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Systematic review

Statistical Methods in Cancer Epidemiology Research in Low- and Middle-Income Countries: A Systematic Review

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Abstract
Cancer epidemiology research in LMICs has grown with the increasing global cancer burden, but the statistical methods used remain diverse and insufficiently evaluated. This review assessed methodological trends, dominant analytical approaches, and the use of advanced statistical methods. A PRISMA 2020–guided systematic review identified 46 eligible studies on cancer epidemiology in LMICs. Data on study characteristics, cancer types, data sources, and statistical methods were extracted and synthesized descriptively. The included studies covered sub-Saharan Africa, Asia, and Latin America, with cervical and breast cancers being the most frequently investigated malignancies. Most included studies employed observational designs, particularly cross-sectional and cohort approaches, relying mainly on hospital-based datasets, cancer registries, and population surveys. Conventional statistical methods predominated, especially descriptive statistics and regression-based analyses, with logistic regression being the most applied inferential method. Survival analysis techniques, including Kaplan–Meier estimation and Cox proportional hazards models, were increasingly used, whereas multilevel modeling, simulation approaches, and machine learning (ML) methods remained comparatively limited. Across studies, consistent patterns included late-stage diagnosis, low screening uptake, poor survival outcomes, and marked socioeconomic and health-system inequalities influencing access to care and treatment outcomes. Cancer epidemiology research in LMICs still relies mainly on traditional methods, with limited use of advanced analytical approaches. Strengthening data systems, research infrastructure, and analytical capacity is crucial for improving evidence generation and cancer control strategies.
Keywords. Cancer Epidemiology, Low- And Middle-income Countries, Statistical Modeling, Machine Learning.

Introduction

Cancer continues to cause millions of deaths each year and remains a major public health challenge worldwide, imposing significant burdens on healthcare systems and economies, especially in developing countries. Cancer causes approximately 10 million deaths annually worldwide. Approximately 70% of these deaths occur in low- and middle-income countries (LMICs), highlighting persistent inequalities in prevention, early detection, diagnosis, and treatment [1].

Studies indicate that several structural and demographic factors are accelerating the cancer burden in LMICs, including aging, urbanization, population growth, and increased exposure to behavioral risk factors, such as tobacco use, unhealthy diets, and physical inactivity [2]. Despite this growing burden, the availability and quality of epidemiological data in these settings remain limited [3]. In many LMICs, there are no comprehensive population-based cancer registries. Where they are available, the challenges posed by underreporting, misclassification, missing data, and little follow-up are numerous. Data collection varies widely within and between LMICs, and the weak integration of health information systems makes it impossible to compare cancer epidemiology in cancer populations in similar or separate countries [4]. It is, therefore, challenging to determine with certainty cancer incidence, prevalence, survival, and mortality in these populations, limiting evidence-based policy [5].

Statistical methods play a central role in cancer epidemiology by supporting the analysis of disease patterns, risk factors, and patient outcomes. At the same time, survival analysis techniques, such as the Kaplan–Meier estimator and the Cox proportional hazards model, help determine patient outcomes [6, 7]. More recently, advanced statistical and computational methods have emerged for analyzing complex and high-dimensional data, including Bayesian approaches, machine learning (ML) algorithms, and spatio-temporal models [8]. These approaches offer improved predictive performance as well as the ability to accommodate partial datasets. However, as previously stated, determining the extent of these methods' adoption in LMIC-based cancer epidemiology remains a challenge. There is some evidence that, despite the increasing number of alternatives, researchers and decision-makers in this field generally assume that more traditional methods are superior due to concerns about data quality and available resources [9]. This systematic review aimed to evaluate the statistical methodologies used in cancer epidemiology studies conducted in LMICs, identify the most applied analytical techniques, and assess the adoption of advanced statistical approaches.

Global burden of cancer in LMICs

Cancer has emerged as a critical global public health challenge, with an increasingly disproportionate burden on LMICs. Current global estimates indicate that approximately 70% of cancer-related deaths occur in LMICs in terms of mortality,

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with this figure being one of the most profound discrepancies between LMICs and high-income countries [10]. Even though the incidence in some LMICs is lower than in some high-income countries, the mortality is higher due to late-stage diagnosis, lack of necessary screening tools, and constrained health care infrastructure [10].

Moreover, recent studies provide evidence that underlines that worldwide cancer incidence and mortality rates are increasing, propelled by demographic changes and epidemiological transitions, including population aging and growing exposure to modifiable risk factors [3]. Novel findings reveal that LMICs face the double challenge of cancer triggered by infection and diseases of lifestyle, adding pressure on the already fragile healthcare system [4]. Recent global evidence suggests that cancer disparities are increasingly driven by structural factors such as health system capacity and access to oncology services, as well as social determinants such as resource disparities [10]. These structural disparities remain the fundamental defining characteristic of cancer epidemiology in LMICs, emphasizing the necessity of an analytical framework and intervention strategies that are based on the specific context.

Data availability and quality challenges

One of the leading challenges in cancer epidemiology research in LMICs is the inadequate availability of reliable data [4]. In LMICs, the development of population-based cancer registries is still ongoing in several countries, characterized by incomplete population coverage. Even when established, substantial underreporting, misclassification, and missing information compromise the validity of the data [11]. Limited reporting of data quality is still a significant limitation of the type of cancer prediction. More recent studies report that several cancer burden estimates for data-scarce regions are achieved using statistical modeling techniques such as Bayesian meta-regression and imputation methods based on predictive modeling approaches [12]. This approach has improved estimates' accuracy, but the predictions remain highly uncertain, particularly for small or under-sampled populations.

