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Mapping Economic Considerations in Clinical Artificial Intelligence Research

Hakan Özcan [*,1]
[*]Department of Computer Technology, Design Vocational School, Amasya University, Amasya, 05100, Türkiye.

ABSTRACT Artificial intelligence (AI) has been rapidly adopted in clinical research over the past decade, yet the extent to which economic considerations are integrated into this literature remains unclear. This study presents a large-scale bibliometric analysis of clinical AI research indexed in the Web of Science. Temporal analyses span 2000–2024 (54,219 clinical AI studies), while network mapping, citation overlay, and density analyses focus on the 2024 snapshot (N = 14,995). A ratio-based indicator was used to track the relative prominence of economic considerations over time. The results show a sharp acceleration in clinical AI publications after 2015, while studies explicitly addressing cost, cost-effectiveness, or economic burden remained persistently rare, accounting for less than 1% of annual output in most years. Structural analyses indicate that economic terms are closely linked to modeling and decision-oriented keywords but do not form independent thematic clusters. Although economics-focused studies achieve moderate normalized citation impact when present, their low frequency limits structural influence. The findings reveal a persistent imbalance between rapid methodological innovation and limited economic evaluation in clinical AI research, highlighting the need for more systematic integration of economic perspectives to support sustainable clinical deployment.

KEYWORDS
Clinical artificial intelligence
Temporal trends
Bibliometrics
Network mapping
Health economics
Economic evaluation

INTRODUCTION

Clinical applications of artificial intelligence (AI) have expanded substantially over the past decade. This expansion has been supported by advances in machine learning, larger digital datasets, and improved computational capacity. AI systems now demonstrate competitive performance across clinical tasks such as image-based classification and computer-aided diagnosis, with several studies reporting specialist-level results in narrow, well-defined settings (Cai *et al.* 2024; Esteva *et al.* 2017; Kremer *et al.* 2025; Wu *et al.* 2020). Alongside technical progress, AI is increasingly positioned as a system-level enabler for healthcare, with proposed benefits that include improved efficiency, decision support, and service delivery at scale (Davenport and Kalakota 2019).

As clinical AI models proliferate, greater attention has been directed toward how model performance is evaluated and communicated (Andersen *et al.* 2024). In practice, performance reporting in the clinical AI literature remains strongly centered on accuracy-based metrics and closely related measures (Kocak *et al.* 2025; Nagendran *et al.* 2020). These metrics provide convenient summaries of predictive behavior and are commonly used to demonstrate technical feasibility in controlled evaluation settings (Rajpurkar *et al.* 2022).

However, an emphasis on accuracy alone offers limited insight into how models operate within real clinical environments (Wiens *et al.* 2019). Important considerations such as robustness, workflow integration, reliability under data shift, and operational constraints are often discussed only briefly or omitted altogether (Rajkomar *et al.* 2019; Sendak *et al.* 2020b). As a result, performance evidence may appear compelling from a technical standpoint while remaining limited in its ability to inform deployment decisions and system-level planning in routine care (Adnan *et al.* 2025; Kelly *et al.* 2019).

Despite rapid technical progress, the economic implications of clinical AI remain insufficiently examined. Many studies focus on predictive performance and technical feasibility, while costs and resource requirements receive comparatively less attention (Kelly *et al.* 2019; Rajkomar *et al.* 2019). Reviews that focus on economic outcomes report that formal cost-effectiveness and budget impact evidence is still limited in volume and uneven across clinical domains (El Arab and Al Moosa 2025; Leigh *et al.* 2025;

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[1]hozcan@amasya.edu.tr (**Corresponding author**)

Wolff *et al.* 2020). When economic evaluations are conducted, they are typically concentrated in specific applications and often rely on modeled assumptions and context-specific parameters rather than broad real-world implementation (Areia *et al.* 2022; Xiao *et al.* 2021). This pattern is illustrated by application-specific analyses that integrate clinical, technical, and financial dimensions within narrowly defined use cases (Gomez Rossi *et al.* 2022). For instance, one study examined local cost structures, staffing models, and institutional priorities in relation to the economic viability of AI tools (Davis *et al.* 2023).

In several cases, economic value is discussed indirectly, for example through expected efficiency gains, without being quantified through explicit cost and outcome comparisons (Khanna *et al.* 2022; Pagallo *et al.* 2024; Teo and Ting 2023). Taken together, these findings indicate that economic considerations are not yet consistently integrated into clinical AI research, complicating efforts to plan and justify sustainable adoption. More recent work emphasizes that economic considerations are inseparable from organizational readiness, governance structures, and delivery models when planning sustainable clinical AI deployment (Hasan *et al.* 2025).

