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THE GEOPOLITICS OF ARTIFICIAL INTELLIGENCE: FROM PUBLIC ATTENTION VIA GOOGLE TRENDS TO SCHOLARLY PRODUCTION ESTIMATED BY GOOGLE SCHOLAR

A GEOPOLÍTICA DA INTELIGÊNCIA ARTIFICIAL: DA ATENÇÃO PÚBLICA VIA GOOGLE TRENDS À PRODUÇÃO ACADÊMICA ESTIMADA PELO GOOGLE SCHOLAR

LA GEOPOLÍTICA DE LA INTELIGENCIA ARTIFICIAL: DE LA ATENCIÓN PÚBLICA VÍA GOOGLE TRENDS A LA PRODUCCIÓN ACADÉMICA ESTIMADA POR GOOGLE SCHOLAR

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ABSTRACT

This article investigates the extent to which public attention to strategic technologies associated with artificial intelligence (AI) corresponds to the scholarly visibility of the same topics. The longitudinal design covers 2016–2025 and integrates two sources: Google Trends as a proxy for public attention and Google Scholar as a broad proxy for scholarly visibility. Four dimensions are examined: artificial intelligence, semiconductors, critical minerals, and data centers. Annual Google Trends averages were compared with annual Google Scholar Estimated Result Counts (GSERC) obtained through exact-phrase queries, as well as combined searches linking “artificial intelligence” to three material components of AI. Associations were assessed using Spearman correlations in levels, first differences, and one-year lags. General Scholar counts did not converge uniformly with public attention: AI showed virtually no association, semiconductors a negative association, critical minerals a very strong positive association, and data centers a non-significant association. By contrast, AI-linked counts were strongly associated with public attention for semiconductors (ρ=.903), critical minerals (ρ=.963), and data centers (ρ=.906). However, in first differences, only critical minerals remained statistically significant. The findings suggest that public attention is more consistently aligned with the increasing embedding of AI within strategic fields than with the estimated raw size of those fields in Google Scholar. Because Scholar hit counts are estimates and can be unstable, they are treated as indicators of scholarly visibility rather than exact publication counts.

KEYWORDS: Artificial intelligence. Geopolitics. Google Trends. Google Scholar. Semiconductors. Critical minerals. Data centers.

RESUMO

Este artigo investiga em que medida a atenção pública a tecnologias estratégicas associadas à inteligência artificial (IA) se relaciona com a visibilidade da produção acadêmica sobre os mesmos temas. O desenho longitudinal cobre 2016–2025 e integra duas fontes: Google Trends, utilizado como proxy de atenção pública, e Google Scholar, utilizado como proxy ampla de visibilidade acadêmica. Quatro dimensões são analisadas: inteligência artificial, semicondutores, minerais críticos e data centers. As médias anuais do Google Trends foram comparadas com contagens anuais estimadas do Google Scholar (GSERC) obtidas por expressões exatas, além de buscas combinadas entre “artificial intelligence” e três componentes materiais da IA. As associações foram avaliadas por correlação de Spearman em níveis, primeiras diferenças e defasagem de um ano. As contagens gerais do Scholar não apresentaram convergência uniforme com a atenção pública: IA mostrou associação praticamente nula, semicondutores associação negativa, minerais críticos associação positiva muito forte e data centers associação não significativa. Em contraste, as

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contagens vinculadas explicitamente à IA apresentaram correlações fortes com a atenção pública em semicondutores (ρ=0,903), minerais críticos (ρ=0,963) e data centers (ρ=0,906). Entretanto, nas primeiras diferenças, apenas minerais críticos permaneceu estatisticamente significativo. Os resultados sugerem que a atenção pública acompanha mais consistentemente a crescente incorporação da IA em campos estratégicos do que o tamanho bruto estimado desses campos no Google Scholar. As limitações das contagens estimadas do Scholar impedem interpretação como números exatos de publicações.

PALAVRAS-CHAVE: Inteligência artificial. Geopolítica. Google Trends. Google Scholar. Semicondutores. Minerais críticos. Data centers.