Methods Landscape in Cancer Epidemiology

Cancer epidemiology relies heavily on statistical methodologies to quantify disease burden, identify risk factors, and support evidence-based decision-making [3]. Traditional methods such as descriptive statistics, logistic regression, Poisson regression, and survival analysis remain widely used, particularly in LMICs, where data limitations and infrastructure constraints favor interpretable and less computationally intensive approaches [13]. Among survival analysis techniques, the Kaplan–Meier estimator and Cox proportional hazards model are fundamental tools in oncology research and have contributed substantially to understanding prognosis, treatment effectiveness, and survival disparities [14]. Despite advances in predictive analytics, recent evidence indicates that conventional linear models still dominate cancer epidemiology research, whereas nonlinear and high-dimensional approaches remain relatively underutilized [13].

Recently, however, the methodological landscape has shifted toward more advanced computational approaches, including ML, deep learning (DL), Bayesian methods, and hybrid modeling frameworks [7]. These approaches are particularly suitable for modeling the multifactorial and high-dimensional nature of cancer. Common ML techniques such as random forests, support vector machines, and neural networks have shown strong performance in risk prediction, diagnostic classification, and prognostic modeling [15]. In addition, ML algorithms can effectively integrate multimodal data sources, including clinical, genomic, and imaging data, while longitudinal ML approaches have increasingly been applied to time-based disease modeling [12, 16]. Despite these methodological advances, important concerns remain regarding equity, bias, and generalizability. Models developed in high-income countries often perform poorly in LMIC populations because of differences in genetic profiles, disease patterns, treatment availability, and data quality [17]. In addition, algorithmic bias in ML-based cancer research continues to raise concerns about fairness, ethical implementation, and contextual applicability in global oncology research [17]. These challenges emphasize the necessity of transparent, context-specific, and equity-oriented analytical frameworks in cancer epidemiology.

Methodological Gaps in LMIC-Based Cancer Epidemiology Research

Despite increasing interest in cancer epidemiology research in LMICs, several methodological limitations continue to affect the quality, reproducibility, and clinical and public health relevance of existing evidence. One major challenge is the limited use of advanced statistical and computational methods. Although ML and Bayesian approaches are widely used in high-income countries to analyze complex and high-dimensional data, their application in LMICs remains limited because of inadequate computational infrastructure, shortage of technical expertise, and insufficient methodological support [13, 16]. Data quality and reporting transparency also remain important concerns. Weak health information systems, fragmented cancer registries, incomplete records, and inconsistent reporting practices reduce data reliability and affect both internal and external validity [11, 13].

Methodology

Data sources and search strategy

Our systematic literature search focused on studies published between January 2000 and March 2026 to identify research on cancer epidemiology and statistical methodologies in LMICs. Relevant studies were retrieved from PubMed, Scopus, and Web of Science using predefined search strategies.

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The search combined free-text keywords with controlled vocabulary terms, including Medical Subject Headings (MeSH) in PubMed. Key search terms included "cancer epidemiology," "neoplasms," "statistical methods," "survival analysis," "regression analysis," "machine learning," "risk factors," and "low- and middle-income countries (LMICs)." Search terms were adapted for each database according to their indexing systems and search requirements. Boolean operators were used to refine the search strategy, with "AND" linking major concepts and "OR" incorporating synonyms and related terms. Truncation and wildcard symbols were also applied where appropriate to capture variations of keywords. Only English-language studies published within the review period were included to ensure relevance to contemporary epidemiological methods and statistical practices. The complete electronic search strategies for all databases are provided in Supplementary Material S1 (Table S1) to ensure transparency and reproducibility.

Eligibility criteria

The eligibility criteria were defined a priori based on the PRISMA 2020 Statement [18], to ensure consistency, transparency, and reproducibility in study selection. Studies were included if they involved human populations from, as classified by the World Bank at the time of the study, and addressed cancer epidemiology, including cancer incidence, prevalence, mortality, survival, stage at diagnosis, or cancer-related risk factors. Eligible studies were required to employ quantitative or mixed-methods research designs and apply statistical or analytical methods relevant to epidemiological investigation. Only original studies published in peer-reviewed journals and written in English were considered eligible for inclusion in this review.

Studies were excluded if they were unrelated to cancer epidemiology or conducted exclusively in high-income countries with no separate LMIC data. Editorials, commentaries, conference abstracts, letters, and studies without accessible full texts were also excluded. In addition, purely qualitative studies, case reports, and studies lacking quantitative epidemiological analysis or adequate statistical reporting were not considered. Studies with unclear outcome measures, incomplete data, major methodological limitations, or a high risk of bias were excluded to ensure the methodological rigor and reliability of the review findings.

Study selection

Study selection followed the PRISMA 2020 guidelines using a two-stage screening process. After duplicate removal, two reviewers independently screened titles and abstracts for relevance based on study population, topic, and design. Potentially eligible studies then underwent full-text review to confirm compliance with all eligibility criteria. Disagreements were resolved through discussion, with consultation from a third reviewer when necessary. A standardized screening form was used throughout the process to ensure consistency. The study selection process is summarized in the PRISMA flow diagram (Figure 1). Although a review protocol was developed before study selection and analysis, it was not registered in PROSPERO or any other systematic review registry.

