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Machine Learning approaches for Predicting Medical Costs in Oncology Patients: A Systematic Literature Review

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Abstract. Although the use of machine learning (ML) in healthcare has increased significantly, a critical systematization of its application to medical cost prediction is still lacking. This paper aims to rigorously examine recent literature to identify methodological approaches, knowledge gaps, and emerging trends related to the economic use of ML in health. To this end, a systematic review of 71 papers was conducted, complemented by bibliometric analysis, journal quartile assessment, and thematic categorization. These strategies were applied across highly recognized academic databases, including Scopus, IEEE Xplore, ACM Digital Library, PubMed, and Springer Nature Link. The main findings indicate that: (1) most studies are concentrated in highly digitalized countries, which restricts their applicability in less developed contexts; (2) although a significant number of publications appear in Q1 journals, they do not always achieve high levels of scientific objectivity; and (3) the predominant topics focus on image-based diagnosis, while the prediction of medical costs remains an emerging and underexplored field. Overall, the results highlight a substantial gap between the technical development of ML and its integration into financial decision-making in healthcare. It is recommended to promote research with greater geographical diversity, grounded in more robust theoretical frameworks and guided by ethical principles that ensure equitable and contextualized implementation.

Keywords. Machine learning, cost prediction, cancer, oncology, deep learning, healthcare cost estimation.

1 Introduction

The growing demand for efficient and sustainable healthcare has driven the search for approaches that facilitate the prediction and management of costs, particularly in critical areas such as the treatment of oncology patients, whose medical expenses are often high and variable. In this context, the application of machine learning (ML) techniques has emerged as a promising alternative to anticipate medical costs with greater accuracy, thereby supporting financial planning and the proper allocation of resources. However, the available knowledge on the implementation of these techniques and their specific impact on cost prediction in oncology is not yet fully consolidated. Various machine learning and deep learning approaches have been applied to oncology prediction using clinical and omics data. A cost-sensitive neural network optimized with Grey Wolf, along with deep models based on genomic data and a multimodal network for breast cancer, demonstrated high accuracy, sensitivity, and specificity in clinical scenarios [2,31, 59]. In parallel, computational imaging has shown promising results: radiomics in CT enabled differentiation between adrenal metastases and benign tumors, while multiparametric MRI predicted the Oncotype DX score in breast cancer, outperforming clinicopathological approaches [14], [82]. Complementarily, in dermatology, two-stage models and CNN-transformer architectures improved the detection of melanoma and the classification of melanocytic nevi, despite limitations caused by data imbalance [15,21,60].

In endoscopy, the use of the SSD framework with InceptionV3 and VGG16 increased polyp detection in colonoscopy, while the incorporation of AI enhanced post-polypectomy surveillance by 35% in the United States and 20% in Europe, although it also raised the clinical workload [33], [40]. Regarding hospital cost prediction, several algorithms have demonstrated usefulness: the MLP model outperformed RFR and multiple regression in pulmonary tuberculosis, Random Forests and SVM proved effective in colorectal cancer, and Random Forest led cost prediction in mental health [20], [22], [34]. In oncology, Random Forest also surpassed Gamma-GLM and PLAQR in complex scenarios, while a hybrid approach combining clustering and Markov chains achieved a MAPE of approximately 6% in breast cancer [39, 48].

From a broader perspective, oncology burden and public health have been linked to AI in early detection, as observed in China, while in the United States a positive correlation was found between healthcare expenditure, GDP, and labor productivity [17,47]. Likewise, the evaluation of public policies using ML presents advantages over traditional methods, although challenges remain regarding interpretability, bias, and equity [32,79].

At the bibliometric level, a SCOPUS analysis revealed accelerated growth in AI research for healthcare since 2019, while another global study on AI in oncology (2012–2022) identified emerging trends such as deep learning, radiomics, and precision oncology, with China leading scientific production [73,75]. Systematic reviews have documented advances in the prediction of adverse drug events, the use of real-world data (RWD), and applications in primary care for chronic diseases such as diabetes and Alzheimer's, highlighting gaps in external validation [74,77,97].

Other contributions emphasize the reliability of medical devices through AI, the prediction of post-acute outcomes after hospitalization, and COVID-19 diagnosis with an AUROC of 0.94, validating the cross-disciplinary applicability of ML [78,80,81]. Finally, impactful clinical applications have been consolidated, including the APCA score for prostate cancer, which reduces unnecessary biopsies; a KAN classifier for early gastric cancer; and a majority-voting model for low-cost, high-precision cervical cancer detection [24,57,61].

The use of machine learning in healthcare has grown rapidly, generating extensive scientific output that is mainly oriented toward clinical applications. However, there is a notable lack of critical reviews that systematize its application to medical cost prediction. This knowledge gap limits a comprehensive understanding of the subject from an economic and healthcare management perspective; in this sense, the present study aims to contribute to filling this gap by offering a rigorous and structured analysis.

Accordingly, the objective of this systematic literature review is to identify, analyze, and synthesize recent studies that employ machine learning models for medical cost estimation, evaluating the algorithms used, the contexts of application, the economic variables considered, the level of objectivity and polarity of the conclusions, as well as their thematic and geographical distribution. Therefore, this paper is organized as follows: Section 2 presents the theoretical framework; Section 3 describes the methodology applied; Section 4 reports the results along with their analysis; and Section 5 presents the conclusions and proposes recommendations for future research.

2 Background

This theoretical framework contextualizes the two central variables of the study: machine learning as a predictive tool and the estimation of medical costs. Establishing a rigorous conceptual basis is essential to understand the foundations of both dimensions before delving into the trends that currently shape this line of research.

2.1 Machine learning

Machine learning is defined as an approach oriented toward the creation and application of predictive models, used in the medical field, for instance, in breast cancer prediction by addressing data imbalance problems through cost-sensitive techniques [2].

It is also understood as the use of computational capacity to represent quantitative relationships between multiple predictors and clinical outcomes [57].

Likewise, it has consolidated itself as one of the most widely used tools to analyze emotional behaviors, by generating intelligent algorithms capable of learning without depending on predefined rules [95].

Finally, its potential is highlighted for optimizing responses through continuous learning processes based on interactions with data [71].