Against this background, and despite growing case-level economic analyses, a structured, literature-wide understanding of how economic considerations intersect with clinical AI research remains limited. Existing reviews predominantly focus on individual applications or summarize reported cost outcomes, but rarely examine how economic language, thematic organization, and citation patterns are distributed across the broader clinical AI corpus. Consequently, it remains unclear whether economic reasoning is becoming systematically embedded within clinical AI research or continues to appear primarily in isolated, application-specific studies.

To address this gap, the present study adopts a bibliometric perspective. Clinical AI publications are organized into analytically defined corpora and examined using network-based mappings, citation overlays, and density visualizations to characterize structural and thematic patterns. A complementary ratio-based indicator is used to capture temporal patterns in economic focus. These elements provide a coherent framework for analyzing how economic discourse is situated within the broader clinical AI landscape.

MATERIALS AND METHODS

This section describes the data sources, corpus construction, bibliometric analyses (network, citation, and density), index formulation and experimental setup used in the study.

Data Retrieval

The data were retrieved from the Web of Science (WoS) Core Collection (Clarivate Analytics). The search targeted peer-reviewed journal articles indexed under topic fields (TS; WoS Topic Search). Structured queries combined clinical terminology with AI–related terms. Only articles written in English were included, and no subject category restrictions were applied. Records were collected in a single search session to ensure consistency. Full records and cited references were exported in plain-text format for subsequent bibliometric analysis. The overall study design is summarized in Figure 1.

Corpus Definition

The study corpus was organized into two analytical groups using topic-level query logic reflecting different scopes of clinical AI research. Group 1 represents the broad clinical AI literature and includes publications in which clinical contexts are explicitly linked with AI–related concepts such as "artificial intelligence," "machine learning," or "deep learning." Group 2 captures a nested subset of this corpus in which clinical AI studies additionally engage with economic or cost-related considerations. In this group, clinical and AI-related terms co-occur with concepts, such as healthcare cost, medical or hospital expenditure, reimbursement, cost-effectiveness, and economic burden. Two complementary analytical components were applied using these groups. Temporal analysis examined year-by-year publication trends over the period 2000–2024, capturing the emergence and expansion of clinical AI research and its economics-focused subset. Bibliometric mapping of the 2024 literature snapshot was performed to characterize the contemporary thematic structure of the field. This separation avoided temporal mixing effects and ensured structural comparability.

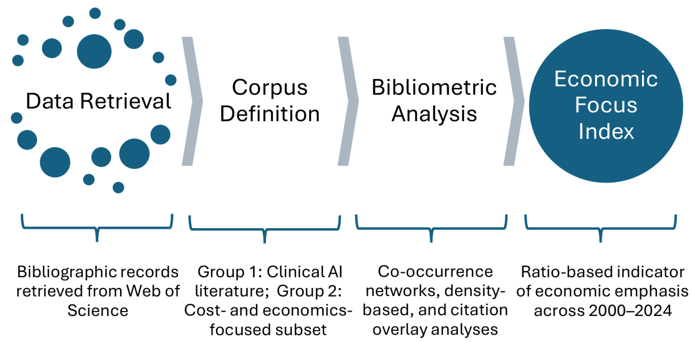

Figure 1 Overview of the study design. The records were retrieved from the Web of Science database and organized into two corpora: (i) clinical AI literature and (ii) an economics-focused subset. The analyses were conducted using co-occurrence networks, density maps, and citation overlays. An Economic Focus Index was then computed as a ratio-based indicator of economic emphasis across the period 2000–2024.

Bibliometric Analysis

Bibliometric analysis was conducted following established bibliometric mapping practices (Donthu *et al.* 2021) and implemented using VOSviewer (Van Eck and Waltman 2010). The analysis comprised three complementary visualizations: keyword co-occurrence networks, citation overlay visualizations, and density maps. Co-occurrence networks were used to represent thematic relationships based on the frequency and strength of shared keywords within each corpus. Citation overlays were derived from average normalized citation scores to assess relative influence across topics. Density maps highlighted regions of thematic concentration by emphasizing areas with high keyword occurrence and connectivity. Collectively, these bibliometric visualizations provide a structured overview of thematic organization, citation prominence, and concentration patterns within and between the two corpora.

Economic Focus Index

An Economic Focus Index (EFI) was defined to quantify the emphasis on economic considerations in the clinical AI literature. The index enables comparison across the defined corpora. It does not measure research quality or impact; rather, it aims to capture the relative strength of the economic signal within clinical AI research.