RESUMEN
Este artículo investiga en qué medida la atención pública hacia tecnologías estratégicas asociadas con la inteligencia artificial (IA) se relaciona con la visibilidad de la producción académica sobre los mismos temas. El diseño longitudinal abarca 2016–2025 e integra dos fuentes: Google Trends, utilizado como proxy de atención pública, y Google Scholar, utilizado como proxy amplio de visibilidad académica. Se analizan cuatro dimensiones: inteligencia artificial, semiconductores, minerales críticos y centros de datos. Los promedios anuales de Google Trends se compararon con conteos anuales estimados de resultados de Google Scholar (GSERC) obtenidos mediante expresiones exactas, además de búsquedas combinadas entre “artificial intelligence” y tres componentes materiales de la IA. Las asociaciones se evaluaron mediante correlaciones de Spearman en niveles, primeras diferencias y rezagos de un año. Los conteos generales de Scholar no mostraron convergencia uniforme con la atención pública. En cambio, los conteos explícitamente vinculados a IA presentaron correlaciones fuertes con la atención pública para semiconductores (ρ=0,903), minerales críticos (ρ=0,963) y centros de datos (ρ=0,906). Sin embargo, en primeras diferencias solo minerales críticos mantuvo significación estadística. Los resultados sugieren que la atención pública se alinea de manera más consistente con la creciente incorporación de la IA en campos estratégicos que con el tamaño bruto estimado de esos campos en Google Scholar. Las limitaciones de los conteos estimados impiden interpretarlos como números exactos de publicaciones.

PALABRAS CLAVE: Inteligencia artificial. Geopolítica. Google Trends. Google Scholar. Semiconductores. Minerales críticos. Centros de datos.

INTRODUCTION

Artificial intelligence has ceased to be merely a software domain and has become strategic infrastructure that connects computing capacity, advanced semiconductors, energy, networks, physical facilities, and mineral supply chains. International relations literature already treats AI as an enabling technology capable of altering competition, power, and security, while growing dependence on chips, computing facilities, and material resources shifts part of the contest toward control of infrastructure and production bottlenecks (Horowitz, 2018; Reinhold, 2026). Recent studies reinforce this material dimension by directly linking data centers, energy, critical minerals, and geopolitics to the physical foundations of AI (STACCIARINI & GONÇALVES, 2025).

This transformation unfolds simultaneously across different arenas of attention. On the one hand, search engines record the public salience of technological and strategic concepts; on the other, academic literature databases reflect the incorporation of these topics into scientific, technical,

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and scholarly documents. Google Trends has become an established source for studies of information behavior, provided that its normalized values are interpreted as relative interest rather than absolute search volume (Mavragani & Ochoa, 2019). Google Scholar, in turn, offers broad and multidisciplinary coverage, often exceeding controlled databases for certain document and citation types, but it also presents important limitations regarding transparency, indexing quality, advanced search, and reproducibility of result counts (HARZING & ALAKANGAS, 2016; HALEVI ET AL., 2017; MARTÍN-MARTÍN ET AL., 2021).

The empirical starting point of this study is IICTEC Research Report No. 001/2026, which documented a recent acceleration in global public attention not only to AI, but also to semiconductors, GPUs, critical minerals, and data centers. The report showed that the public visibility of AI was expanding toward its physical and material base, but it relied exclusively on Google Trends and had an institutional and exploratory character (IICTEC, 2026). The present article extends that design by introducing a second empirical layer: estimated scholarly visibility in Google Scholar.

The research problem is formulated as follows: to what extent do changes in public attention to strategic dimensions of artificial intelligence correspond to changes in the visibility of scholarly production on the same topics between 2016 and 2025? The question matters because convergence may indicate that certain infrastructures are becoming simultaneously more salient to the public and more integrated into the academic AI agenda; divergence, by contrast, may reveal differences between cycles of public curiosity, scientific maturity, and the characteristics of indexing mechanisms.

The general objective is to compare, longitudinally, public attention and scholarly visibility related to the material geopolitics of AI. The specific objectives are to:

• convert monthly Google Trends series into comparable annual indicators for 2016–2025;

• estimate the general scholarly visibility of Artificial Intelligence, Semiconductor, Critical Minerals, and Data Center through standardized annual Google Scholar result counts;

• measure scholarly visibility explicitly linked to AI through combined searches between “artificial intelligence” and semiconductor, critical minerals, and data center;

• assess contemporaneous associations, annual variations, and possible lagged relationships between public attention and scholarly visibility.