Quality assessment and risk of bias

Methodological quality was assessed using the Newcastle–Ottawa Scale (NOS) for non-randomized studies [19]. The NOS evaluates studies based on (i) selection of study groups, (ii) comparability of groups, and (iii) ascertainment of exposure or outcomes. Two reviewers independently assessed each study, assigning up to nine stars. Studies were categorized as high quality (≥7 stars), moderate quality (5–6 stars), or low quality (<5 stars). Discrepancies were resolved through discussion.

Statistical analysis and sensitivity analysis

Due to substantial heterogeneity in study designs and analytical approaches, a narrative synthesis was conducted. Descriptive statistics were used to summarize studies by geographic region, cancer type, study design, and statistical methods applied. Findings were further grouped according to analytical models and epidemiological outcomes to identify patterns in the use of statistical techniques in cancer epidemiology research in LMICs. Because of methodological heterogeneity across studies, a formal meta-analysis was not performed.

Sensitivity analyses were conducted to evaluate the robustness of the findings by excluding studies classified as low quality according to the NOS. This approach assessed whether the overall conclusions remained consistent after the removal of studies with a higher risk of bias.

Results

Study identification and selection

The study selection process using the PRISMA 2020 flow diagram was illustrated in (Figure 1). A total of 1,812 records were initially identified through systematic database searching (PubMed: n = 758; Scopus: n = 510; Web of Science: n = 544). After removing 182 duplicate records, 1,630 unique studies remained and were subjected to title and abstract screening. After this initial screening, 65 studies were considered potentially eligible and retrieved for full-text assessment. Nineteen studies were excluded at the full-text eligibility stage; 19 studies were excluded

The main reasons for exclusion at this full-text stage were as follows: (i) lack of alignment with the review objectives or target population (n = 11); (ii) inappropriate study design (e.g., narrative reviews, editorials, commentaries, case reports, or conference abstracts without primary data) (n = 1); (iii) insufficient or incomplete reporting of outcomes, precluding

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meaningful analysis (n = 3); and (iv) methodological limitations or high risk of bias, including unclear study design or inappropriate statistical methods (n = 4).

The systematic documentation of inclusion and exclusion decisions, as illustrated in (Figure1), ensured full compliance with the PRISMA 2020 reporting standards and enhanced the methodological rigor of the review.

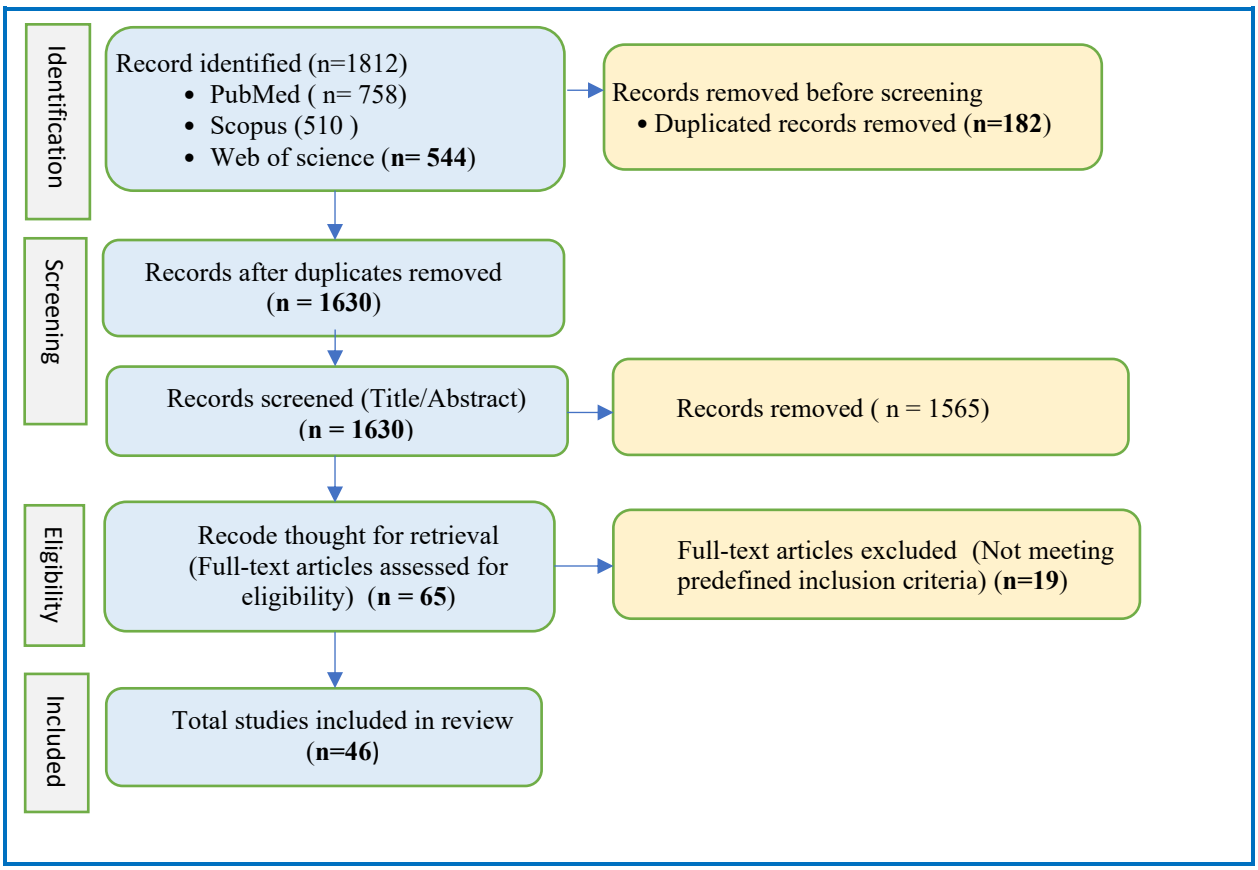

Figure 1. Selection process using the PRISMA 2020 flow diagram.