2.2 Medical Cost Prediction

Medical cost prediction is defined as the use of historical data and relevant variables to estimate future healthcare expenses, thereby enabling better financial planning and resource allocation [2].

Similarly, it can be understood as the application of predictive techniques and statistical models to estimate the costs associated with medical care, facilitating more efficient financial resource management for both healthcare professionals and institutions [15].

It is also conceived as the estimation of costs related to medical services, treatments, or procedures through predictive models based on historical data and relevant variables [21].

In a broader sense, it involves the development of predictive models capable of calculating expenses linked to medical procedures by considering multiple variables such as hospital stay, intensive care, and comorbidities.

These models assist in financial planning and improve cost management in the healthcare domain [63].

3 Methodology

3.1 Systematic Literature Review

The Systematic Literature Review (SLR) constitutes a rigorous, transparent, and reproducible methodological approach whose purpose is to identify, evaluate, and synthesize the available empirical evidence around a clearly defined research question. Unlike traditional or narrative reviews, the SLR is based on a pre-established protocol that defines the stages of the process, the inclusion and exclusion criteria, as well as the sources of information. This methodological design contributes to minimizing bias and strengthening the validity of the findings, in line with the guidelines proposed by Kitchenham and Charters [72]. Likewise, Rojas [96] emphasizes that the SLR is an iterative process that combines existing literature to address research questions and generate new perspectives.

3.2 Research Questions and Objectives

To ensure the rigor of a systematic review, it is essential to clearly define both the central objective of the study and the research questions that will guide the analysis. Within this framework, the present review aims to explore, classify, and analyze the scientific literature related to the use of machine learning techniques in medical cost prediction. These questions establish a reference framework that delineates the scope of the analysis, defines the search criteria, and organizes the synthesis of the most relevant findings.

Table 1 presents the research questions and objectives, specifically adapted to the context of this study.

3.3 Sources of Information and Search Strategies

For the identification and extraction of relevant content, academic databases of recognized prestige were selected to ensure coverage and quality of the indexed literature. Complementarily, specific search equations were designed to maximize both the relevance and

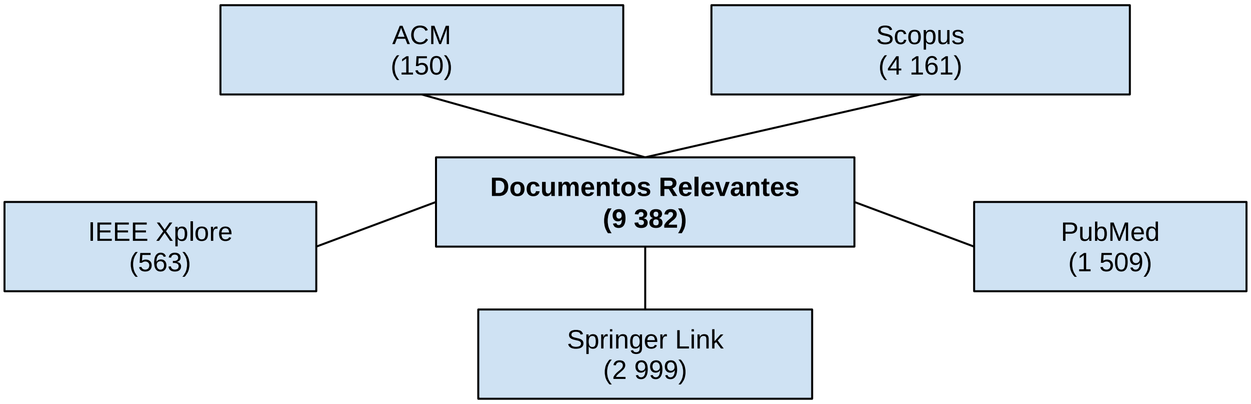

Fig. 1. Relevant results

Table 2. Descriptors and synonyms used in the search strategy

Descriptor	Description
machine learning/ predictive models/ data mining / artificial intelligence/ prediction algorithms/ data analysis/ ml	Machine Learning
medical cost prediction + cancer patient/ medical expense estimation + patient with cancer/ healthcare cost forecasting + oncology patient/ medical cost projection + individual diagnosed with cancer/ prediction of healthcare expenses + person affected by cancer/ health cost estimation + cancer-diagnosed individual/ prediction of healthcare service costs + patient undergoing cancer treatment/ medical cost modeling + cancer patient/ forecasting of medical expenses + patient with cancer/ prediction of medical disbursements + oncology patient/ estimation of economic burden in healthcare + patient undergoing cancer treatment	Medical cost prediction in oncology patients

comprehensiveness of the results. These strategies were applied in the following platforms: IEEE Xplore, ACM Digital Library, PubMed, Springer Nature Link, and Scopus.

Table 2 presents the selection of synonyms used to broaden the search field and maximize the retrieval of relevant results. This strategy made it possible to identify publications related to similar topics, even when the variables considered in this study were not explicitly mentioned.

Table 3 presents the search equations designed for each database, aimed at retrieving relevant studies on medical cost prediction in oncology patients using machine learning techniques.3.4 Identified Studies

Figure 1 illustrates the study identification phase, obtained through the application of the previously designed search equations across the selected databases.

3.5 Study Selection

Eight Exclusion Criteria (EC) were established in order to refine the literature and ensure the quality, relevance, and methodological consistency of the studies included. In line with the PRISMA and Kitchenham guidelines, the EC were defined to: (i) reduce bias and ensure comparability (peer-reviewed publications, primary studies, full-text availability, and English-language writing); (ii) preserve timeliness and external validity (publication window limited to the last seven years); and (iii) guarantee methodological evaluability (document uniqueness, thematic alignment, and relevance of titles, keywords, and abstracts). These criteria were applied systematically during the screening and eligibility phases, and their effect on the initial pool of records is summarized in the PRISMA flow diagram (Figure 2).