The scientific rationale lies in bringing together two types of signal that are usually studied separately. While the Google Trends literature emphasizes information behavior, traditional bibliometrics privileges structured databases. Here, the combination is deliberately exploratory: not to replace Scopus or Web of Science, but to observe whether a broad-coverage academic search engine produces temporal signals capable of dialoguing with public attention. The expected

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contribution is therefore both methodological and substantive: to propose a replicable framework for comparing public attention, general scholarly visibility, and AI-linked scholarly visibility.

1 - THEORETICAL FRAMEWORK

1.1 Artificial intelligence, power, and strategic infrastructure

The geopolitics of AI can be understood at two complementary levels. The first involves algorithmic capabilities, talent, data, models, and organizational adoption; the second involves the physical assets that make those capabilities executable at scale. Horowitz (2018) characterizes AI as an enabling technology with the potential to alter international competition and relative power, while emphasizing that its effects depend on diffusion, adoption, and organizational capacity. This perspective helps avoid technological determinism while also explaining why computing infrastructure acquires strategic significance.

The expansion of AI is also changing the circuits through which knowledge is produced and disseminated. In a publication in Revista Científica SOL21, Carmo and Figueredo (2025) show that generative AI has already become a subject of debate in higher education, especially regarding responsible use, ethics, and regulation. In another contribution to the journal, Magera Conceição et al. (2025) discuss the growing convergence among doctoral education, scientific production, and industrial sectors, reinforcing the idea that academic knowledge and strategic applications circulate beyond the university environment. These developments are relevant to the present research because they suggest that public attention, scholarly production, and sectoral adoption may evolve at different but interconnected rates.

At the physical level, advanced semiconductors concentrate design, manufacturing, and equipment capabilities in highly specialized global chains. The growing militarization and securitization of AI and semiconductors demonstrate how technologies that originated as commercial assets are increasingly treated as security assets and instruments of economic policy (Reinhold, 2026). The dispute is not limited to chip availability: it also involves intellectual property, manufacturing equipment, fabrication capacity, advanced packaging, and access to processors suited to compute-intensive AI workloads.

Data centers constitute another material layer. They concentrate on servers, accelerators, network systems, cooling, and power supply, making AI dependent on territorial and energy infrastructure. Masanet et al. (2020) had already highlighted that the expansion of digital services and data-intensive technologies, including AI, has important implications for energy demand. The current scale of AI makes data centers even more central to debates over location, energy availability, water, networks, and computational sovereignty.

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Critical minerals complete this material architecture. In addition to being embedded in electronics, power grids, and energy equipment, some minerals have concentrated processing chains that are exposed to geopolitical risks. Vespignani and Smyth (2024) show that AI and critical minerals are also related in the opposite direction: AI can help reduce risks and increase productivity in mineral projects. Stacciarini and Gonçalves (2025), in turn, directly synthesize the interdependence among data centers, critical minerals, energy, and geopolitics as part of the material foundation of artificial intelligence.

The growing materiality of AI is accompanied by a normative and institutional layer. Alves Correia et al. (2026) propose an AI governance standardization protocol based on international standards and regulations, emphasizing risk classification, data and model governance, impact assessment, human oversight, and continuous monitoring. Santana et al. (2026) position explainability as a component of transparency, auditability, and accountability in AI systems. In sensitive applications such as public security, the use of facial recognition also expands ethical concerns (Alves & Conceição, 2025). At the organizational level, data protection and a culture of privacy remain relevant to data-intensive ecosystems, both through the role of the data protection officer/DPO (Lima & Alves, 2021) and through corporate awareness strategies concerning data protection (Alves et al., 2025). Although the present study does not directly evaluate regulatory regimes, this literature shows that the geopolitics of AI is not limited to physical infrastructure: it also involves governance, rights, trust, and institutional legitimacy.

1.2 Public attention and Google Trends

Public attention is not the same as public opinion. Search-engine queries may express curiosity, concern, professional interest, media exposure, investment intent, or educational need. Even so, aggregated search series make it possible to observe when particular topics become more salient in the information environment. Mavragani and Ochoa (2019) propose a methodological framework for Google Trends that emphasizes explicit definition of terms, period, region, category, and search type.