The formal definition is given in Equation (1).

$$\mathrm{EFI}_y = \frac{|G_{2,y}|}{\max(1,\ |G_{1,y} \setminus G_{2,y}|)} \tag{1}$$

Here, $G_{1,y}$ denotes the set of all clinical AI publications in year y, and $G_{2,y}$ denotes the subset of publications in the same year that explicitly address economic aspects. The numerator represents the volume of economically focused clinical AI studies, while the denominator represents the remaining clinical AI literature in that year without explicit economic focus and is lower-bounded by 1 for numerical stability.

Experimental Setup and Parameter Configuration

Key text-mining, bibliometric, and index computation settings are summarized in Table 1. Corpus definitions, keyword dictionaries, and inclusion rules were specified a priori and applied consistently across analyses. Identical preprocessing, normalization, and clustering procedures were used for both corpora; thresholds differed only for corpus size. All analyses were conducted in December 2025. Temporal trends and subfield distributions were computed in Python (v3.12) and visualized using Matplotlib (Hunter 2007). Subfield assignment (Imaging, Screening, Decision support) was implemented via rule-based keyword matching applied to titles, abstracts, and normalized keywords, using hierarchical dominance rules after thesaurus normalization. Bibliometric network construction and visualization were performed in VOSviewer (v 1.6.20) (Van Eck and Waltman 2010), using association-strength normalization and modularity-based clustering on the full keyword set.

RESULTS

This section reports the main empirical findings of the study, organized around temporal trends, bibliometric structure, functional subfield distribution, and comparative patterns between the general clinical AI literature and its economics-focused subset.

Clinical AI Growth and Economic Focus

The temporal evolution of clinical AI research and its economic focus is examined across the study period. Across 2000–2024, the clinical AI corpus comprises 54,219 articles, while the economics-focused subset comprises 659 articles. Figure 2 summarizes the corresponding publication trends and index values.

In the upper panel, the total volume of clinical AI publications shows strong and sustained growth. Annual counts increase from 18 publications in 2000 to 14,995 in 2024, with particularly rapid expansion after 2017. In contrast, economically focused studies remain scarce over time despite a cumulative total of 659 studies across the full period. Several early years report zero publications, and many others include only one study per year. Even in recent years, Group 2 counts remain modest, rising to 81 publications in 2022 and reaching 137 in 2024.

The lower panel shows the EFI values computed on a yearly basis. The values are zero or near zero throughout the early period and remain consistently low across the full time span. For example, EFI is approximately 0.010 in 2018, 0.0097 in 2020, and 0.0092 in 2024. The smoothed trend indicates gradual stabilization rather than rapid increase.

The two panels show that the sharp rise in clinical AI research volume is not matched by a comparable increase in economic focus. Despite large absolute growth, economically focused studies consistently represent less than 1% of the non-economic clinical AI literature throughout the study period.

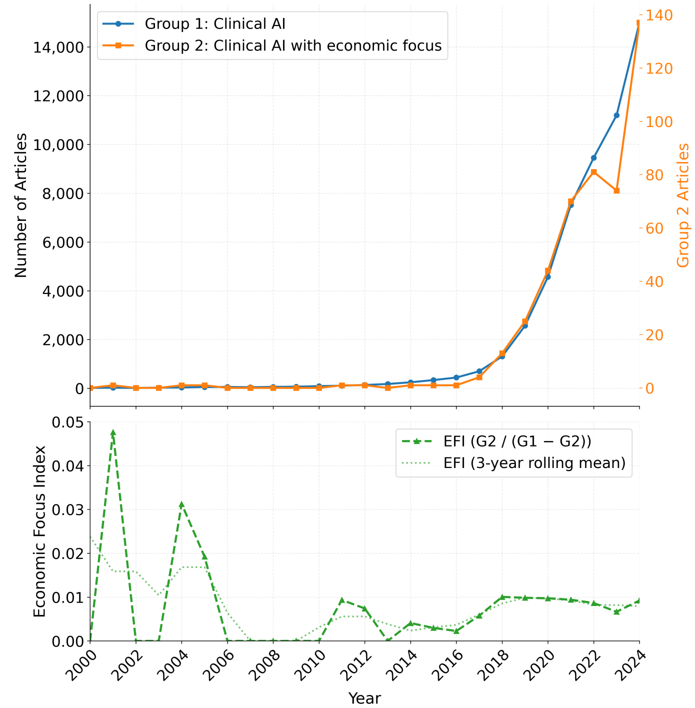

Figure 2 Temporal trends in clinical AI research and economic focus from 2000 to 2024. The upper panel shows annual publication counts for the overall clinical AI literature (Group 1, left axis) and the economically focused subset (Group 2, right axis). The lower panel shows the Economic Focus Index (EFI), with a smoothed rolling mean to highlight longer-term trends.

