BAYESIAN INFERENCE AS A TOOL FOR REDUCING DIAGNOSTIC UNCERTAINTIES IN CANCER

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Abstract

The increasing complexity of oncological diagnosis, associated with tumor heterogeneity and limitations of traditional methods, highlights the need for approaches capable of reducing clinical uncertainties and improving decision-making. In this context, Bayesian inference emerges as a relevant tool by enabling the integration of prior probabilities with new clinical evidence. This study aimed to analyze the application of Bayesian inference in reducing diagnostic uncertainties in cancer through an integrative literature review. The search was conducted in the SciELO, PubMed, and Scopus databases, considering publications from 2021 to 2026 in Portuguese, English, and Spanish. Studies addressing the use of Bayesian methods in diagnosis, prognosis, and clinical trials in oncology were included. The results demonstrated that Bayesian inference significantly enhances clinical reasoning by allowing continuous updating of diagnostic probabilities and reducing cognitive biases. Furthermore, its application in predictive models, survival analysis, and adaptive clinical trials showed greater methodological flexibility and statistical robustness, especially in scenarios involving high uncertainty and small sample sizes. Its role in precision oncology was also highlighted, particularly in integrating clinical and molecular data to support personalized care. It is concluded that Bayesian inference represents a promising approach to improve oncological diagnosis, contributing to more accurate and evidence-based clinical decisions.

Keywords: Bayesian Inference, Cancer, Diagnosis, Diagnostic Uncertainty, Oncology.

INTRODUCTION

The complexity inherent to oncological diagnosis represents one of the greatest contemporary challenges in the field of health, especially due to the biological variability of tumors, the clinical heterogeneity of patients, and the limitations of traditional diagnostic methods. In this context, clinical decision-making often occurs under conditions of uncertainty, which may compromise diagnostic accuracy and, consequently, the effectiveness of therapeutic interventions. Evidence-based medicine has sought strategies to minimize such uncertainties, among which the use of advanced probabilistic approaches stands out, such as Bayesian inference, which allows the integration of prior information with current clinical data to improve diagnostic reasoning (Sousa; Aguiar, 2022).

Bayesian inference is grounded in Bayes' theorem, which enables the continuous updating of probabilities as new evidence is incorporated into the decision-making process. This approach has been widely discussed as both a pedagogical and practical tool in the clinical context, promoting greater diagnostic accuracy by considering both pre-test probability and the results of complementary examinations (Lorca; Aguila, 2024). In addition, its applicability goes beyond teaching, being incorporated into clinical studies and advanced statistical models, which reinforces its relevance in contemporary medicine, especially in complex areas such as oncology (Taylor et al., 2025).

In this sense, Figure 1 illustrates the probabilistic updating process characteristic of Bayesian inference, highlighting the relationship between prior knowledge, observed evidence, and posterior probability in the diagnostic context.

Figure 1

Diagram of Bayesian Inference in the Diagnostic Process

$$P(H \mid E) = \frac{P(E \mid H) \cdot P(H)}{P(E)}$$

Source: A matemática por trás das decisões clínicas *[The mathematics behind clinical decisions]* (2024)

Bayesian inference, represented in Figure 1, is based on the continuous updating of probabilities as new evidence is incorporated into the analytical process. From this perspective, the posterior probability P(H/E) expresses the chance that a hypothesis H is true after the observation of evidence E, being calculated from the prior probability P(H), which reflects initial knowledge, and the likelihood P(E/H), which indicates the degree of compatibility between the observed evidence and the hypothesis considered. The term P(E), in turn, acts as a normalization factor, ensuring that the resulting probabilities are consistent within the model.

The application of Bayesian inference to cancer diagnosis has proven particularly promising, as it enables the integration of multiple sources of data, including laboratory tests, imaging findings, genomic information, and the patient's clinical history. Recent evidence indicates that Bayesian models are capable of increasing accuracy in prognostic prediction and early detection of neoplasms, favoring more assertive clinical decisions (Chu et al., 2022; Teng et al., 2022). Furthermore, the use of dynamic and adaptive models allows monitoring disease progression over time, continuously adjusting risk estimates (Zhou et al., 2021).

Another relevant aspect concerns the ability of Bayesian inference to deal with scenarios characterized by small samples and incomplete data, a recurrent situation in oncological studies, especially in rare cancers or in early phases of clinical investigation. In this context, the incorporation of prior evidence and the use of methods such as information borrowing become essential to increase the robustness of analyses and reduce the uncertainty associated with estimates (Sondhi et al., 2021; Su et al., 2022). This characteristic gives the Bayesian approach a significant advantage over traditional frequentist methods, which generally depend on large samples to ensure statistical validity.