Google Trends normalizes relative interest on a scale from 0 to 100 within the universe of each query. Thus, a higher value does not necessarily mean a larger absolute number of searches across countries, nor does it allow series obtained from independent queries to be mechanically added together. The IICTEC report addressed this issue by using paired comparisons with overlapping terms and robustness checks, an approach used by the present article to construct the annual averages of the four focal indicators (IICTEC, 2026).

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1.3 Scholarly visibility and Google Scholar

Google Scholar differs from controlled bibliographic databases by combining broad coverage with less transparency about indexing, updating, and deduplication criteria. Comparative studies show that its coverage can exceed that of Scopus and Web of Science, especially for document types and fields that are less well represented in traditional databases (Harzing & Alakangas, 2016; Martín-Martín et al., 2021). This breadth is consistent with the objective of this article to observe scholarly production in a broad sense, including articles, books, chapters, theses, preprints, and technical documents.

At the same time, this coverage advantage does not justify treating the number shown at the top of a results page as an exact publication count. Halevi et al. (2017) highlight limitations in quality control, indexing guidelines, and data extraction. Bramer (2016), by tracking repeated searches over time, found large fluctuations in result counts and concluded that the number of occurrences reported by Google Scholar is a weak measure when exact repeatability is required. For this reason, this study adopts the term Google Scholar Estimated Result Count (GSERC) and interprets the indicator as estimated scholarly visibility rather than exact bibliometric production.

1.4 Hypotheses

Integrating the two sources allows four exploratory expectations to be tested:

• H1: public attention is positively associated with the general scholarly visibility of the same topics;

• H2: the strength and direction of this association vary across the strategic dimensions of AI;

• H3: the explicit incorporation of AI into the literature on semiconductors and data centers increases over the period, reflecting growing convergence between infrastructure and the AI agenda;

• H4: increases in public attention precede, with a one-year lag, increases in AI-linked scholarly visibility.

2 - METHODOLOGY

2.1 Research design and period

The study adopts a longitudinal, quantitative, and exploratory design with an annual time unit. The main analysis covers 2016–2025, totaling ten complete years. Data for 2026 were collected from both sources but were excluded from the tests because the year was incomplete at the time of collection. The strategy combines signals of public attention and scholarly visibility without assuming that one causes the other.

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2.2 Google Trends: public attention

Google Trends data derive from the empirical base of IICTEC Research Report No. 001/2026, collected on August 24, 2026. The configuration was Worldwide, All Categories, and Web Search. To reduce scale compression for lower-volume terms, the report also collected paired comparisons. For each dimension, the present article uses the highest-resolution focal series available and previously validated against the main extraction: Artificial Intelligence, Semiconductor, Critical Minerals, and Data Center. Monthly values were aggregated using the arithmetic mean from January to December of each year between 2016 and 2025.

2.3 Google Scholar: collection protocol

Manual collection in Google Scholar was conducted on August 25, 2026, using the Portuguese-language interface. For each query, a custom single-year interval was applied, from 2016–2016 through 2025–2025. The “include patents” and “include citations” options were unchecked; no language filter was applied; and results remained sorted by relevance. The number displayed as “Approximately X results” was recorded as GSERC. The protocol used exact phrases in quotation marks, preserving the terms in English for international standardization.

Layer	Dimension	Query / configuration	Interpretation
Public attention	AI Core	Google Trends: Artificial Intelligence; Worldwide; Web Search; annual mean	Relative search interest
Public attention	Compute	Google Trends: Semiconductor; Worldwide; Web Search; annual mean	Relative search interest
Public attention	Resources	Google Trends: Critical Minerals; Worldwide; Web Search; annual mean	Relative search interest
Public attention	Infrastructure	Google Trends: Data Center; Worldwide; Web Search; annual mean	Relative search interest
General scholarly	AI Core	“artificial intelligence”	General GSERC
General scholarly	Compute	“semiconductor”	General GSERC
General scholarly	Resources	“critical minerals”	General GSERC
General scholarly	Infrastructure	“data center”	General GSERC
AI-linked scholarly	Compute	“artificial intelligence” “semiconductor”	AI-linked GSERC
AI-linked scholarly	Resources	“artificial intelligence” “critical minerals”	AI-linked GSERC
AI-linked scholarly	Infrastructure	“artificial intelligence” “data center”	AI-linked GSERC

Table 1 – Integrated data-collection protocol and operationalization of variables
Source: author’s own elaboration based on Google Trends, Google Scholar, and IICTEC (2026).