All subsequent bibliometric network, citation overlay, and density analyses are based on the 2024 snapshot, comprising 14,995 publications from Group 1 and 137 from Group 2, as defined in the Methods section.

Clinical AI Bibliometric Structure

The bibliometric structure of the clinical AI corpus is characterized by a small number of high-frequency concepts that organize most of the research activity. The following visualizations summarize how dominant keywords co-occur, how their citation influence varies, and where thematic concentrations form within Group 1.

Figure 3 presents the keyword co-occurrence network. A compact core is formed around general AI and modeling terms, led by "machine learning" (4,257 occurrences), "artificial intelligence" (3,298), and "deep learning" (2,752). Clinical-task terms also sit close to this core, such as "diagnosis" (1,103) and "classification" (975), indicating that methodological keywords and clinical objectives are tightly coupled in the literature. Link strengths reinforce this structure, with strong ties between "machine learning" and "artificial intelligence" (733), "deep learning" and "artificial intelligence" (510), and "diagnosis" and "artificial intelligence" (295), consistent with a consolidated methodological backbone.

Figure 4 overlays normalized citation impact on the same keyword space, highlighting where relative influence concentrates within the network. The highest average normalized citation impact is observed for "health care" (2.80), indicating strong citation attention at the interface of clinical AI and healthcare systems research. Closely following are recent language-model–related terms, including "llm" (2.22) and "chatgpt" (2.21), reflecting the

Table 1 Text-mining and bibliometric analysis setup

Component	Description
Data source	Web of Science Core Collection (full records and cited references)
Text fields analyzed	Title (TI), Abstract (AB), Author Keywords (DE), Keywords Plus (ID)
Language filter	English only
Corpus definition (Group 1)	TS = (clinical AND ("artificial intelligence" OR "machine learning" OR "deep learning"))
Corpus definition (Group 2)	TS = (clinical AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (cost OR expense* OR economic OR expenditure* OR reimburs* OR "cost-effectiveness"))
Keyword normalization	Thesaurus-based harmonization (lowercasing, spelling and plural normalization, synonym merging)
Thesaurus construction	Manually curated term lists informed by prior reviews, mapping lexical variants and synonyms to canonical forms; generic non-informative terms excluded
Minimum occurrence threshold	Group 1: t = 100; Group 2: t = 3 (size-adjusted)
Clustering method	VOSviewer association-strength normalization with modularity-based clustering
Visualization outputs	Co-occurrence network, citation overlay, density map
Citation metric	Average normalized citation score (field- and year-normalized)
Ratio metric	Economic Focus Index (EFI)
Temporal scope	Yearly analysis (2000–2024); structural snapshot focused on 2024

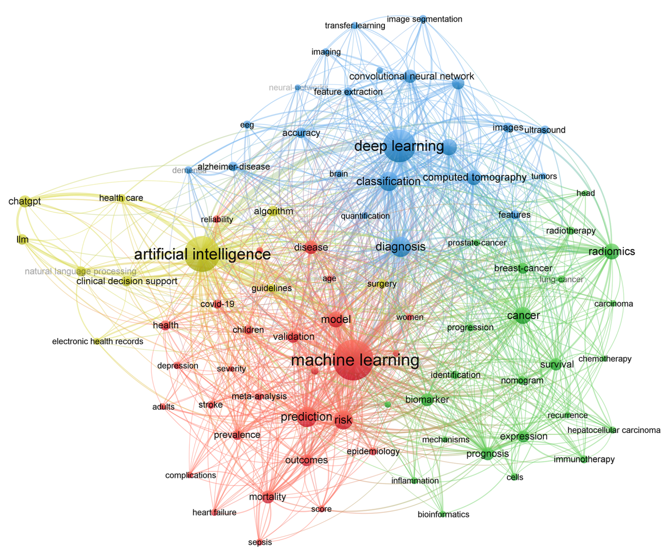

Figure 3 Keyword co-occurrence network of clinical AI literature (Group 1). The network visualizes high-frequency keywords using a minimum occurrence threshold (t = 100) after thesaurus-based harmonization. Node size reflects keyword frequency, while links indicate co-occurrence strength.