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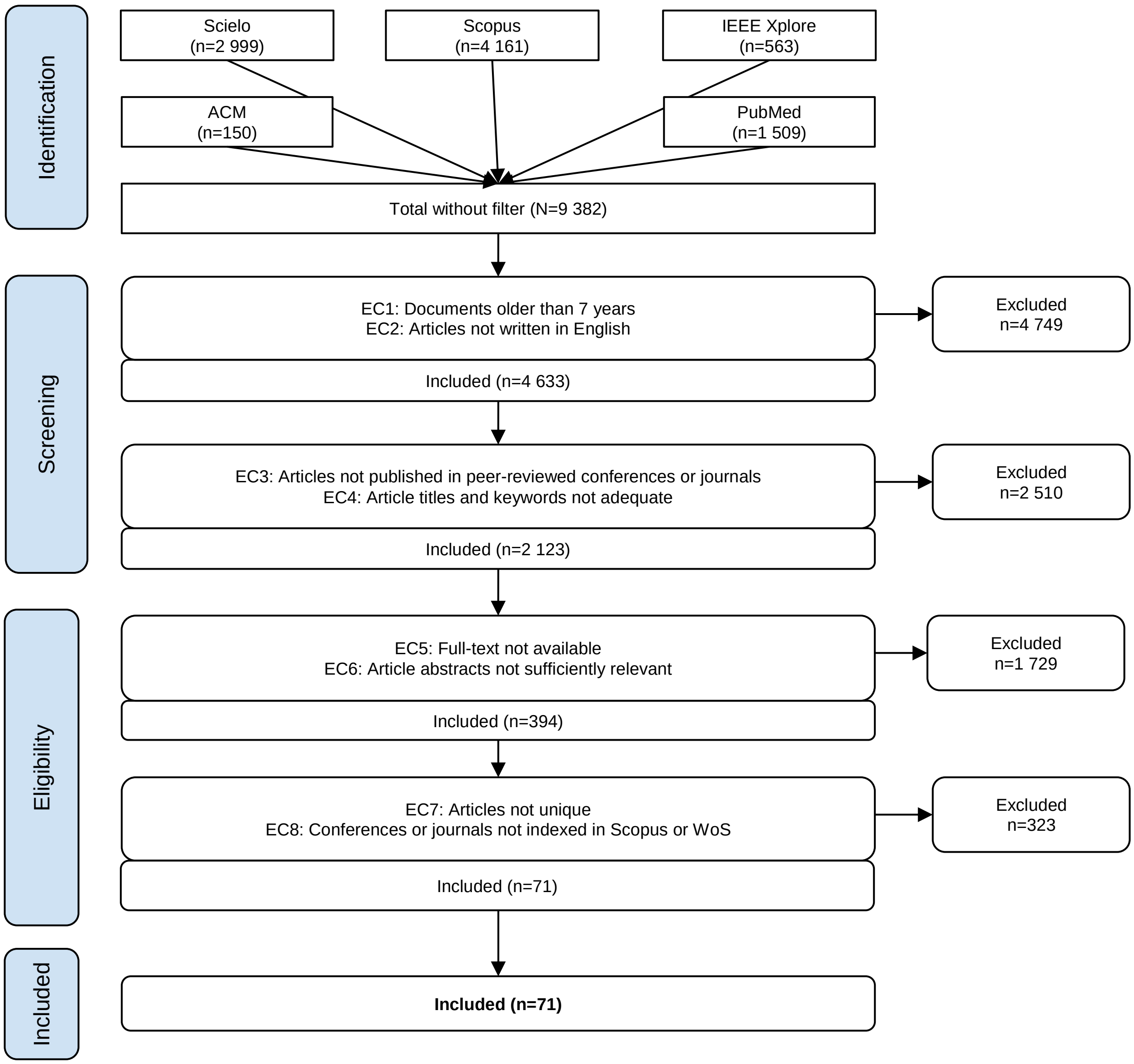

Fig. 2. PRISMA flow diagram

3.6 Quality Assessment

As the final stage of the selection process, a critical evaluation of the methodological quality of the studies included in this systematic review was conducted. For this purpose, a set of quality assessment (QA) criteria was applied to evaluate the robustness and transparency of each study. The criteria considered were as follows:

QA1. Is the study based on a sample of fewer than 30 participants?

QA2. Have the instruments used for data collection been properly and fully cited?

QA3. Are the instructions provided in the paper written with clarity and precision?

QA4. Does the author provide contact information to clarify doubts or expand on the study?

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Table 4. Quality assessment results