Two Google Scholar searches were inadvertently repeated during data collection—Semiconductor in 2018 and 2023—and returned the same values recorded on the first access, 404,000 and 245,000, respectively. This is treated only as a spot check of within-session consistency

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and does not replace formal replication across different days, locations, and browsers, especially given the reproducibility limitations documented by Bramer (2016).

2.4 Derived variables and visual normalization

For semiconductors, critical minerals, and data centers, a descriptive indicator of the intensity of AI linkage was calculated: AI-Linkage Ratio (AILR) = GSERC of the combined query / GSERC of the general query × 100. The AILR should not be interpreted as a true proportion of publications because both numerator and denominator are Google Scholar estimated counts. Its use is exclusively comparative and exploratory, to assess whether the relative presence of the expression “artificial intelligence” within the retrieved universe of each field increases over time.

In the figures, each series was independently normalized by its maximum value in 2016–2025, defined as 100. This transformation facilitates comparison of trajectories with different units and scales without suggesting equivalence between the absolute magnitudes of Google Trends and Google Scholar.

2.5 Statistical analysis

Spearman correlations were calculated by dimension. The first analysis uses annual levels, which is suitable for detecting monotonic association between trajectories. Because series that grow over time can generate high correlations simply by sharing a trend, a second analysis was conducted using annual first differences. The third analysis explores a one-year lag by correlating public attention in year t with scholarly visibility in year t+1; additionally, the test was repeated in first differences to assess whether annual increases in attention precede academic increases in the following period. The p-values are presented as exploratory support, using the conventional 0.05 reference, but they are not interpreted as causal evidence because of the small number of annual observations and the estimated nature of the Scholar data.

2.6 Limitations

The main limitations derive from the sources. Google Trends is a normalized sample of searches and does not measure public opinion or absolute volume. Google Scholar offers broad coverage, but its top-line counts are estimates, may fluctuate with changes in algorithms and indexing, do not provide a reproducible search history equivalent to structured bibliographic databases, and do not allow auditing of all retrieved records. In addition, exact-phrase searches may locate terms in the full text even when the thematic relationship is not the document’s main focus. The results are therefore treated as signals of attention and visibility rather than as census measures of behavior or scientific production.

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3 - RESULTS AND DISCUSSION

3.1 Annual public attention

Annual Google Trends averages show an acceleration of public attention at the end of the period. Artificial Intelligence rises from 5.83 in 2016 to 34.58 in 2025; Semiconductor, from 6.08 to 25.75; and Data Center, from 4.00 to 25.67. Critical Minerals shows the most abrupt proportional change: it remains near zero until the end of the 2010s, reaches 6.50 in 2024, and 31.92 in 2025. This trajectory is consistent with the late shift identified and validated in the earlier institutional report (IICTEC, 2026).

These series must be read internally for each term because Google Trends normalization does not allow one to conclude, for example, that an annual index of 25 for Data Center represents the same absolute search volume as 25 for Semiconductor. The relevant result is the temporal trajectory of each indicator.