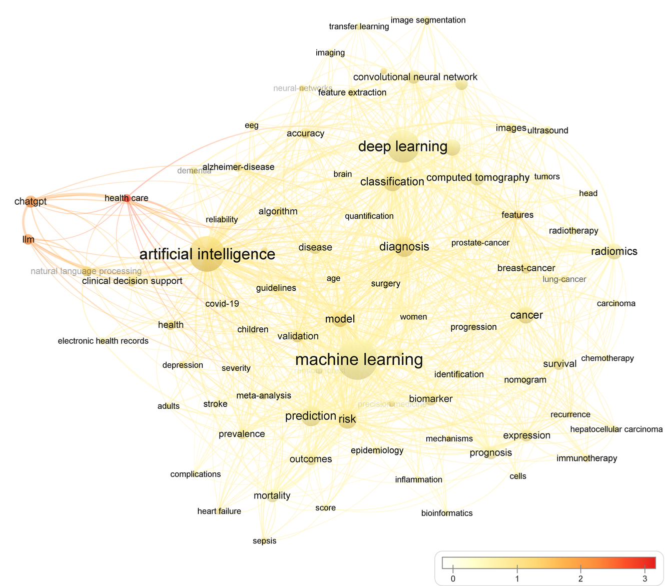

Figure 4 Citation overlay visualization of clinical AI literature (Group 1). Keywords are colored according to average normalized citation impact, with warmer colors indicating higher relative citation influence. Node size reflects keyword occurrence frequency.

rapid uptake and high visibility of generative AI topics. Elevated influence is also evident for "features" (1.45) and "natural language processing" (1.38), while core methodological terms such as "artificial intelligence" (1.26), and broader domain terms such as "health" (1.25), maintain above-average normalized citation levels. Together, these patterns indicate that both emerging AI paradigms and established clinical modeling concepts attract disproportionate citation attention within the 2024 clinical AI literature.

Figure 5 provides a density view of keyword occurrences, emphasizing dominant concentrations rather than individual links. The highest-density regions align with the same methodological and diagnostic core, with sustained prominence for "machine learning" (4,257 occurrences), "artificial intelligence" (3,298), "deep learning" (2,752), and clinical framing terms such as "diagnosis" (1,103) and "classification" (975). Imaging-related terms also contribute to dense thematic areas, including "computed tomography" (583 occurrences), "magnetic resonance imaging" (697; spatially overlapping with "deep learning" and therefore unlabeled), and "radiomics" (686), indicating that a substantial portion of the corpus concentrates around imaging-driven clinical AI workflows.

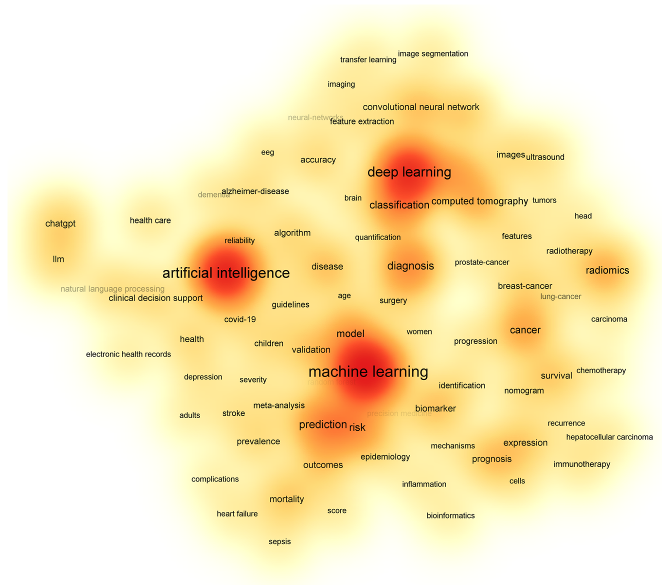

Figure 5 Keyword density map of clinical AI literature (Group 1). Density visualization based on keyword occurrence frequency, highlighting dominant thematic concentrations.

The corpus expands primarily through intensification of a core methodological vocabulary and its applications in diagnosis, prediction, and imaging, rather than through diversification toward explicitly economic language. This aligns with the earlier observation that economics-focused studies remain rare relative to the overall clinical AI output, even as annual publication counts rise sharply in recent years.

Economics-Focused Clinical AI Bibliometric Structure

The economics-focused subset of clinical AI research exhibits a markedly different bibliometric structure from the broader corpus. While overall publication counts remain low, the thematic organization reveals a tighter coupling between methodological terms and economic evaluation concepts, reflecting a more targeted and application-oriented literature. This structure is examined using complementary network, citation, and density perspectives.

Figure 6 shows the keyword co-occurrence network for economics-focused clinical AI studies. A tightly connected core forms around "artificial intelligence" (51 occurrences) and "machine learning" (35), closely linked with "cost-effectiveness" (24), "risk" (19; spatially overlaps with "artificial intelligence" and is therefore lightly colored), and "classification" (13). Economic terms such as "cost" (4) and "economic burden" (5) appear directly connected to clinical and modeling keywords rather than forming a separate cluster. This structure indicates that economic language is embedded within clinical modeling discussions rather than treated as an independent theme.