Ref.	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	Score	Ref.	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	Score
[1]	Conference	2	2	3	2	2	3	2	16	[37]	Journal	3	3	2	2	3	2	3	18
[2]	Journal	2	3	2	2	3	2	3	17	[38]	Conference	3	2	2	3	3	3	2	18
[3]	Conference	3	3	3	2	2	2	2	17	[39]	Journal	2	1	1	3	2	2	1	12
[4]	Conference	2	3	2	2	2	2	3	16	[40]	Journal	2	2	3	3	3	1	3	17
[5]	Conference	1	2	3	2	2	2	2	14	[41]	Conference	3	2	3	3	3	2	3	19
[6]	Conference	3	3	2	2	3	2	3	18	[42]	Conference	2	3	3	3	3	3	2	19
[7]	Conference	3	2	2	2	2	2	2	15	[43]	Conference	1	2	3	3	3	2	1	15
[8]	Journal	2	3	2	2	3	3	1	16	[44]	Conference	1	2	3	2	2	2	2	14
[9]	Conference	3	1	2	3	2	2	2	15	[45]	Conference	1	3	3	3	2	3	3	18
[10]	Conference	2	2	2	2	3	3	3	17	[46]	Conference	2	2	3	2	2	2	2	15
[11]	Conference	1	3	3	2	3	2	2	16	[47]	Journal	2	2	3	2	2	2	2	15
[12]	Conference	3	2	3	2	3	2	1	16	[48]	Journal	2	2	3	3	2	3	2	17
[13]	Conference	2	3	2	1	2	2	2	14	[49]	Conference	1	1	1	2	3	3	1	12
[14]	Journal	3	2	2	2	3	2	3	17	[50]	Conference	3	2	1	1	3	3	3	16
[15]	Journal	2	3	2	2	2	2	2	15	[51]	Conference	3	3	2	2	3	2	2	17
[16]	Conference	1	3	3	2	3	1	1	14	[52]	Conference	2	2	3	2	3	2	2	16
[17]	Journal	2	2	1	3	2	2	2	14	[53]	Conference	3	1	1	2	3	3	1	14
[18]	Conference	2	1	2	2	3	2	3	15	[54]	Conference	2	2	2	2	2	2	3	15
[19]	Conference	2	3	3	1	2	3	3	17	[55]	Journal	2	2	3	2	2	1	3	15
[20]	Journal	2	2	2	1	3	2	3	15	[56]	Conference	3	1	2	2	3	2	2	15
[21]	Journal	2	3	1	2	2	2	2	14	[57]	Journal	2	2	2	2	2	3	3	16
[22]	Journal	2	1	2	3	3	1	1	13	[58]	Conference	1	3	3	3	3	2	2	17
[23]	Conference	3	2	2	2	2	1	2	14	[59]	Journal	2	2	3	2	2	2	2	15
[24]	Journal	1	2	3	2	3	2	3	16	[60]	Journal	3	1	3	2	3	2	3	17
[25]	Journal	3	3	2	1	3	2	1	15	[61]	Journal	2	2	2	3	3	3	3	18
[26]	Conference	2	2	3	2	2	3	2	16	[62]	Conference	1	3	1	2	3	2	1	13
[27]	Conference	1	3	2	2	3	2	3	16	[63]	Journal	2	2	2	3	2	1	2	14
[28]	Conference	2	2	3	3	2	1	3	16	[64]	Conference	3	1	3	2	3	2	3	17
[29]	Conference	3	1	2	1	3	2	2	14	[65]	Conference	2	2	3	2	2	2	2	15
[30]	Conference	2	2	2	2	2	3	3	16	[66]	Journal	2	2	3	1	2	2	3	15
[31]	Journal	1	3	2	3	3	2	2	16	[67]	Journal	3	1	3	2	3	1	2	15
[32]	Journal	2	2	3	3	2	2	1	15	[68]	Journal	2	3	3	1	2	2	1	14
[33]	Journal	3	3	1	2	3	3	2	17	[69]	Journal	1	2	3	1	3	3	3	16
[34]	Journal	2	2	2	3	3	2	3	17	[70]	Journal	2	1	3	2	2	2	3	15
[35]	Conference	2	2	3	2	2	2	2	15	[71]	Journal	2	2	2	1	3	1	2	13
[36]	Conference	2	2	1	3	2	2	2	14	[67]	Journal	3	1	3	2	3	1	2	15

QA5. Is the process of sample selection and extraction described in detail?

QA6. Is the research methodology explained accurately and with sufficient detail?

QA7. Does the author have an academic background in engineering that supports the research presented?

These criteria were systematically applied to each selected paper, allowing the assessment of validity, consistency, and reliability prior to the final analysis. Table 4 presents the integrated evaluation process, where each paper was rated according to the seven predefined criteria, with a score of 1 (poor), 2 (acceptable), or 3 (outstanding). Only studies achieving a total score equal to or greater than 11.5 were considered suitable for inclusion in the analysis. After reviewing the 71 initially selected papers, it was confirmed that all primary studies met this minimum quality threshold, thereby consolidating the final list of publications included in this review.

3.7 Data Extraction Strategies

The data extraction strategy was implemented using the Mendeley Desktop tool, selected for its intuitive interface and functional design, which enable efficient organization, management, and analysis of bibliographic references. Figure 3 illustrates how these functionalities were leveraged during the execution of this study.

4 Results and Discussion

This section presents the findings obtained from the systematic review process, organized according to the previously formulated research questions. The selected studies are analyzed and compared in relation to their initial objectives,

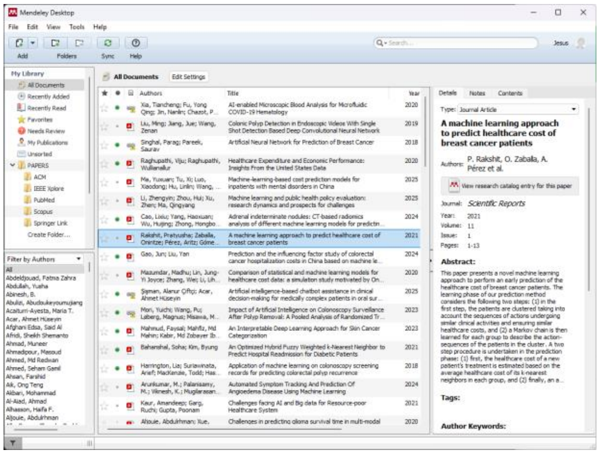

Fig. 3. Document management with Mendeley

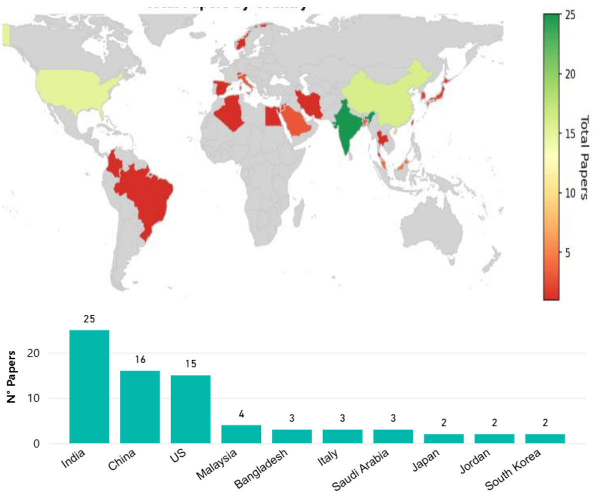

Fig. 4. Distribution of papers by country and contributions

providing a comprehensive, critical, and updated overview of the current state of knowledge.

4.1. Overview of the Studies

Figure 4 and Table 5 display the geographical distribution of the selected articles, as well as the impact indicators associated with each country. These results highlight the regions with the greatest dynamism in scientific production on machine learning and medical cost prediction.

The findings show that India leads in publication volume (25), although with a low average impact index, while China (16) and the United States (15) combine higher output with greater citation influence. The participation of countries with lower production (e.g., Colombia, Egypt, Iran) is also observed; although marginal in number, they indicate an emerging interest in the field. Notably, Jordan reports the highest average citations per paper (43.0), underscoring the quality and relevance of its contributions despite low production. Overall, the distribution highlights a concentration in Asia and North America, with limited contributions from Latin America and Europe.