Characteristics of included studies

The principal characteristics of the included studies are summarized in (Table 1), while detailed methodological and analytical characteristics are presented in (Table S1). The final synthesis included 46 studies conducted across diverse LMICs, spanning multiple geographic regions and healthcare settings. Collectively, these studies provide a broad overview of cancer epidemiology research in resource-constrained environments, including variations in study design, statistical methodologies, cancer types, and healthcare system contexts.

Table 1. Summary characteristics of the 46 included studies

Author (Year)	Country /Region	Study Design	Cancer Type	Data Source	Statistical Methods
Triayudi, et al. [20]	Indonesia	AI modeling study	Thyroid cancer	Clinical datasets	Fuzzy co-clustering
Desta, et al. [21]	Ethiopia	Cross-sectional	Cervical cancer	Survey	Logistic regression
Mwenda, et al. [22]	Kenya	Case-control	Cervical cancer	Hospital data	Logistic regression
Knight, et al. [23]	Multinational	Prospective observational	Multiple cancers	Multicenter data	Multilevel modeling
Dzobo, et al. [24]	Zimbabwe	Discrete choice experiment	Cervical cancer	Survey	Choice modeling
Salgado, et al. [25]	Argentina	Simulation modeling	Lung cancer	Secondary data	Mathematical modeling
Khalil, et al.[26]	Kenya	Retrospective cohort	Breast cancer	Hospital data	Survival analysis

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Author (Year)	Country /Region	Study Design	Cancer Type	Data Source	Statistical Methods
Wadasadawala, et al. [27]	India	Prospective cohort	Breast cancer	Clinical and economic data	Generalized Linear Models
Diallo, et al. [28]	Multinational (LMICs)	Retrospective cohort with ML	Multiple conditions	Cohort	ML
Somé, et al. [29]	Burkina Faso	Case-control	Liver cancer	Hospital data	Logistic regression
Yadav, et al. [30]	India	Multilevel analysis	Cervical cancer	National survey	Multilevel modeling
Muddather, et al. [31]	Sudan	Cohort	Breast cancer	Hospital data	Survival analysis
Boateng, et al. [32]	Caribbean	Mixed-methods	Childhood cancers	Multi-country data	Comparative analysis
Manga, et al. [33]	Cameroon	Retrospective cohort	Cervical cancer	Clinical data	Logistic regression
Phakathi, et al. [34]	South Africa	Cohort	Breast cancer	Clinical data	Survival analysis
Yong, et al. [35]	Malaysia	Discrete choice experiment	Advanced cancers	Survey	Choice modeling
Viani, et al. [36]	Brazil	retrospective cross-sectional	Pediatric cancers	Hospital data	Survival analysis
da Silva, et al. [37]	Brazil	Population-based	Multiple cancers	Registry	Trend analysis
da Silva, et al. [38]	Brazil	Time-trend study	Gynecologic cancers	Registry	Trend analysis
Ramirez, et al. [39]	Colombia	Cohort	Pediatric cancers	Registry	Survival analysis
Canfell, et al. [40]	Multinational (LMICs)	Modeling study	Cervical cancer	Secondary data	Simulation modeling
Memon, et al. [41]	Multinational (LMICs)	Retrospective cohort	Pediatric cancers	ICU data	Regression analysis
DeBoer, et al. [42]	Rwanda	Retrospective cohort study	Cervical cancer	Hospital data	Outcome analysis
Chikandiwa, et al. [43]	South Africa	Registry study	HPV-related cancers	Registry	Trend analysis
Nartey, et al. [44]	Ghana	Cohort	Cervical cancer	Hospital data	Survival analysis
Obel, et al. [45]	Pacific Region	Systematic review	Cervical cancer	Published literature	Descriptive synthesis
Turkistanli, et al. [46]	Turkey	Narrative review	Cervical cancer	Published literature	Descriptive analysis
Francis [47]	Global	Narrative review	Maternal cancers	Global reports	Conceptual analysis
Srivatanakul, et al. [48]	Multinational (Asia)	Review	Liver cancer	Published literature	Descriptive epidemiology