Figure 7 presents the citation overlay visualization, highlighting which topics carry disproportionate citation influence within this small subset. Although "artificial intelligence" remains the most frequent node, higher normalized citation values are observed for specific clinically grounded terms, including "mild cognitive impairment" (5.26) and "alzheimer-disease" (5.22), followed by

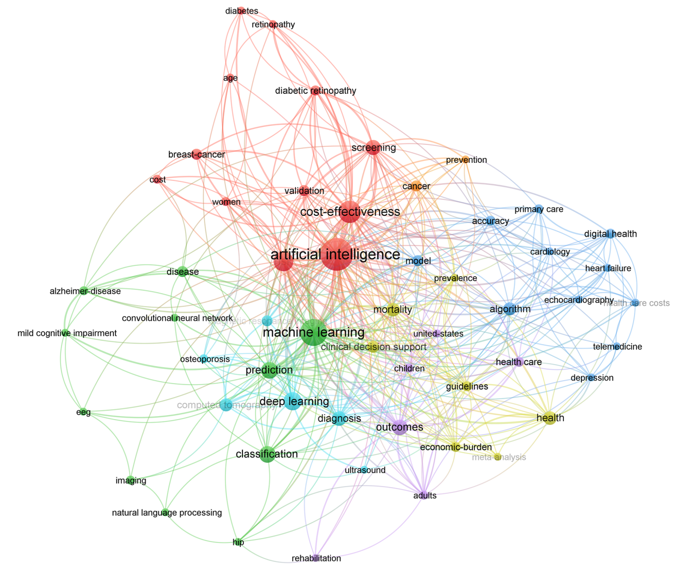

Figure 6 Keyword co-occurrence network of economics-focused clinical AI studies (Group 2). The network visualizes high-frequency keywords using a minimum occurrence threshold ($t = 3$), selected to accommodate the smaller corpus size after thesaurus-based harmonization. Node size reflects keyword frequency, while links indicate co-occurrence strength.

care- and population-oriented nodes such as "health care" (2.48), "women" (1.86), and "primary care" (1.61). These patterns indicate that economics-focused studies attract greater citation impact when anchored in concrete clinical conditions, care pathways, or population contexts rather than generic modeling themes.

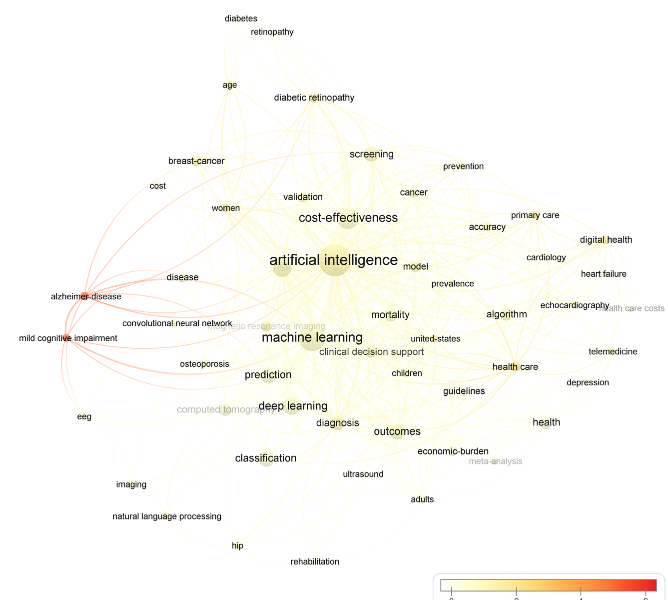

Figure 7 Citation overlay visualization of economics-focused clinical AI studies (Group 2). Keywords are colored by average normalized citation impact, with warmer colors indicating higher relative citation influence. Node size reflects keyword occurrence frequency.

Figure 8 provides a density view that emphasizes thematic concentration rather than individual links. The highest-density regions are anchored by core AI terminology, led by "artificial intelligence" (51 occurrences) and "machine learning" (35), around which economics-oriented concepts cluster. Within this core, "cost-effectiveness" (24) and "risk" (19) form the most prominent decision-focused extensions, followed by methodological and task-level terms such as "deep learning" (16), "classification" (13), "prediction" (13), and "outcomes" (12). Clinical processes including "screening" (11) and "diagnosis" (10) further contribute to dense regions but remain visually compressed due to overlap with dominant methodological nodes. Overall, the density pattern confirms that economic considerations in clinical AI are concentrated within a narrow, decision-oriented thematic core rather than broadly dispersed across clinical domains.