Additionally, Bayesian inference has been widely applied in the development and analysis of clinical trials in oncology, contributing to the construction of more flexible and efficient experimental designs. Bayesian models allow adaptations throughout the study, such as dose adjustments, early stopping for efficacy or futility, and incorporation of external data, optimizing the process of developing new therapies (Chen et al., 2022; Song; Wen, 2023). At the same time, innovative approaches, such as Bayesian generative models and informed survival analyses, have expanded the possibilities for understanding tumor dynamics and therapeutic response (Pourzanjani et al., 2024; Bartoš et al., 2022).

Within the scope of precision oncology, the integration of multi-omics data with Bayesian models has enhanced care personalization, enabling more accurate identification of biomarkers and patient stratification. This approach favors individualized therapeutic decisions contributing to the reduction of uncertainties and increased clinical effectiveness (Correa-Aguila et al., 2022). Complementarily, Bayesian tools have been incorporated into clinical decision-making environments, such as tumor boards, assisting professionals in interpreting complex data and defining more appropriate management strategies (Pasetto et al., 2021).

Moreover, Bayesian analysis has been employed in the evaluation of therapeutic interventions, including radiotherapy and pharmacological regimens, providing a more in-depth understanding of treatment effects in real-world contexts (Fornacon-Wood et al., 2022). The use of advanced predictive models, such as deep Bayesian networks and survival models with multiple change points, reinforces the potential of this approach in anticipating clinical outcomes and reducing prognostic uncertainties (Zhang et al., 2022; Xu, 2026).

Another relevant point concerns the applicability of Bayesian inference in the validation of health instruments and metrics, as evidenced by the use of the Bayesian omega coefficient, which contributes to greater precision in assessing the reliability of clinical and psychometric measures (Banos-Chaparro; Caycho-Rodriguez, 2024). This methodological advance strengthens the quality of evidence used in diagnostic and therapeutic processes, increasing the safety of clinical decisions.

In view of this context, it is observed that Bayesian inference has become established as a robust and versatile tool in reducing diagnostic uncertainties in cancer by integrating different sources of information and promoting a more dynamic, adaptive, and personalized approach to clinical practice. Its application ranges from individual clinical reasoning to the development of clinical trials and complex predictive models, highlighting its significant impact on contemporary oncology.

Thus, the present study aims to analyze the application of Bayesian inference as a tool for reducing diagnostic uncertainties in cancer, highlighting its contributions to improving clinical reasoning, decision-making, and diagnostic accuracy in the oncological context.

METHODOLOGY

This is an integrative literature review, qualitative in nature and with a descriptive-analytical approach, whose objective was to gather, analyze, and synthesize scientific evidence regarding the application of Bayesian inference as a tool for reducing diagnostic uncertainties in cancer. The choice of this type of review is justified by its ability to integrate results from studies with different methodological designs, enabling a comprehensive understanding of the investigated phenomenon and contributing to the consolidation of knowledge in the area.

The conduct of the study was guided by the following stages: (1) identification of the theme and development of the guiding question; (2) definition of inclusion and exclusion criteria; (3) establishment of the search strategy; (4) selection of studies; (5) analysis and interpretation of results; and (6) synthesis of knowledge. These stages were systematically organized, ensuring methodological rigor and reproducibility.

The guiding question that directed this review was: “How has Bayesian inference been applied to reduce diagnostic uncertainties in cancer in the clinical context and in oncological research?” This question was structured to encompass both practical applications in clinical reasoning and the use of Bayesian models in diagnostic and prognostic studies.

The search for studies was conducted in the Scientific Electronic Library Online (SciELO), PubMed, and Scopus databases, recognized for their relevance and scope in the health field. Controlled and uncontrolled descriptors were used, combined by Boolean operators AND and OR, in Portuguese, English, and Spanish. The main descriptors employed were: “Inferência Bayesiana,” “Bayesian Inference,” “Diagnóstico,” “Diagnosis,” “Câncer,” “Cancer,” “Oncologia,” “Oncology,” “Incerteza Diagnóstica,” and “Diagnostic Uncertainty.” The search strategy was adapted according to the specificities of each database, aiming to broaden the sensitivity and scope of study retrieval.