Although India and China lead in the number of publications on AI for medical cost prediction in oncology, bibliometric reviews show that the United States and European countries dominate in studies with robust clinical validation and access to integrated health data systems, aspects essential for accurate cost prediction [93]. This reveals a disparity between publication volume and actual economic impact. While India and China have rapidly increased their scientific output, their studies tend to appear in lower-impact journals with limited clinical validation, in contrast to the U.S. and Europe, which emphasize quality and clinical relevance [75]. This difference suggests that volume does not necessarily translate into influence or practical applicability in healthcare [94]. Moreover, the quality and impact of research in the U.S. and Europe surpass that of India and China [90]. In the systematic review conducted by Gamboa-Cruzado and colleagues [76], it was found that most papers on the application of machine learning in healthcare originated from India (29.27%), the United Kingdom (21.95%), and the United States (17.07%). Consistent with these findings, though with some variations, the results of this study indicate that production is concentrated mainly in India, China, and the U.S., highlighting the marked leadership of India and the U.S.

These results suggest the need to extend the application of machine learning for medical cost prediction to other sectors and business areas, such as logistics and finance. They also underscore the opportunity to replicate such experiences in regions with limited scientific presence, such as Latin America and Africa. Finally, they open the possibility of evaluating the

Table 5. Impact indicators by country

Country	Avg H-Index	Total Papers	Total Citations	Citations/ Paper
India	0	25	148	5.9
China	170.2	16	318	19.9
US	76.2	15	371	24.7
Malaysia	97.3	4	54	13.5
Bangladesh	0	3	19	6.3
Italy	88.3	3	1	0.3
Saudi Arabia	96.7	3	38	12.7
Japan	110	2	5	2.5
Jordan	136.5	2	86	43
Korea	206.5	2	1	0.5
Algeria	0	1	0	0
Brazil	40	1	0	0
Colombia	8	1	2	2
Egypt	0	1	0	0
Iran	28	1	1	1
Maldives	0	1	11	11
Norway	220	1	1	1
Total	**79.7**	**87**	**1067**	**12.3**

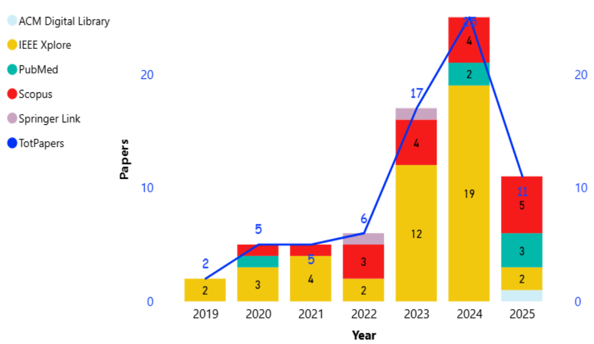

Fig. 5. Distribution of papers by year and source

evolution of this research line across different time periods, exploring trends and future projections.

Figure 5 shows the annual evolution of publications and their distribution across different academic databases, allowing visualization of both the growth and concentration of scientific production in this research line.

A sustained growth has been observed since 2019, with a notable increase starting in 2022 and reaching its peak in 2024 with 27 articles. IEEE Xplore and Scopus concentrate most of the production, while PubMed and Springer Link provide fewer but relevant contributions in terms of clinical validation. The decline in 2025 (up to July) does not necessarily indicate an actual drop in production, but rather reflects the partial nature of the period analyzed. The diversity of sources highlights the cross-disciplinary nature of the topic across engineering, medicine, and computational sciences. Overall, the growth curve confirms that the field is in a phase of academic consolidation.

4.2. Responses to the Research Questions

This section presents the answers to the research questions previously formulated, articulating the most relevant findings along with a critical analysis and the implications for consolidating future lines of research on medical cost prediction using Machine Learning. The results stem from an exhaustive systematic review process, developed under rigorous methodological criteria that ensure the validity and reliability of the evidence gathered. After a progressive filtering procedure, a final corpus of 71 primary studies was established, which constitutes the empirical basis of the analysis. From this set, the results are structured according to the defined research questions, with the aim of providing a comprehensive, critical, and updated overview of the state of knowledge.

RQ1: What indicators are used to evaluate the performance of Machine Learning models?

Table 6 and Figure 6 present the main effectiveness criteria employed in the selected studies to assess the performance of machine learning models in medical cost prediction. Their analysis allows identifying both the diversity of metrics and the relative frequency of their use.

The most frequently used indicator was the Mean Squared Error (MSE), with 33.3%, confirming its relevance for assessing the magnitude of errors and its sensitivity to outliers. With a presence of 20%, the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) were also employed, complementing the evaluation by considering different perspectives on accuracy and stability. To a lesser extent, the Coefficient of Determination (R^2) was applied (6.7%), showing that although it is a classic metric, its specific use in medical cost prediction is limited. The combination of metrics demonstrates that studies do not restrict themselves to a single criterion but

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Table 6. Effectiveness criteria employed

Criterion	Reference	Qty(%)
Mean Absolute Error (MAE)	[22] [23] [63]	3(20)
Mean Squared Error (MSE)	[20] [34] [60] [63] [68]	5(33.33)
Root Mean Squared Error (RMSE)	[20] [63] [68]	3(20)
Coefficient of Determination	[22]	1(6.67)
Mean Absolute Percentage Error (MAPE)	[22] [48] [63]	3(20)

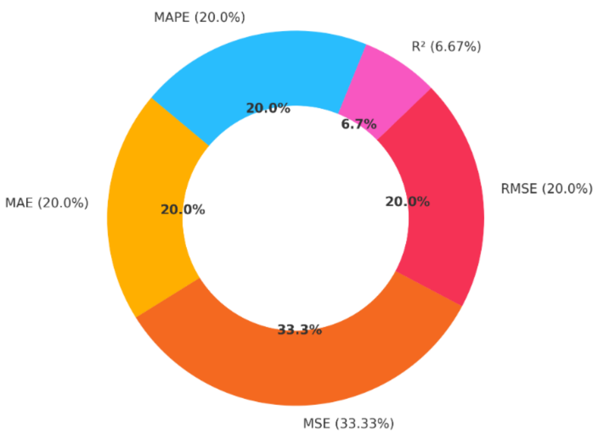

Fig. 6. Distribution of Evaluation Metrics

Table 7. Programming languages used in the studies

Language programming	Reference	Qty(%)
Python	[2] [4-7] [12] [20] [25] [26] [30] [34] [36] [43] [45] [57] [61] [66] [68]	24(58.4)
Java	[36]	1(2.4)
C#	[59]	1(2.4)
MatLab	[21] [29] [42] [48]	4(9.8)
Scala	[3] [4] [19] [25] [38] [43] [48] [52] [54] [68]	10(24.4)
JavaScript	[36]	1(2.4)

rather seek robustness through multiple evaluations. Finally, the preference for metrics based on absolute and squared errors reflects a practical focus on reducing direct prediction deviations.