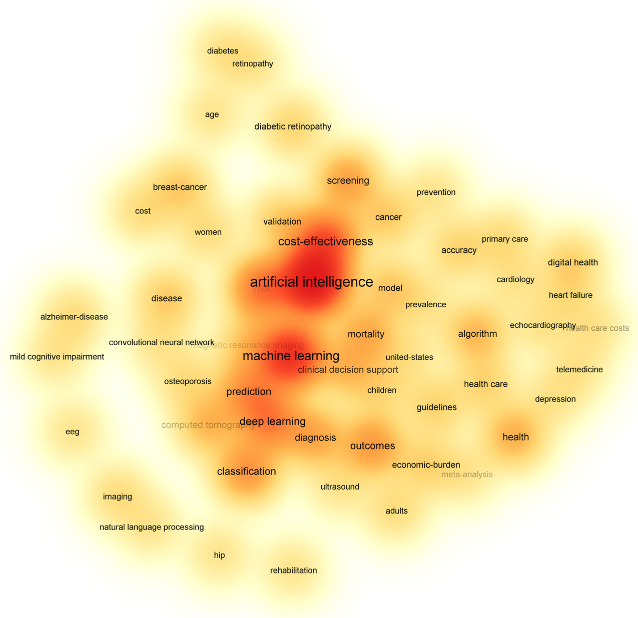

Figure 8 Keyword density map of economics-focused clinical AI studies (Group 2). Density visualization based on keyword occurrence frequency, highlighting dominant thematic concentrations.

These results reinforce the quantitative findings reported earlier. Despite the rapid expansion of clinical AI research overall, economics-focused contributions remain sparse and structurally compact. Economic concepts are embedded within existing clinical AI frameworks rather than forming independent thematic clusters.

Functional Distribution of Economic Focus Across Clinical AI Subfields

To assess how economic considerations are distributed across clinical AI applications, the economics-focused subset of clinical AI research was analyzed at the subfield level. Subfields were defined according to the primary clinical function through which AI systems generate economic impact, namely Imaging, Screening, and Decision support, with a residual Other category for cross-cutting studies. Assignment was operationalized using thesaurus-normalized keywords extracted from titles, abstracts, and keyword fields.

As shown in Table 2, economic evaluation in clinical AI is strongly concentrated in imaging-based applications, which account for 65.7% of the publications. Screening-oriented studies represent 14.6%, while decision-support applications comprise 13.9% of the corpus. Only 5.8% of studies address broader economic or organizational themes without a dominant clinical function.

Table 2 Distribution of economics-focused clinical AI studies across function-based subfields

Subfield	Count	Percent (%)
Imaging	90	65.69
Screening	20	14.6
Decision	19	13.87
Other	8	5.84

Note: Subfields were assigned based on thesaurus-normalized keywords indicating the dominant clinical function of each 2024 publication.

This distribution indicates that, despite the broad expansion of clinical AI, economic analysis remains predominantly anchored in imaging workflows, with substantially more limited representation in screening and decision-support contexts.

Comparative Patterns Between Groups

A marked imbalance exists between the two corpora in both scale and thematic breadth. Across the 2000–2024 study period, the clinical AI literature (Group 1) comprises 54,219 publications, whereas the economics-focused subset (Group 2) includes only 659 studies, representing a marginal fraction of the overall output. The same imbalance appears in the bibliometric analysis, where Group 1 includes 14,995 studies compared with only 137 economics-focused contributions.

At the keyword level, the contrast extends further. Dominant methodological terms in Group 1 occur at very large scale, with thousands of occurrences (e.g., "machine learning" = 4,257; "artificial intelligence" = 3,298), whereas in Group 2 even the most frequent terms appear only a few dozen times ("artificial intelligence" = 51; "machine learning" = 35). Structural and impact patterns diverge between the groups. Group 1 exhibits a broad, multi-clustered network spanning modeling, diagnosis, and imaging, while Group 2 forms a compact structure in which economic concepts are embedded directly within the methodological core, most prominently through "cost-effectiveness" (24) and "risk" (19). Citation overlays also differ. In Group 1, citation influence largely tracks keyword frequency, whereas in Group 2 several clinically specific topics achieve disproportionately high normalized citation impact (e.g., "mild cognitive impairment" = 5.26; "alzheimer-disease" = 5.22), exceeding the near-unity levels typical of most Group 1 terms. Together, these contrasts indicate that economic focus is selective and context-dependent rather than scaling proportionally with overall clinical AI research growth.