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Author (Year)	Country /Region	Study Design	Cancer Type	Data Source	Statistical Methods
Solikhah and Nurdjannah [49]	Multinational (Asia)	Systematic review	Breast cancer	Published literature	Systematic synthesis
Juneja, et al. [50]	India	Narrative review / risk factor survey	Cervical cancer	Literature review	Descriptive analysis
Dhar, et al. [51]	Multinational (LMICs)	Review	Multiple cancers	Published literature	Descriptive analysis
Yiheyis, et al. [52]	Ethiopia	Cross-sectional study	Cervical cancer	Female university students	Descriptive statistics and logistic regression
Nene, et al. [53]	India	Observational	Cervical cancer	Trial data	Multivariate analysis
Teame, et al. [54]	Ethiopia	Case-control	Cervical cancer	Hospital data	Logistic regression
Thulaseedharan, et al. [55]	India	Cohort	Cervical cancer	Cohort data	Regression analysis
Ohno, et al. [56]	Multinational (Asia)	Clinical trial	Nasopharyngeal cancer	Trial data	Survival analysis
El Saghir, et al. [57]	Arab countries	Registry analysis	Breast cancer	Registry	Trend analysis
Seckinger, et al. [58]	Multinational	Clinical trial analysis	Multiple myeloma	Trial data	Survival analysis
Agide, et al. [59]	Ethiopia	Cross-sectional	Breast cancer	Survey	Logistic regression
Kutz, et al. [60]	Madagascar	Cross-sectional	Cervical cancer	Field data	Regression analysis
Halder, et al. [61]	India	Observational study	Multiple cancers	Registry	Regression analysis
Desalegn, et al. [62]	Ethiopia	Cross-sectional	Multiple cancers	Hospital data	Logistic regression
Amanat, et al. [63]	Pakistan	Cross-sectional	Oral cancer	Hospital data	Regression analysis
Singh, et al. [64]	India	Descriptive epidemiological	Cervical cancer	National data	Descriptive analysis
Colney, et al. [65]	India	Prospective cross-sectional	Cervical cancer	Clinical samples	ROC curve and Logistic regression

LMICs: Low- and middle-income countries
ML: Machine learning

Geographical distribution and study contexts

The included studies demonstrated strong geographical diversity, with substantial representation from sub-Saharan Africa (e.g., Ethiopia, Kenya, Uganda, Ghana, Cameroon, and Sudan) [22, 32, 33, 59, 58]. South and Southeast Asia (e.g., India, Malaysia, Vietnam, and Bangladesh) [49, 50, 56] and Latin America (e.g., Brazil, Colombia, Argentina, and Caribbean countries) [36, 37, 39]. Several multinational and global analyses have further enriched the dataset, particularly in areas such as modeling, survival analysis, and health systems research [40, 45].

Study designs and methodological approaches

The review focused on a heterogeneous mix of study designs. More specifically, a large proportion of the included studies used various observational designs, such as cross-sectional surveys, case-control, and retrospective or prospective cohort

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analyses. However, cross-sectional studies were more commonly used in analyses of screening uptake, awareness, and behavioral risk factors, while case-control and cohort analytical methods were several times more frequently applied in assessing risk factors and survival outcomes [23, 40].

The review included a heterogeneous range of study designs, predominantly observational studies such as cross-sectional surveys, case-control studies, and retrospective or prospective cohort analyses. Cross-sectional studies were more commonly used to assess screening uptake, awareness, and behavioral risk factors, whereas cohort and case-control designs were frequently applied to evaluate risk factors and survival outcomes [50, 54]. In addition, several studies applied advanced methodological approaches, including multilevel modeling to assess hierarchical determinants of screening and health inequalities [53], discrete choice experiments to evaluate patient preferences and healthcare decision-making [24], and simulation and mathematical models to assess screening strategies and policy interventions [40].

Cancer types and research focus

The distribution of cancer types across studies was uneven. Most studies focused on: Cervical cancer is the most frequently studied, reflecting its high burden and preventability in LMICs [51, 53, 55]; breast cancer is widely studied in relation to risk factors, survival, and health system challenges [26, 49]; and liver cancer and nasopharyngeal cancer are less frequently represented but still significant in specific regions [29, 56].

Data sources and population characteristics

(Table 1) indicates that the primary data sources for most of the included studies were hospital-based datasets, cancer registries, and population-based surveys [37, 57]. Registry-based data served as the main source for trend analyses and survival estimation, whereas hospital-based datasets were primarily intended to provide information on clinical outcomes and treatment-related factors [31, 39, 61]. In contrast, survey-based data were generally used to assess knowledge, attitudes, practices, and access to services.

The study populations were also diverse and included general adult populations [30, 65], women of reproductive age [50], patients with cancer undergoing treatment, survivors and their informal caregivers, as well as vulnerable subgroups [34, 64].

Key variables and outcomes

Based on the selected studies, multiple variables and outcomes were examined to reflect the complex nature of cancer epidemiology and management (Table S1). Frequently examined variables included sociodemographic, behavioral, reproductive, and clinical factors [27, 29, 61]. Moreover, clinical characteristics invariably included the stage of cancer at diagnosis and types of treatment, along with health system–related factors such as access to care, health system performance, and financial barriers [28]. Concerning the outcomes, most studies were concerned with cancer incidence and mortality rates; screening and early detection levels; prognosis; and access to, adherence to, and timing of treatment [31]. Finally, many studies focused on the economic risk of cancer and broader indicators of health system performance.

Quality assessment and risk of bias results

The NOS for observational research, with modifications suitable for cross-sectional and non-comparative designs, was used to examine the methodological quality of the included research (Table S1). An evaluation of each study included the following aspects: how participants were selected, the comparability between the groups, and how the outcomes or exposures were ascertained. (Figure 2) summarizes the methodological quality assessment of the included studies. Overall, 76% of studies were rated as excellent quality, 22% as moderate quality, and 2% as poor quality. Moderate-quality studies commonly showed inadequate adjustment for confounding variables, whereas poor-quality studies were mainly affected by selection bias, lack of control groups, and incomplete reporting of key variables.