The inclusion criteria were: (a) scientific articles published between 2021 and 2026; (b) studies available in full text; (c) publications in Portuguese, English, or Spanish; (d) research addressing the application of Bayesian inference in diagnosis, prognosis, or decision-making in oncology; and (e) studies with diverse methodological designs, including clinical trials, observational studies, reviews, and statistical modeling.

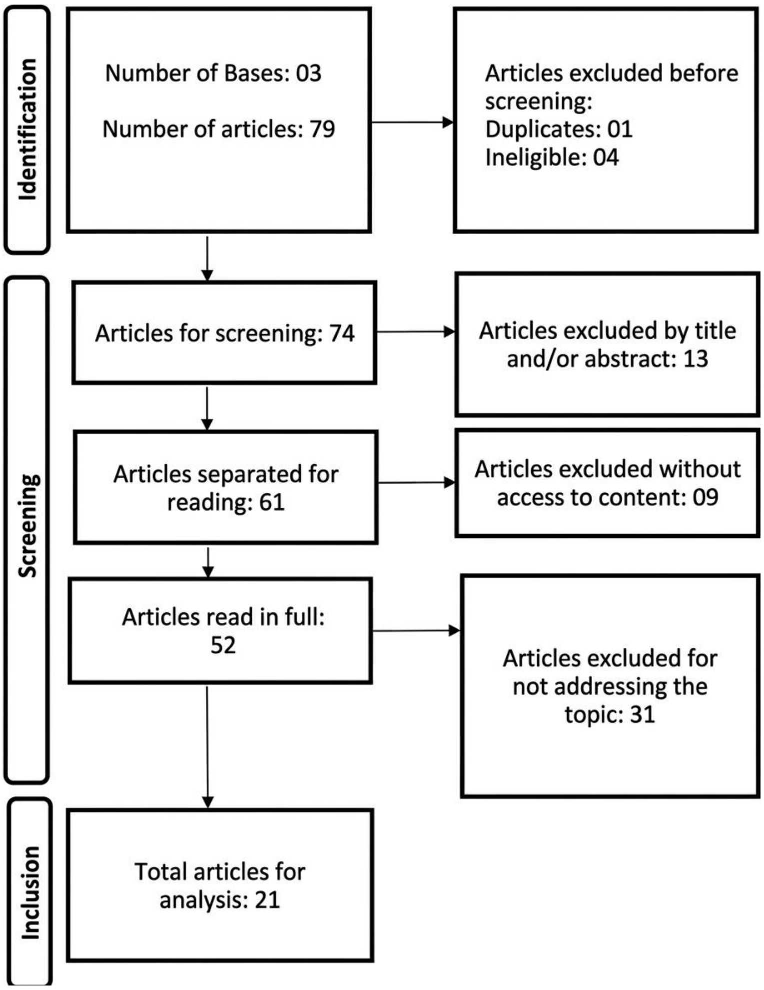
The exclusion criteria were: (a) duplicate articles; (b) studies that did not answer the guiding question; (c) incomplete publications, such as abstracts, editorials, letters to the editor, and expert opinions without methodological support; and (d) studies whose focus was not directly related to the use of Bayesian methods in oncology.

The study selection process occurred in three stages: initially, titles and abstracts were read to identify potential relevance; subsequently, the full texts of preselected articles were read; finally, studies that met all established criteria were included in the final sample. To ensure greater rigor, selection was conducted carefully, prioritizing studies with higher levels of evidence and scientific relevance.

In this context, Figure 2 presents the flowchart of the study selection process, detailing the stages of identification, screening, eligibility, and inclusion, according to the criteria established in this review.

Figure 2

Flowchart of the Study Selection Process



Source: Authors (2026)

Data analysis was conducted through critical reading and interpretation of the included studies, followed by the organization of information into thematic categories aligned with the research objectives. Aspects such as study type, application of Bayesian inference, clinical context, contributions to oncological diagnosis, and the main limitations identified by the authors were considered. This approach enabled the identification of patterns, gaps, and advances in the use of Bayesian methods in oncology.

Finally, the synthesis of results was carried out in a narrative and analytical manner, articulating findings from different studies and highlighting the contributions of Bayesian inference to reducing diagnostic uncertainties in cancer. The methodological rigor adopted throughout all stages aims to ensure the reliability of the presented results and their relevance to clinical practice and future research in the field.