DISCUSSION

This study provides a corpus-level view of how economic considerations are positioned within the clinical AI literature. By combining bibliometric mapping with a ratio-based indicator, the analysis moves beyond individual case studies to examine the visibility and integration of economic discourse at scale. The results reveal a clear imbalance between rapid methodological expansion and limited attention to economic evaluation.

Clinical AI research has grown sharply since the mid-2010s, consistent with prior reports of accelerated adoption across healthcare. In contrast, the economics-focused subset remains small throughout the study period. Even in recent years, studies explicitly addressing cost, cost-effectiveness, or economic burden account for only a narrow fraction of the overall corpus. This finding aligns with earlier reviews showing that economic analysis has not kept pace with technical development (El Arab and Al Moosa 2025; Wolff *et al.* 2020). The persistence of this gap suggests a structural, rather than temporary, underrepresentation of economic perspectives.

Network-based analyses clarify how economic language appears within clinical AI research. In the general corpus, methodological and diagnostic terms form a dense, highly connected core, reflecting a consolidated research structure. In the economics-focused subset, the network is smaller and more compact. Terms such as "cost-effectiveness" and "economic burden" are closely linked to modeling and decision-oriented keywords but do not form independent clusters, a finding reinforced by citation overlay and density views. Although some clinically grounded terms achieve high normalized citation impact, their low frequency limits their influence on overall network structure. Economic concepts cluster within specific applications rather than extending across the broader literature. This organization is consistent with prior observations that cost-related analysis in clinical AI is typically task-specific and context-dependent (Areia *et al.* 2022; Xiao *et al.* 2021).

Several structural factors help explain why this marginal position persists. Economic assessment of AI systems is constrained by dynamic model behavior, unclear comparators, and limited reporting transparency, which restrict generalizable cost-effectiveness evidence (Gomez Rossi *et al.* 2022). Recent empirical analyses of large language model deployment indicate that cost considerations become salient mainly at the operational stage, where execution time, infrastructure requirements, and usage-based pricing shape feasibility in healthcare systems (Burns *et al.* 2025). Regulatory pathways prioritize safety and effectiveness, with little direct emphasis on economic value at approval (Benjamens *et al.* 2020). In implementation settings, economic impact depends on workflow integration and local reimbursement conditions, limiting transferability across institutions (Sendak *et al.* 2020a). Systematic evidence likewise reports heterogeneous and context-specific evaluation practices despite the rapid growth of AI applications (Wu *et al.* 2025).

The ratio-based indicator supports these interpretations. Although modest increases appear in recent years, overall values remain low. Short-term fluctuations point to episodic attention to economic issues rather than sustained integration across the research lifecycle. This is reflected in the bibliometric analysis, where economic focus is concentrated in a limited set of decision-oriented applications. Formal economic evaluation thus tends to emerge in response to implementation or policy pressures, rather than being incorporated during early model development (Kelly *et al.* 2019; Pagallo *et al.* 2024). This observation aligns with recent work emphasizing that long-term economic implications of clinical AI remain largely conceptual rather than empirically examined (Al Meslamani 2023).

Overall, economic perspectives occupy a marginal role in clinical AI research. They are visible and sometimes highly cited, yet weakly integrated into the core literature. This imbalance helps explain why technically successful systems often struggle to scale, as performance gains alone do not ensure economic sustainability, and organizational and governance barriers remain substantial (Adnan *et al.* 2025; Khanna *et al.* 2022).

LIMITATIONS

This analysis relies on topic-based queries and bibliometric representations, which capture explicit economic language but may overlook implicit or indirectly framed cost considerations embedded within technical or clinical discussions. As a result, keyword filtering and co-occurrence structures are sensitive to terminology choice and reporting practices rather than underlying economic relevance alone. Citation-based metrics reflect scholarly visibility rather than real-world adoption, economic impact, or implementation success. The EFI quantifies relative prominence, not the depth or quality of economic analysis, and should therefore be interpreted as an indicator of thematic emphasis. Alternative approaches, such as topic-modeling–based theme proportions or temporal co-occurrence analyses, could capture subtler or evolving economic signals. However, such methods would introduce greater model dependence and reduce interpretability. Finally, the analysis is limited to peer-reviewed journal articles indexed in WoS; inclusion of additional databases may reveal complementary patterns.

CONCLUSION

This study identifies a persistent gap between methodological innovation and economic evaluation in clinical AI research. By situating economic discourse within the broader clinical AI landscape, the findings show that economic considerations remain selectively integrated rather than systematically embedded. These results highlight the need for closer alignment between algorithm development, clinical evaluation, and economic analysis as AI systems transition from experimental settings to routine healthcare practice.

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Ethical standard

The author has no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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