Several common sources of bias were identified across the studies. Selection bias was evident, particularly in hospital-based studies that may not represent the broader population [33]. Information bias was also noted, especially in studies relying on self-reported data. In addition, confounding remained a concern where socioeconomic or clinical variables were not fully accounted for [33]. Outcome misclassification was another issue, particularly in studies lacking standardized diagnostic criteria or validated registry data.

Despite the presence of incomplete records and potential sources of bias, the overall body of evidence was considered sufficiently robust for qualitative synthesis. High-quality cohort studies, randomized trials, and well-designed case-control studies provided reliable evidence on survival outcomes, screening effectiveness, and risk prediction [35, 40]. Nevertheless, substantial heterogeneity across studies was likely influenced by structural limitations in LMICs, including inadequate data systems, underdeveloped cancer registries, and limited research infrastructure [37, 45, 57]. These findings highlight the need to strengthen data quality, reporting standards, and research capacity in LMIC-based cancer epidemiology studies [31, 39, 65].

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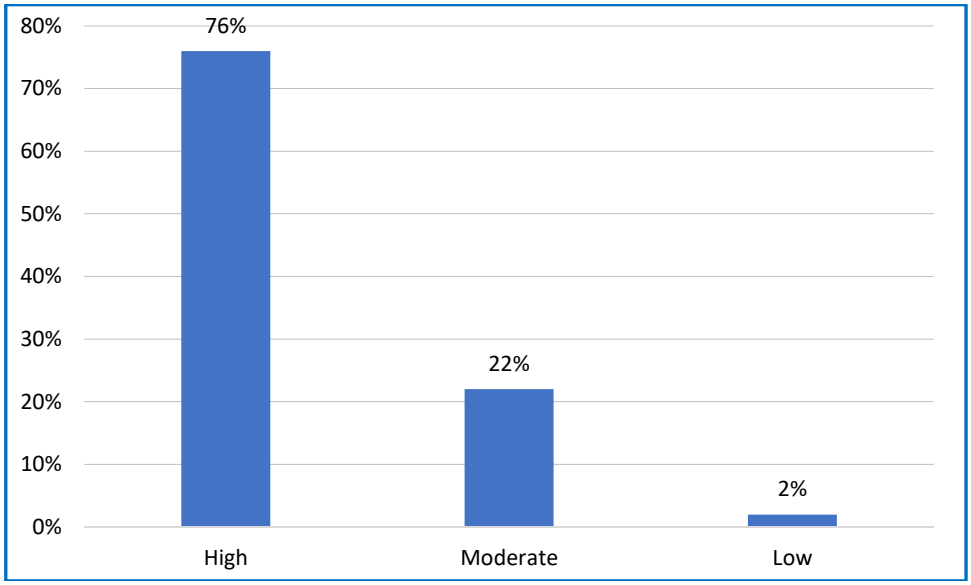

Figure 2. Quality assessment of included studies

Main findings and evidence synthesis

This section synthesizes the key findings across the 46 included studies, highlighting consistent patterns in cancer epidemiology, risk factors, screening behaviors, treatment access, and outcomes in LMICs (Table S1).

Burden and epidemiological trends

Across the included studies, cancer burden in LMICs was substantial and showed marked regional disparities. Cervical and breast cancers were reported most frequently in terms of morbidity and the most significant in terms of public health [27, 36, 42, 44, 50].

The included studies demonstrated a high and increasing burden of cancer-related morbidity and mortality across LMICs, particularly in Sub-Saharan Africa and South Asia [38, 65]. This trend was associated with the growing impact of noncommunicable diseases driven by demographic and epidemiological transitions [45, 47, 51]. Regional variations were also observed, especially in tropical and subtropical areas where infection-related cancers linked to HPV and HBV/HCV infections were more prevalent [21, 48, 60]. Despite some improvements in awareness and early detection in selected settings, the overall trend suggests that cancer control efforts remain insufficient in many LMICs [21, 53].

Risk factors and determinants of cancer

The included studies identified multiple interrelated risk factors contributing to cancer burden in LMICs. Sociodemographic factors such as low education, low income, and rural residence were consistently associated with increased cancer risk, delayed diagnosis, and poorer survival outcomes among underserved populations [30, 59]. Gender inequality and disparities in healthcare access further limited the utilization of screening and treatment services in many LMIC settings [47, 53].

Behavioral and reproductive factors were also frequently reported, particularly in studies of cervical and breast cancer. Commonly identified determinants included early marriage, early childbearing, high parity, reproductive history, and low screening uptake [50, 52, 59]. In addition, lifestyle and environmental exposures contributed to the risk of several cancers, including stomach and liver cancer [29, 48].

Biological and clinical factors also played a major role in cancer burden and outcomes. Infection-related cancers associated with HPV, schistosomiasis, and HBV/HCV infections were commonly reported [48, 60]. Moreover, late-stage diagnosis was strongly associated with reduced survival and poorer treatment outcomes [22, 26, 44]. Overall, these findings highlight the complex interaction between biological, behavioral, socioeconomic, and health system–related determinants of cancer in LMIC populations.