RESULTS AND DISCUSSION

The analysis of the selected studies revealed that the application of Bayesian inference in the oncological context has expanded significantly in recent years, particularly with respect to reducing diagnostic uncertainties, improving clinical reasoning, and developing more robust predictive models. The included studies exhibited methodological diversity, encompassing clinical trials, statistical modeling, observational studies, and theoretical reviews, reinforcing the versatility of the Bayesian approach in contemporary oncology. Overall, the findings point to three main axes of application: (1) support for diagnostic reasoning and clinical decision-making; (2) development of prognostic and predictive models; and (3) optimization of clinical trials and evaluation of therapeutic interventions. These axes reflect the breadth of use of Bayesian inference, from the individual patient level to the planning of complex clinical research.

In this context, Table 1 synthesizes the main characteristics of the analyzed studies, including authors, year of publication, type of study, and main contributions related to the use of Bayesian inference in oncology.

Table 1

Characterization of the Studies Included in the Review

Author/Year	Application Context	Analytical Synthesis of Contributions
Sousa; Aguiar (2022)	Medical education and clinical reasoning	Structuring of probabilistic clinical reasoning, integrating deduction and induction in a Bayesian approach applied to decision-making
Lorca; Aguila (2024)	Clinical diagnosis	Application of Bayes' theorem to enhance clinical judgment and reduce cognitive biases
Cerda *et al.* (2025); Taylor *et al.* (2025)	Clinical trials	Consolidation of Bayesian analysis as a more flexible and clinically meaningful interpretive alternative in experimental studies
Sondhi et al. (2021); Su et al. (2022)	Small samples and data integration	Strengthening inference in scenarios of high uncertainty through the incorporation of external evidence (information borrowing)
Chen et al. (2022); Song; Wen (2023)	Oncological clinical trials	Development of Bayesian adaptive designs, expanding efficiency and methodological flexibility
Chu et al. (2022)	Cancer prognosis	Integration of clinical and molecular data to construct more accurate prognostic models
Teng et al. (2022); Zhang et al. (2022)	Oncological prognosis	Use of dynamic models and deep Bayesian networks to improve the prediction of clinical outcomes
Zhou et al. (2021); Bartoš et al. (2022)	Survival models	Application of Bayesian averaging and informed models for greater robustness in the analysis of longitudinal data
Yao et al. (2023)	Immuno-oncology	Integrated longitudinal modeling for the analysis of complex clinical outcomes
Fornacon-Wood et al. (2022); Pourzanjani et al. (2024); Xu (2026)	Tumor dynamics and interventions	Expanded understanding of tumor evolution and therapeutic effects through advanced Bayesian models
Pasetto et al. (2021); Correa-Aguila et al. (2022); Agema et al. (2025)	Precision oncology and clinical decision-making	Integration of complex data and support for personalized clinical decision-making in multidisciplinary settings
Banos-Chaparro; Caycho-Rodriguez (2024)	Instrument validation	Application of the Bayesian omega coefficient for greater precision in assessing the reliability of measures

Source: Authors (2026)

From the analysis of the studies, it was found that Bayesian inference has been widely used as a tool to support clinical reasoning, enabling the integration of prior probabilities with new diagnostic evidence. According to Sousa and Aguiar (2022), this approach contributes to the development of more structured clinical reasoning by articulating deductive and inductive elements within a dynamic probabilistic model. Corroborating this perspective, Lorca and Aguila (2024) emphasize that applying Bayes' theorem in the diagnostic process favors more grounded decisions, reducing cognitive biases and increasing clinical accuracy.

With regard to prognostic models, the analyzed studies demonstrate significant advances in the use of Bayesian methods for predicting cancer outcomes. Chu et al. (2022) show that these models allow integration of clinical and molecular data, resulting in more accurate prognostic estimates. Complementarily, Teng et al. (2022) present a dynamic Bayesian model applied to breast cancer, capable of continuously updating survival predictions based on new clinical data. In the same context, Zhang et al. (2022) highlight the use of deep Bayesian networks, which expand the capacity to model complex relationships among clinical variables.

Another relevant aspect concerns the application of Bayesian inference in oncological clinical trials. Taylor et al. (2025) emphasize that this approach allows greater flexibility in experimental designs, enabling adaptations during the study based on emerging evidence. Chen et al. (2022) highlight the use of two-stage designs that optimize therapeutic efficacy evaluation, while Song and Wen (2023) point to the relevance of innovative designs in neuro-oncology. In addition, Cerda et al. (2025) emphasize that Bayesian analysis of clinical trials provides more intuitive interpretations of results, facilitating clinical decision-making.