Abdeldjouad and collaborators [84] reported that sensitivity was the primary metric used to evaluate machine learning models in the prediction of adverse reactions, reaching a combined value of 0.82 with high heterogeneity across studies. On the other hand, Hu and colleagues [74] indicated that the AUC was essential for assessing model performance, with an overall average of 76.68% and values above 80% in architectures such as ANN, GBM, CatBoost, and XGBoost. Although additional metrics such as precision, sensitivity, and F1-score were also applied, the AUC stood out for consistently reflecting the solid performance of the algorithms analyzed.

Similarly, Morid and his team [85] evaluated performance in cost prediction using MAPE, R^2, Hit Ratio, and Penalty Error, while excluding MAE due to its dependency on absolute values. Finally, Drewe-Boss and colleagues [86] employed metrics such as Pearson's correlation (r), Spearman's rank correlation (ρ), the Mean Absolute Percentage Error (MAPE), the Coefficient of Determination (R^2), and Cumming's Prediction Measure (CPM), which enable the analysis of the relationship between predictions and actual values, as well as the accuracy and explanatory capacity of the models.

These findings suggest that error metrics applied in medical cost prediction can be extrapolated to other sectors such as logistics, finance, and manufacturing to optimize resource forecasting. They also highlight the need to promote the use of complementary indicators in underrepresented regions to strengthen model reliability. Finally, they open the possibility of projecting their use into future time horizons to compare the evolution of dominant metrics in different business and social application contexts.

RQ2: What programming languages are being used for the development of Machine Learning?

Table 7 and Figure 7 present the distribution of programming languages employed in the selected studies, allowing the identification of the scientific community's preferences in the implementation of machine learning models.

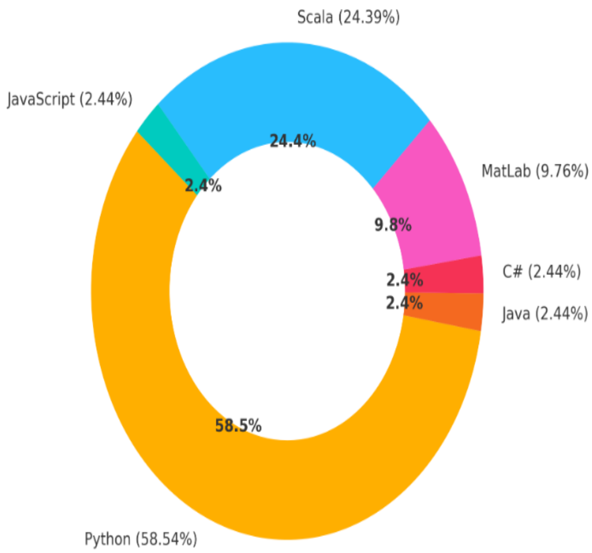

Fig. 7. Distribution of Programming Languages

Table 8. Distribution of papers by quartile and source

Source	Q1	Q2	Q3	Q4	NQ	Total
Scopus	12	2	2	0	2	18
Springer	0	1	0	1	0	2
PubMed	4	2	0	0	0	6
IEEE Xplore	4	1	0	0	39	44
ACM	1	0	0	0	0	1
Total	**21**	**6**	**2**	**1**	**41**	**71**

The most widely used language is Python (58.4%), consolidated as the standard in research due to its flexibility, large community, and ecosystem of libraries such as TensorFlow and scikit-learn. The second most used is Scala (24.4%), whose adoption is linked to the integration of distributed environments and big data platforms such as Apache Spark. Languages like Java, C#, and JavaScript appear with marginal presence (2.4% each), reflecting specific applications rather than widespread use in the domain of medical cost prediction. This landscape confirms that, although diverse alternatives exist, Python's dominance is explained by both its ease of use and its capacity for interdisciplinary integration.

According to Marcos-Zambrano and colleagues [87], in recent years there has been a significant increase in the use of interpreted languages such as Python and R in machine learning tasks applied to the microbiome, displacing compiled languages such as C++ or Java. Similarly, Pezoulas and collaborators [88] identified Python as the most frequently used language (75.3% of the studies), followed by R (14.8%), and, to a lesser extent, C++, Java, and Matlab (9.9%). In another study, Albites-Tapia and his team [90] noted that Python is also the most widely used language for developing chatbots due to its characteristics, while JavaScript, Java, and PHP occupy secondary positions, each with particular advantages. Likewise, Gamboa-Cruzado and colleagues [91] confirmed that Python is the most widely adopted language in chatbot development, representing 30.2% of the total, mainly because of its accessibility, ease of use, and versatility across different environments. Finally, Gamboa-Cruzado, Menéndez-Morales, and collaborators [92] highlighted that in the development of e-commerce chatbots, Python maintains the greatest adoption and impact, although C++ and Ruby are also used to a lesser extent, while Node.js is the least employed language.

These findings suggest that Python's predominance in healthcare can be extrapolated to other sectors such as finance, manufacturing, and logistics, where robust and adaptable predictive models are required. Moreover, the presence of emerging languages like Scala reflects opportunities for expansion into contexts where large-scale data processing is critical, such as telecommunications or smart cities. Finally, future developments may show diversification in underrepresented regions and in new generations of languages, adapting to technological and business demands at different historical stages.

RQ3: What are the quartile levels of the journals that publish research on the impact of Machine Learning in predicting medical costs in oncology patients?

Table 8 and Figure 8 present the distribution of the papers according to the quartile level of the journals and databases in which they were published, highlighting both the editorial quality and the temporal trajectory of the scientific production.