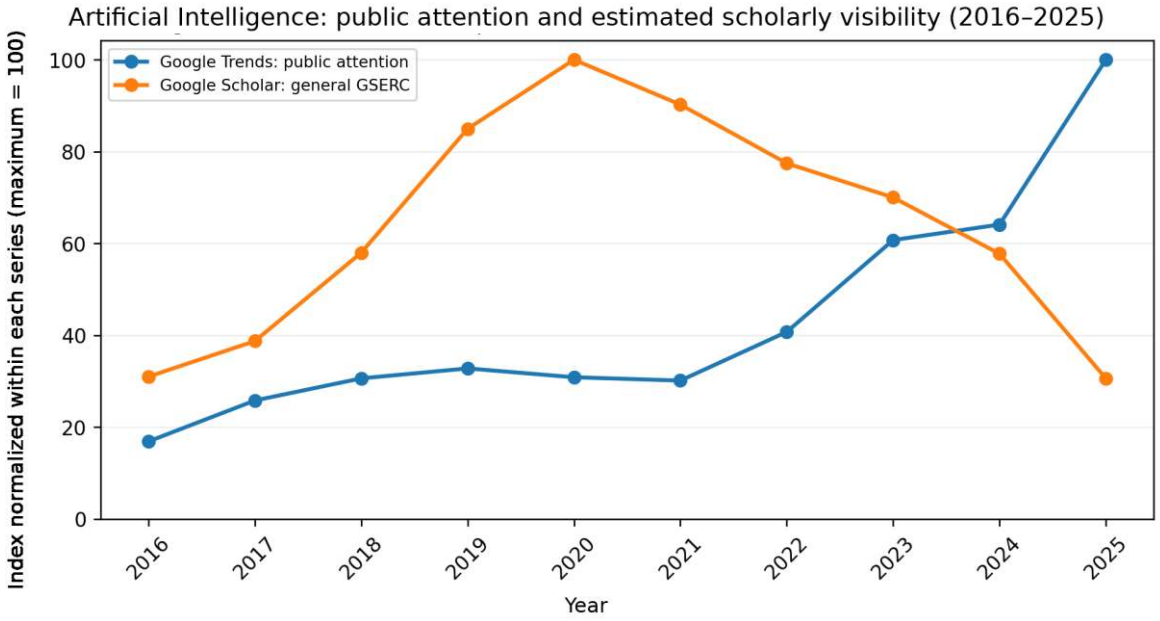

Figure 1 – Artificial intelligence: public attention and estimated scholarly visibility, 2016–2025
Source: author's own elaboration. Each series was independently normalized by the maximum for 2016–2025 = 100.

3.2 General scholarly visibility: divergent trajectories

General Google Scholar counts do not reproduce a single pattern. The exact query "artificial intelligence" grows from an estimated 412 thousand results in 2016 to 1.33 million in 2020, but falls back to 407 thousand in 2025. Semiconductor remains close to 400 thousand through 2020 and then progressively declines to 130 thousand in 2025. Data Center rises from 42.7 thousand to 64.6 thousand between 2016 and 2021 and returns to 47.1 thousand in 2025. In the opposite direction, Critical Minerals grows from an estimated 409 results in 2016 to 10.1 thousand in 2025.

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These differences are substantively interesting, but they also expose the main weakness of using hit counts as a proxy. A literal interpretation would suggest a decline in production on AI, semiconductors, and data centers in recent years, which is difficult to sustain without validation in controlled databases. The literature on Google Scholar shows that result estimates can vary and do not necessarily correspond to stable document counts (Bramer, 2016; Halevi et al., 2017). Accordingly, this article avoids turning the decline in general GSERC into a claim that scientific production actually fell.