The studies also highlight the importance of Bayesian inference in analyzing data with small samples and high uncertainty. Sondhi et al. (2021) demonstrate that incorporating additional evidence improves estimate robustness, while Su et al. (2022) discuss information borrowing methods as strategies to integrate data from different sources. Zhou et al. (2021) complement this analysis by presenting mediation models based on Bayesian averaging, enabling understanding of complex relationships among variables in survival studies.

Furthermore, Bayesian inference has been applied to the evaluation of therapeutic interventions and modeling of tumor dynamics. Fornacon-Wood et al. (2022) highlight its usefulness in analyzing real-world radiotherapy data, while Pourzanjani et al. (2024) present generative models capable of estimating tumor evolution from published data. Xu (2026) reinforces this approach by proposing survival models with multiple change points, expanding the ability to detect relevant clinical patterns.

In the field of precision oncology, Correa-Aguila et al. (2022) demonstrate that integrating multi-omics data with Bayesian models allows greater accuracy in biomarker identification, contributing to treatment personalization. Pasetto et al. (2021) complement this perspective by demonstrating the applicability of Bayesian frameworks in tumor boards, supporting multidisciplinary clinical decision-making.

Additionally, Bartoš et al. (2022) emphasize the importance of informed Bayesian survival analysis, while Yao et al. (2023) present predictive averaging models applied to immuno-oncology clinical trials. Agema et al. (2025) point to the application of Bayesian models in dose optimization in oncology, reinforcing the relevance of this approach in clinical practice.

Finally, Banos-Chaparro and Caycho-Rodriguez (2024) demonstrate the application of the Bayesian omega coefficient in validating health instruments, contributing to greater precision in measuring clinical and psychometric variables.

Table 2 presents a synthesis of the main contributions of Bayesian inference in oncology, organized by thematic categories identified in the analysis.

Table 2

Synthesis of the Contributions of Bayesian Inference in Oncology

Analytical Category	Application Dimension	Epistemological and Clinical Contributions
Probabilistic clinical reasoning	Integration between pre-test and post-test probability	Restructuring of the diagnostic process based on probabilistic inference, reducing cognitive biases and promoting more rational decisions
Oncological diagnosis	Integrated interpretation of clinical, laboratory, and imaging data	Expansion of diagnostic accuracy through the continuous updating of probabilities
Prognostic modeling	Prediction of survival and tumor progression	Development of dynamic and adaptive models capable of incorporating new evidence over time
Adaptive clinical trials	Planning and analysis of experimental studies	Methodological flexibilization, allowing dynamic adjustments and greater efficiency in the production of evidence
Management of uncertainty in small samples	Integration of prior and external data	Reduction of statistical variability and increase in inferential robustness
Precision oncology	Integration of multi-omics and clinical data	Therapeutic personalization based on individual biological profiles
Modeling of tumor dynamics	Longitudinal analysis and simulation of clinical scenarios	Expanded understanding of disease evolution and treatment response
Evaluation of therapeutic interventions	Analysis of efficacy in real-world contexts	Support for clinical decision-making based on probabilistic evidence
Multidisciplinary clinical decision-making	Application in tumor boards	Integration of multiple sources of knowledge and specialties
Instrument validation	Evaluation of the reliability of measures	Strengthening methodological quality and the precision of clinical inferences

Source: Authors (2026)

The analysis of the studies shows that Bayesian inference represents a paradigmatic shift in how uncertainty is understood and managed in the oncological context. Unlike traditional approaches, which often treat uncertainty as a methodological limitation, the Bayesian model incorporates it as a central element of the analytical process, allowing quantification and continuous updating. In this sense, Sousa and Aguiar (2022) emphasize that probability-based clinical reasoning favors more consistent decisions by integrating multiple sources of information in a structured manner.

The applicability of this approach to cancer diagnosis is particularly relevant given the disease's inherent complexity. Lorca and Aguila (2024) argue that using Bayes' theorem in the diagnostic process contributes to reducing cognitive biases often associated with subjective interpretation of clinical data. This perspective is reinforced by Taylor et al. (2025), who state that Bayesian analysis provides more intuitive and clinically relevant interpretations of results, facilitating decision-making.

In prognostic modeling, Bayesian inference enables significant advances in predicting clinical outcomes. Chu et al. (2022) highlight that integrating clinical and molecular data enhances predictive capacity, while Teng et al. (2022) emphasize the importance of dynamic models in continuously updating risk estimates. Moreover, Zhang et al. (2022) demonstrate that deep Bayesian networks allow modeling of complex relationships, contributing to greater prognostic accuracy.