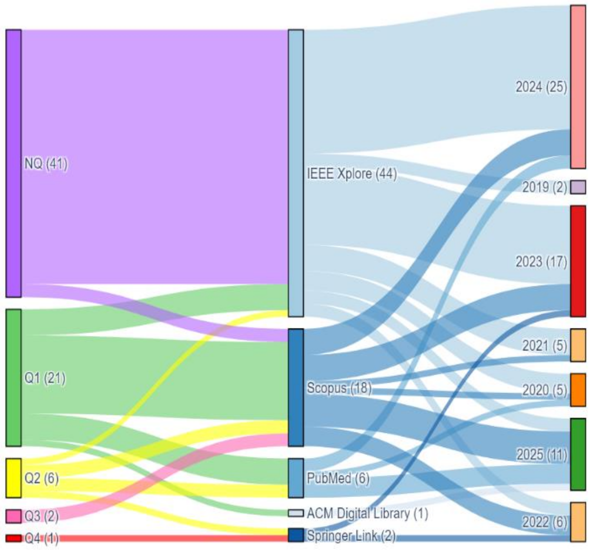

Fig. 8. Distribution of papers by quartile, source, and year of publication

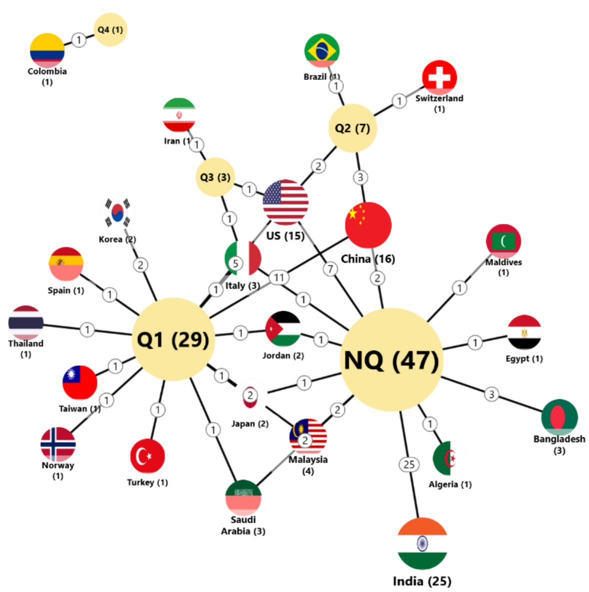

Fig. 9. Distribution of papers by quartile and country

Most of the papers are concentrated in non-quartile journals (NQ, 41 studies), primarily indexed in IEEE Xplore, which reflects a predominance of publications in conferences or technical repositories rather than in high-impact journals. However, a significant proportion is also found in Q1 (21 studies), distributed across databases such as Scopus, PubMed, and ACM, indicating that a relevant part of the literature meets high standards of editorial quality. Finally, the diversity of sources (IEEE, Scopus, PubMed, Springer, and ACM) confirms the interdisciplinary nature of the topic and its dissemination across both clinical and engineering domains.

These results suggest that strengthening publication in Q1 and Q2 journals is key to increasing the global visibility of research applied to medical costs, a strategy that can also be extrapolated to other sectors such as energy, transportation, and finance. Moreover, they highlight the need to encourage regions with high production but low indexation to transfer their knowledge to higher-impact forums. Finally, they allow projecting future studies that compare this evolution with other periods and disciplines, in order to evaluate how the editorial quality of research consolidates across different geographies and business contexts.

Figure 9 presents a combined analysis of quartiles and country distribution, which allows simultaneous visualization of editorial quality and the geography of scientific production.

The largest volume of publications is concentrated in non-quartile journals (NQ, 47 papers), with India (25) and China (16) leading, which highlights a strong quantitative growth but with lower presence in high-impact forums. In contrast, Q1 groups 29 papers, distributed across the United States (5), China (11), and Malaysia (2), showing that research with greater visibility is concentrated in countries with consolidated scientific ecosystems. Q3 accounts for 3 studies and Q4 (1 paper) represents isolated cases, reinforcing the disparity between quantity and editorial quality. The pattern reveals a dual dynamic: a massive output from emerging countries in NQ and a more selective production from developed countries in Q1. Finally, the network shows limited interconnections, reflecting that high-quality publication remains centralized in a few countries.

This scenario suggests that in other sectors, such as renewable energy, smart transportation, or digital finance, the same tension between production volume and editorial quality may be replicated. Moreover, it invites the expansion of analysis toward less-represented regions,

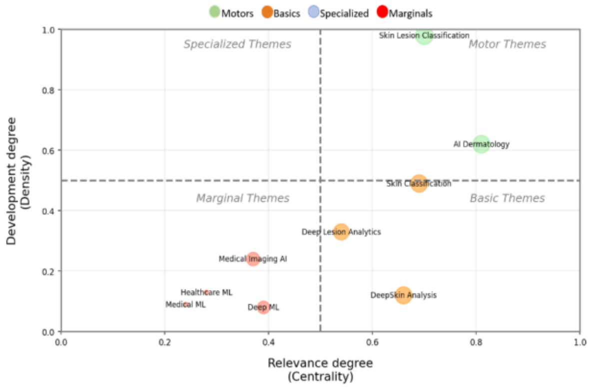

Fig. 10. Thematic map

Table 9. Quantitative Thematic Analysis

Theme	Density	Centrality	Total Citations	Category
Skin Lesion Classification	0,98	0,70	390	Motor
AI Dermatology	0,62	0,81	281	Motor
Skin Classification	0,49	0,69	348	Basics
Deep Lesion Analytics	0,33	0,54	230	Basics
Medical Imaging AI	0,24	0,37	162	Marginals
Healthcare ML	0,13	0,28	13	Marginals
DeepSkin Analysis	0,12	0,66	262	Basics
Medical ML	0,09	0,24	14	Marginals
Deep ML	0,08	0,39	143	Marginals

promoting the internationalization of results. Finally, it projects the need to assess in future periods whether the emerging output in NQ manages to transition toward Q1 and Q2, consolidating a greater global impact of applied research in machine learning.

RQ4: What thematic typologies are identified in research on Machine Learning and its impact on predicting medical costs in oncology patients?