Screening and early detection

Despite the differences in analyzed issues and approaches, low uptake of cancer screening, especially for cervical and breast cancer, remains a major and widely recognized concern. The problem was frequently exacerbated by limited awareness of cancer prevention, cultural barriers, stigma, financial hardship, inadequate insurance coverage, weak primary healthcare systems, and limited screening infrastructure [21, 45, 59]. The review also revealed the impact of socio-economic inequality and education level, as well as geographic access, on screening utilization [20, 61]. Evidence suggests that community-based and primary care-driven programs significantly increase participation, especially when paired with educational interventions and increased professional engagement. Furthermore, a review of preferences revealed the

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critical importance of affordability, access, and a patient-centered approach. However, the problem persists, and the screening is too low to reduce the incidence of late diagnosis in most LMICs [24, 34, 65].

Diagnosis, treatment access, and health system barriers

The synthesized evidence highlighted major barriers to timely diagnosis and treatment initiation. As shown in the studies, several studies reported substantial delays between symptom onset, diagnosis, and treatment initiation due to weak referral systems and limited diagnostic capacity [22,61]. This, in turn, led to severe social effects and, in some cases, treatment discontinuation and financial hardship [27, 32].

In addition, the results of multiple studies have shown the effects of institutional readiness, social health insurance cooperation, medical care, and financial access to facilities and the patient survival outcomes based on the accessibility indicators and the final outcome of patient survival [23, 33, 39]. Therefore, the development of a health system is critical to ensure effective, accessible, equitable cancer care in LMIC settings [45, 47].

Survival outcomes and prognostic factors

Studies across LMICs consistently reported poor survival outcomes, particularly for cervical and breast cancers [26, 31]. Cancer stage at diagnosis was identified as the strongest prognostic factor, with early detection associated with improved survival [22]. Treatment-related factors, including access to chemotherapy, surgery, and radiotherapy, as well as socioeconomic conditions, also influenced patient outcomes [35, 39, 61]. Despite some improvements associated with integrated care approaches, substantial survival disparities persist across LMIC settings, highlighting the importance of timely diagnosis and equitable access to cancer care [44, 47].

Distribution of statistical methods

The distribution of statistical methods across the included studies (n = 46) demonstrated a predominance of traditional analytical approaches, with a gradual but limited integration of advanced computational methods. Overall, the methodological profile showed strong reliance on descriptive statistics, logistic regression, survival analysis, and trend analysis [21, 38, 39]. More advanced analytical approaches, including ML, simulation modeling, and artificial intelligence–based methods, were identified in a smaller subset of studies [28, 30].

Conventional statistical methods

Most studies employed conventional statistical techniques, particularly descriptive and regression-based analyses. Descriptive statistics, including frequencies, proportions, means, and standard deviations, were widely used to summarize participant characteristics and outcome distributions [50, 65]. Logistic regression was the most frequently applied inferential method for assessing associations between risk factors and cancer-related outcomes [21, 28, 58]. In addition, chi-square tests and t-tests were commonly used for bivariate analyses, especially in cross-sectional studies [52, 65]. These methods were predominantly applied in hospital-based and cross-sectional investigations examining screening uptake, awareness, behavioral risk factors, and clinical outcomes [21, 52]. Their widespread use likely reflects their interpretability and suitability for relatively small or less complex datasets commonly available in LMIC settings [29, 50, 63].

Use of survival analysis techniques

A considerable proportion of cohort- and registry-based studies applied survival analysis methods to evaluate time-to-event outcomes. The most frequently used techniques included Kaplan–Meier survival estimation and Cox proportional hazards regression models [26, 31, 34]. These approaches were mainly used to assess overall survival, disease-free survival, and prognostic factors, particularly in studies focusing on breast and cervical cancers [26, 27, 31]. The increasing application of survival analysis reflects growing attention to longitudinal outcomes and patient prognosis in LMIC-based cancer research [34, 44, 58].

Emerging use of advanced and computational methods

A smaller but notable group of studies applied advanced analytical approaches, including ML algorithms for classification and predictive modeling [20, 28. 58], simulation and mathematical models for evaluating screening strategies and policy interventions [25, 34], and discrete choice experiments to assess patient preferences and healthcare decision-making [24, 35].

Although these approaches demonstrated enhanced analytical depth and predictive capability, their use remained relatively limited and was often restricted to specific research settings or secondary data sets [20, 28, 61]. This suggests that advanced computational methods are emerging within LMIC-based cancer research but have not yet been widely integrated into routine epidemiological practice [40, 45].

Discussion

This systematic review synthesizes evidence from 46 studies examining cancer epidemiology in LMICs, offering a comprehensive assessment of methodological practices, epidemiological patterns, and health system constraints. The

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findings reveal a field that is expanding in scope but uneven in methodological sophistication, with important implications for research, policy, and practice.

Methodological landscape: Progress with persistent gaps

The key outcome of this review is the identification of a clear methodological gradient in LMIC-based cancer research. The dominance of traditional methods, such as cross-sectional design and logistic regression models, appears to be persistent across most studies [21. 22, 29], but there is an emerging trend concerning more advanced approaches, including survival analysis, multilevel modeling, simulation modeling, and ML techniques [23, 25, 26, 28, 30]. At the same time, the use of these advanced methods remains relatively rare and unevenly distributed. Most applications are concentrated in a limited number of settings and often rely on secondary rather than routine health system data [37, 39]. In this sense, methodological advancement appears partially disconnected from field-level implementation needs, particularly under resource-constrained health systems [45].