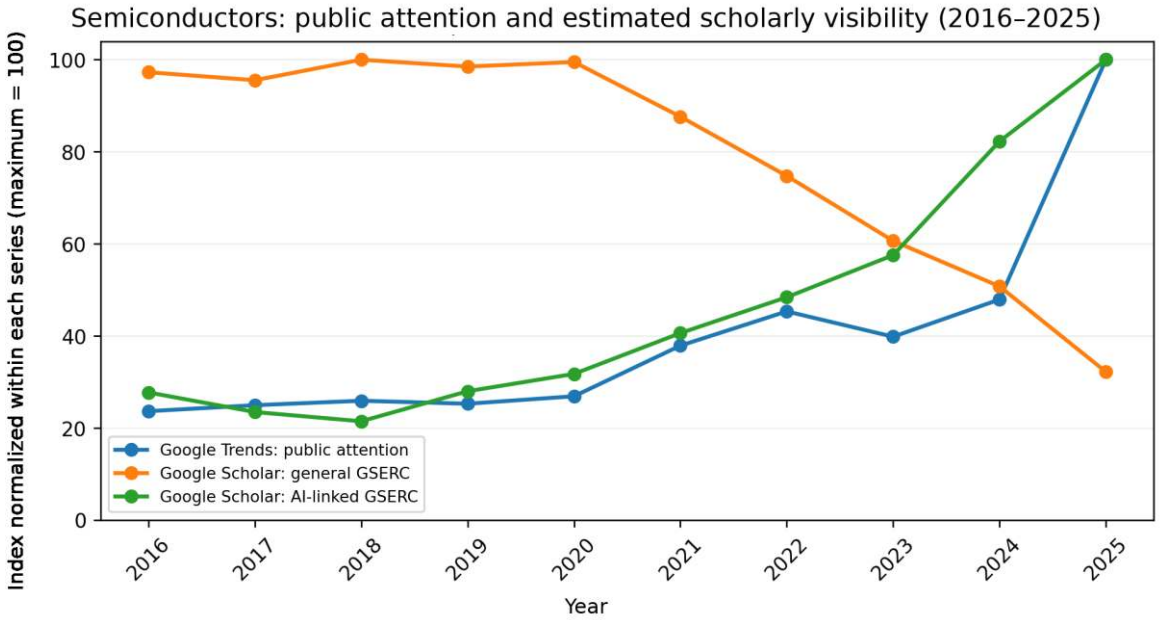

Figure 2 – Semiconductors: public attention, general GSERC, and AI-linked GSERC
Source: author's own elaboration. Series independently normalized by the maximum for 2016–2025 = 100.

3.3 Explicit AI linkage grows in infrastructure fields

The combined queries produce a much more consistent picture. The estimated co-occurrence of "artificial intelligence" and "semiconductor" rises from 10.3 thousand in 2016 to 37.2 thousand in 2025, equivalent to an approximate compound annual growth rate of 15.3%. The query "artificial intelligence" + "data center" grows from 1.89 thousand to 21.9 thousand, with a compound annual growth rate of 31.3%. For critical minerals, the initial base is much smaller, but growth is even more intense: from 82 to 2,310, or approximately 44.9% per year over the period.

Comparison with the general universe reinforces the notion of AI "incorporation." The semiconductor AILR rises from 2.62% in 2016 to 28.62% in 2025 and shows a positive monotonic correlation with time ($\rho=0.915$; $p<0.001$). For data centers, the AILR rises from 4.43% to 46.50% and increases monotonically in every observed year ($\rho=1.000$; $p<0.001$). For critical minerals, the indicator fluctuates between approximately 14% and 26%, ending at 22.87%, with no significant monotonic trend. This suggests that the critical-minerals literature already contained, proportionally,

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some intersection with AI from the beginning of the window, while semiconductors and data centers undergo a much more pronounced relative incorporation of the AI theme.