Another relevant aspect concerns the flexibility of clinical trial designs based on Bayesian inference. Chen et al. (2022) emphasize that adaptive models allow adjustments throughout the study, optimizing resources and increasing research efficiency. Song and Wen (2023) complement this analysis by highlighting innovative designs in neuro-oncology, while Cerda et al. (2025) underscore the relevance of probabilistic interpretation of results for clinical practice.

The ability to handle small samples and incomplete data is one of the main advantages of the Bayesian approach. Sondhi et al. (2021) show that incorporating additional evidence improves analytical robustness, while Su et al. (2022) highlight the role of information borrowing in integrating data from different sources. Zhou et al. (2021) reinforce this perspective by presenting Bayesian averaging models that elucidate complex relationships in survival studies.

In precision oncology, integrating multi-omics data represents a significant advance in care personalization. Correa-Aguila et al. (2022) argue that combining multiple layers of biological information with Bayesian models allows greater accuracy in biomarker identification. Pasetto et al. (2021) add that Bayesian frameworks can be incorporated into clinical decision-making environments, promoting a more collaborative and evidence-based approach.

Furthermore, applying Bayesian inference to evaluate therapeutic interventions and model tumor dynamics expands possibilities for understanding disease progression. Fornacon-Wood et al. (2022) highlight its usefulness in real-world data analysis, while Pourzanjani et al. (2024) and Xu (2026) demonstrate advances in modeling dynamic processes and identifying clinical patterns.

Finally, the use of Bayesian metrics in instrument validation strengthens the quality of scientific evidence. Banos-Chaparro and Caycho-Rodriguez (2024) emphasize that the Bayesian omega coefficient provides greater precision in reliability assessment, contributing to safer clinical decisions.

Thus, Bayesian inference has become established as an essential tool in contemporary oncology, not only due to its ability to reduce diagnostic uncertainties, but also because it promotes a more integrated, adaptive, and patient-centered approach. Its methodological advances and practical applications point to a promising path for improving clinical practice and health research, especially in scenarios marked by high complexity and uncertainty.

CONCLUSION

This integrative review enabled a comprehensive understanding of the role of Bayesian inference as a strategic tool in reducing diagnostic uncertainties in the oncological context, highlighting its relevance in both clinical reasoning and the development of statistical models applied to healthcare practice. Revisiting the proposed objective—to analyze the application of this approach in reducing diagnostic uncertainties in cancer—the results fully address the investigated problem by demonstrating that Bayesian inference significantly contributes to improving clinical decision-making.

Regarding the guiding question, the findings indicate that its application occurs in a transversal and integrated manner, ranging from support for individual clinical reasoning to the construction of predictive models and the conduct of clinical trials. In this sense, the use of updatable probabilities allows greater precision in interpreting clinical and diagnostic data, reducing subjectivity and promoting more grounded decisions.

Among the main results identified, the ability of Bayesian inference to integrate multiple sources of information stands out, including clinical, laboratory, imaging, and molecular data, favoring a more robust and dynamic diagnostic approach. Its applicability in high-uncertainty scenarios, such as studies with small samples where traditional methods face limitations, was also evident. The flexibility of Bayesian models—especially in adaptive clinical trials and survival modeling—represents a relevant differential, expanding methodological efficiency and result reliability.

Another important aspect concerns the contributions of Bayesian inference to precision oncology, as it enables personalized therapeutic decisions through the integration of complex and heterogeneous data. Incorporating this approach into clinical decision-making environments, such as tumor boards, reinforces its potential to improve multidisciplinary care by aligning scientific evidence with clinical practice. Moreover, its use in evaluating therapeutic interventions and modeling tumor dynamics demonstrates significant advances in understanding disease progression.

The contributions of this research lie mainly in systematizing knowledge on the applications of Bayesian inference in oncology, highlighting its relevance as both a methodological and clinical tool. By bringing together recent and diverse evidence, the study broadens understanding of this approach's potential and identifies gaps that may guide future investigations. Thus, it reinforces the importance of incorporating advanced probabilistic methods into the education and practice of health professionals, particularly in contexts marked by high diagnostic complexity.

Finally, empirical research in the Brazilian context is recommended, especially in oncological services within the Unified Health System, to assess the practical applicability of Bayesian models in routine clinical care and their impact on diagnostic quality and decision-making. Studies integrating real patient data and combining Bayesian tools with clinical decision-support systems may significantly contribute to consolidating this approach, promoting advances in diagnostic precision and the quality of oncological care.

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