378-83.
17. Sathian B, Fazil A, Sreedharan J, Pant S, Kakria A, Sharan K, et al. Statistical modelling and forecasting of cervix cancer cases in radiation oncology treatment: A hospital based study from western nepal. Asian Pac J Cancer Prev. 2013;14(3):2097-100. https://doi.org/10.7314/apjcp.2013.14.3.2097.
18. Li L, Shan T, Zhang D, Ma F. Nowcasting and forecasting global aging and cancer burden: Analysis of data from the globocan and global burden of disease study. J Natl Cancer Cent. 2024;4(3):223-32. https://doi.org/10.1016/j.jncc.2024.05.002.
19. Pinker I, Wetzlmair-Kephart L, da Costa AM, Pilleron S. The role of healthcare professionals' attitudes in treatment decision-making for older adults with cancer: A scoping review. J Geriatr Oncol. 2025;16(3):102151. https://doi.org/10.1016/j.jgo.2024.102151.
20. Mackenzie P, Vajdic C, Delaney G, Comans T, Morris L, Agar M, et al. Radiotherapy utilisation rates for patients with cancer as a function of age: A systematic review. J Geriatr Oncol. 2023;14(3):101387. https://doi.org/10.1016/j.jgo.2022.10.002.
21. Rodrigues ED, Bento MJ, Calisto R, Rodrigues J, Almeida P, López E, et al. Utilisation patterns of radiotherapy among older patients: Insights from portuguese national cancer registry data. J Cancer Policy. 2025;43:100522. https://doi.org/10.1016/j.jcpo.2024.100522.
22. Evers J, Kerkmeijer LGW, van den Bergh RCN, van der Sangen MJC, Hulshof M, Bloemers M, et al. Trends and variation in the use of radiotherapy in non-metastatic prostate cancer: A 12-year nationwide overview from the netherlands. Radiother Oncol. 2022;177:134-42. https://doi.org/10.1016/j.radonc.2022.10.028.
23. Bae BK, Yu JI, Park HC, Goh MJ, Paik YH. Radiotherapy trend in elderly hepatocellular carcinoma: Retrospective analysis of patients diagnosed between 2005 and 2017. Radiat Oncol J. 2023;41(2):98-107. https://doi.org/10.3857/roj.2023.00353.
24. Suhag V, Bs S, Vats P, Singh S, Jain M, Vashisht R. Radiotherapy and geriatric cancer patients: A single institute experience. Indian J Med Sci.71. https://doi.org/10.25259/IJMS_10_2019.

25. Gendari AH, Ameen HA, Ramzi ZS, Amin AF, Mohammed SA, Majeed SS, et al. Geriatric radiotherapy in a war-torn country: Experience from iraq. J Geriatr Oncol. 2018;9(4):346-51. https://doi.org/10.1016/j.jgo.2018.03.006.
26. Wirasorn K, Suwanrungruang K, Sookprasert A, Limpawattana P, Sirithanaphol W, Chindaprasirt J. Hospital-based population of elderly cancer cases in northeastern thailand. Asian Pac J Cancer Prev. 2016;17(2):767-70. https://doi.org/10.7314/apjcp.2016.17.2.767.
27. Morris L, Turner S, Thiruthaneeswaran N, O'Donovan A, Simcock R, Cree A, et al. An international expert delphi consensus to develop dedicated geriatric radiation oncology curriculum learning outcomes. Int J Radiat Oncol Biol Phys. 2022;113(5):934-45. https://doi.org/10.1016/j.ijrobp.2022.04.030.
28. Middelburg JG, Middelburg RA, van Zwienen M, Mast ME, Bhawanie A, Jobsen JJ, et al. Impaired geriatric 8 score is associated with worse survival after radiotherapy in older patients with cancer. Clin Oncol (R Coll Radiol). 2021;33(4):e203-e10. https://doi.org/10.1016/j.clon.2020.09.002.
29. Kenis C, Decoster L, Van Puyvelde K, De Grève J, Conings G, Milisen K, et al. Performance of two geriatric screening tools in older patients with cancer. J Clin Oncol. 2014;32(1):19-26. https://doi.org/10.1200/jco.2013.51.1345.
30. Nehlsen A, Agarwal P, Mazumdar M, Dutta P, Goldstein NE, Dharmarajan KV. Impact of radiotherapy on daily function among older adults living with advanced cancer (rt impact on function in advanced cancer). J Geriatr Oncol. 2022;13(1):46-52. https://doi.org/10.1016/j.jgo.2021.07.007.
31. Paal K, Stranz B, Thurner EM, Langsenlehner U, Renner W, Brunner TB, et al. Comprehensive geriatric assessment predicts radiation-induced acute toxicity in prostate cancer patients. Strahlenther Onkol. 2024;200(3):208-18. https://doi.org/10.1007/s00066-023-02132-3.
32. Lingamaiah D, Bushi G, Gaidhane S, Balaraman AK, Padmapriya G, Kaur I, et al. Falls among geriatric cancer patients: A systematic review and meta-analysis of prevalence and risk across cancer types. BMC Geriatr. 2025;25(1):179. https://doi.org/10.1186/s12877-025-05722-1.
33. Janbabaee G, Nadi-Ghara A, Afshari M, Ashrafi M, Aarabi M, Hedayatizadeh-Omran A, et al. Forecasting the incidence of breast, colorectal and bladder cancers in north of iran using time series models; comparing bayesian, arima and bootstrap approaches. Asian Pac J Environ Cancer. 2021;4:3-7. https://doi.org/10.31557/apjec.2021.4.1.3-7.
34. Sekeroglu B, Tuncal K. Prediction of cancer incidence rates for the european continent using machine learning models. Health Informatics J. 2021;27(1):1460458220983878. https://doi.org/10.1177/1460458220983878.
35. Wah W, Papa N, Ahern S, Earnest A. Forecasting of overall and aggressive prostate cancer incident counts at the small area level. Public Health. 2022;211:21-8. https://doi.org/10.1016/j.puhe.2022.06.029.
36. Wah W, Stirling RG, Ahern S, Earnest A. Forecasting of lung cancer incident cases at the small-area level in victoria, australia. Int J Environ Res Public Health. 2021;18(10). https://doi.org/10.3390/ijerph18105069.