Figure 10 and Table 9 present the classification of emerging themes based on keyword analysis, considering centrality as the degree of relevance and density as the level of development. This visualization makes it possible to position trends according to their role in the evolution of research.

The results show that Skin Lesion Classification (0.98/0.70) and AI Dermatology (0.62/0.81) stand out as motor themes, indicating high relevance and solid development, thus consolidating as central axes of research. In the category of basic themes, Skin Classification (0.49/0.69), Deep Lesion Analytics (0.33/0.54), and DeepSkin Analysis (0.12/0.66) stand out, serving as methodological and conceptual foundations. On the other hand, marginal themes include Medical Imaging AI, Healthcare ML, Medical ML, and Deep ML, with low density and centrality, reflecting areas still incipient or with limited research maturity. This thematic structure reveals a fragmented field, where the core is strongly linked to dermatological applications, while broader approaches to machine learning in healthcare are less developed.

According to Senthil and colleagues [73], the thematic map shows that in the field of artificial intelligence applied to healthcare, neither fully consolidated topics nor incipient emerging areas are identified. Instead, lines such as deep learning, data analytics, and personalized medicine stand out, considered relevant and transversal, reflecting a field in constant evolution with broad research opportunities.

These findings suggest that motor themes in oncology can be extrapolated to other medical sectors such as cardiology or neurology, where image classification is equally critical. Likewise, the development of marginal themes opens opportunities to consolidate ML applications in hospital management and cost prediction in underrepresented regions. Finally, the thematic framework obtained can serve as a comparative reference in future periods and in other business contexts seeking to integrate AI and predictive analytics to optimize resources.

RQ5: What keywords tend to appear recurrently in co-occurrence within studies analyzing the use of Machine Learning and its impact on predicting medical costs in oncology patients?

Figure 11 shows a bibliometric network illustrating the collaborative relationships among keywords.

The results reveal that machine learning (ML) constitutes the central axis of the network, linking with terms such as AI, deep learning, medical imaging, healthcare, and cost prediction,

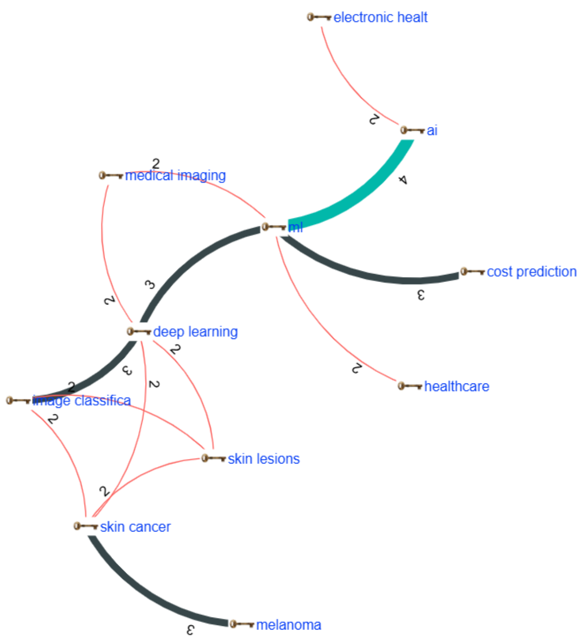

Fig. 11. Keyword Co-Occurrence Bibliometric Network

highlighting the transversal nature of the field. The highest density of connections is concentrated in applications related to image and skin lesion classification, with keywords such as skin cancer and melanoma standing out. The co-occurrence of cost prediction and healthcare indicates that research is not limited to diagnosis but also incorporates components of health management and economics.

According to Senthil and colleagues [73], the keyword co-occurrence network (KCN) is structured into three clusters differentiated by color, where the largest nodes correspond to the most frequent keywords. In Cluster 1, artificial intelligence and healthcare stand out, with the strongest connection, indicating a high level of co-occurrence. Meanwhile, Tao Wu and collaborators [75], through a similar analysis, identified six thematic clusters in artificial intelligence applied to oncology, highlighting tumor segmentation through radiomics, prediction of therapy response, risk stratification in screening programs, and the integration of biomarkers and imaging with genomic data. These clusters reflect the main research lines and the thematic evolution of the field.

These findings suggest that the integration of machine learning with economic management keywords could extend to other business sectors such as insurance, banking, or logistics. Finally, the dynamics of co-occurrences may serve as a basis for longitudinal studies analyzing how thematic cores evolve across different periods and socioeconomic contexts.

5 Conclusions and Future Research

The findings of this systematic literature review indicate that the use of machine learning in predicting medical costs for oncology patients is in the process of academic consolidation, although significant gaps remain in its practical validation. Regarding RQ1, the predominance of metrics such as MSE, MAE, RMSE, and MAPE confirms that studies prioritize indicators focused on error magnitude, reflecting an emphasis on reducing quantitative deviations. However, there is still a need to integrate explanatory metrics that strengthen clinical applicability. With respect to RQ2, Python emerges as the dominant language due to its flexibility and extensive library ecosystem, while Scala positions itself as an alternative in distributed processing environments.

This demonstrates that technological choices respond not only to ease of programming but also to the nature of the data and the scalability required. Within the framework of RQ4, the driving themes are concentrated in dermatology and image classification, whereas areas such as Healthcare ML or Medical ML remain marginal, underscoring the need to expand the scope beyond specific niches toward broader challenges in hospital management and health economics. Finally, regarding RQ5, the co-occurrence of keywords reveals that machine learning is articulated not only with terms linked to clinical diagnosis but also with concepts of health management and economics, highlighting a trend toward integrating predictive models with components of strategic decision-making.

Overall, these results suggest that, although methodological exploration and diversity of approaches have advanced, significant gaps persist in the standardization of metrics, the consolidation of programming languages in clinical production environments, and the expansion of thematic areas beyond specific medical fields. This opens a fertile space for interdisciplinary research that integrates technology, healthcare, and cost management.

Based on the gaps identified, it is necessary to extend studies toward the incorporation of more explanatory and comparable metrics, explore alternative programming languages that enhance large-scale clinical data processing, and diversify thematic approaches to include other medical specialties and business sectors. Likewise, longitudinal research will enable the evaluation of these trends over different regions and historical periods, facilitating the transfer of knowledge to broader socioeconomic and geographic contexts.

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