This gap is fundamentally important from a policy perspective, as without robust longitudinal data systems, causal inference frameworks, and predictive analytics, policymakers lack adequate tools for designing evidence-based, efficient, and context-specific cancer control strategies [23, 30]. Thus, strengthening methodological capacity and data infrastructure should be prioritized within both national and international health agendas to support more effective cancer epidemiology and control in LMICs [25, 45, 47].

Epidemiological patterns and inequalities

The review confirms that cervical and breast cancers dominate the research landscape in LMICs, reflecting their high burden and public health relevance [52, 57, 65]. Several consistent epidemiological patterns emerged across studies. Late-stage diagnosis was common and was largely driven by limited screening coverage, low awareness, and structural barriers to care [21, 22]. Survival outcomes remained substantially lower than those reported in high-income countries [26, 34, 39]. In addition, socioeconomic, geographic, and gender-based inequalities significantly influenced cancer risk, healthcare access, and survival outcomes [30, 47, 61]. These findings make it prominent that cancer in LMICs is a social phenomenon rather than merely a biomedical concern. Education and income disparities result in unequal access to cancer care, leading to preventable mortality [30, 32]. Of note is the evidence that modifiable system-related factors—such as the availability of screening, early detection programs, and timely treatment—can substantially improve outcomes [40, 45, 53]. This further emphasizes the importance of well-developed health systems as a cornerstone of effective cancer control in LMIC settings.

Health system constraints and policy implications

A recurring finding across the included studies was the limited capacity of health systems in LMICs to effectively prevent, diagnose, and manage cancer. Common challenges included low screening uptake, delayed diagnosis, limited access to specialized treatment services, high out-of-pocket healthcare costs, and weak palliative care infrastructure [32, 38, 47, 61]. These constraints contribute to late presentation, poor survival outcomes, and increased cancer-related mortality [26, 57]. The findings emphasize the need for comprehensive cancer control strategies in LMICs, including expansion of population-based screening programs, strengthening cancer registries and health information systems, reducing financial barriers through universal health coverage mechanisms, and improving access to treatment and palliative care services, particularly in underserved areas [37, 51, 63]. In addition, evidence on facility-level and system-level determinants highlights the importance of quality improvement initiatives and standardized care pathways to reduce disparities and improve cancer outcomes [23, 38].

Emerging role of advanced analytics

The incorporation of ML, AI, and simulation modeling studies indicates a critical transformation in the field [20, 25, 28]. These methods have substantial potential to provide early detection and prediction of risks [20], personalized treatment planning, and optimized screening strategies [25, 40] as well as health system performance evaluation [23, 3]. Nevertheless, their implementation remains limited because of inadequate data infrastructure and limited technical capacity, as well as the failure to integrate these applications into clinical workflows in LMICs [20, 28, 61]. These findings highlight the need for investment in interoperable datasets, digital health infrastructure, and capacity building in data science and advanced analytics [45, 47].

Strengths and limitations of the review

This review has several important strengths. To our knowledge, it represents one of the first comprehensive syntheses of statistical methods and epidemiological findings in cancer research across LMICs. The review included studies from diverse geographic regions, providing broad representation of different cancer burdens, healthcare systems, and research settings. Another major strength was the inclusion of methodological quality assessment, which enabled evaluation of the robustness and potential risk of bias of the included studies. Furthermore, the review integrated both epidemiological and statistical perspectives, allowing a more comprehensive understanding of cancer patterns, risk factors, survival outcomes, and analytical practices in LMIC-based cancer research.

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The review also has several constraints and limitations. The substantial heterogeneity apparent in study designs, methodologies, and reported outcomes made it difficult to complete a quantitative synthesis [44, 49]. Several included studies lacked complete methodological descriptions or did not report sample size details clearly, which limits reproducibility and comparability across studies [31, 38, 64]. Several portions of the registry-based and hospital-based data on oncology findings are less generalizable to the overall population level [47, 57]. These constraints are highly significant since the current review aimed to summarize LMIC evidence on the underassessed cancer care settings. These limitations reflect the broader structural and resource constraints affecting cancer research and care delivery in many LMIC settings.

Conclusion

This systematic review provides a synthesis of the cancer epidemiology research on LMICs. It demonstrates that more and more investigations are performed to address existing challenges despite the same identification of methodological and structural limitations. Despite certain disparities between the reviewed articles, the dominant methodology featured the use of traditional statistical approaches of descriptive analysis and regression modeling. At the same time, a certain positive trend is to be noted regarding the gradual employment of survival modeling, multilevel analysis, and ML applications.

There are several reasons for this lack, and one of them is that the emerging analytical approaches, although they show great promise to enhance existing prediction, risk stratification, and policy evaluation, have not been extensively applied and integrated into standard cancer research and health systems development. The methodological translation into practice is the first and foremost bottleneck on the path of cancer epidemiology improvement in low-resource countries. Furthermore, LMICs should focus on bolstering a coordinated approach. Among the primary measures to consider are the improvement of cancer registries and HISs, the increased capacity for advanced analytics using statistics and computation, and the promotion of equal access to preventative, early detection, and treatment services.

In conclusion, methodological advances must be reconciled with the real-world context for the epidemiology of cancer to advance from novel concept to actionable strategy. If the above is not addressed, it is doubtful that the disparities in cancer metrics between LMICs and HICs will be mitigated, and the success in achieving equity and control will fall short.

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Conflicts of interest

The authors have no conflicts of interest relevant to this article.

Declaration of Generative AI and AI-Assisted Technologies

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