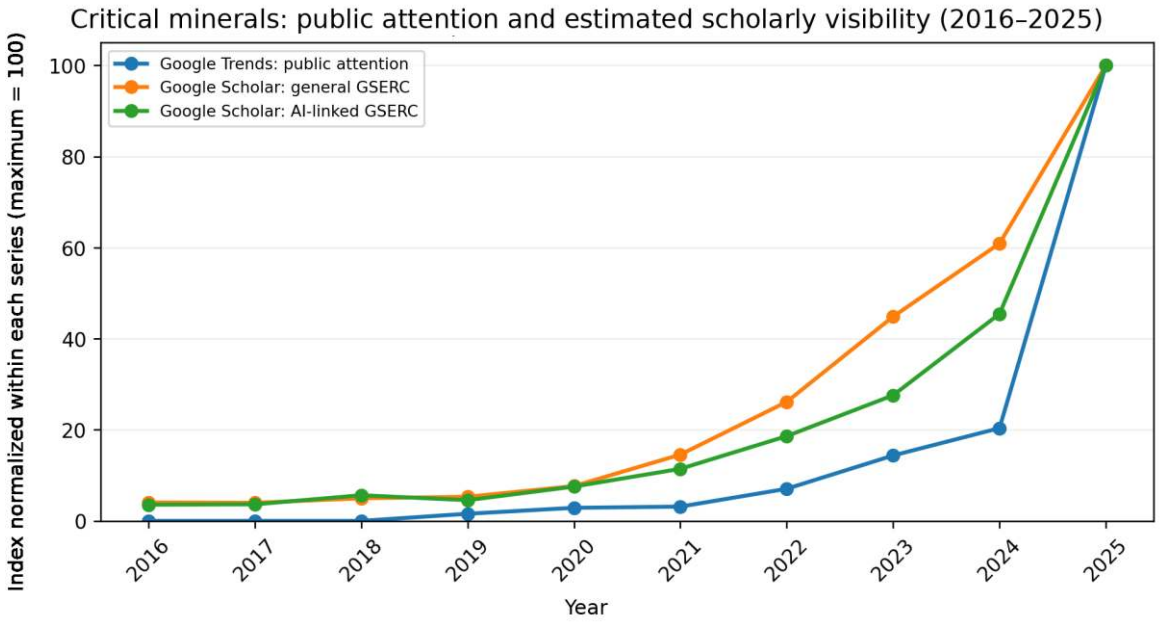

Figure 3 – Critical minerals: public attention, general GSERC, and AI-linked GSERC
Source: author's own elaboration. Series independently normalized by the maximum for 2016–2025 = 100.

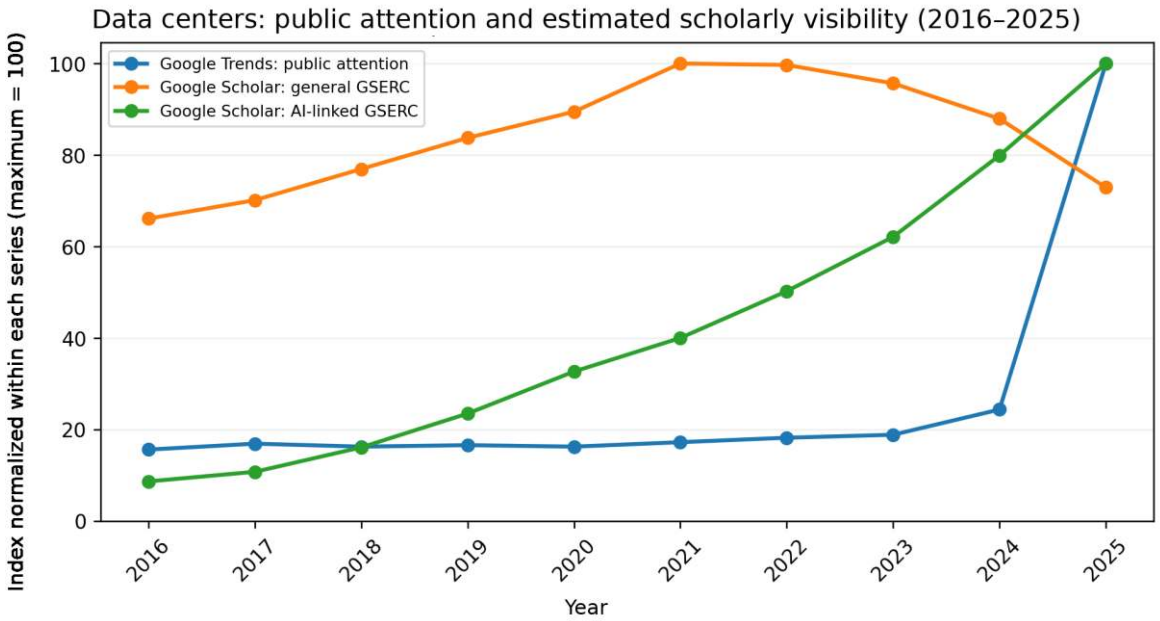

Figure 4 – Data centers: public attention, general GSERC, and AI-linked GSERC
Source: author's own elaboration. Series independently normalized by the maximum for 2016–2025 = 100.

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Dimension	AI-linked 2016	AI-linked 2025	CAGR 2016–25	AILR 2016	AILR 2025	ρ AILR×year
Semiconductor	10.300	37.200	15,3%	2,62%	28,62%	0,915***
Critical Minerals	82	2.310	44,9%	20,05%	22,87%	-0,358
Data Center	1.890	21.900	31,3%	4,43%	46,50%	1,000***

Table 2 – Growth of AI-linked scholarly visibility and relative linkage intensity (AILR)
*Source: author's own elaboration. *** p<0.001. AILR is a descriptive indicator based on Google Scholar estimated counts.*

3.4 Correlations between public attention and scholarly visibility

Spearman tests confirm that the result depends strongly on how the academic dimension is operationalized. When general counts are used, Artificial Intelligence shows virtually no association with Google Trends (ρ=-0.079; p=0.829); Semiconductor shows a strong negative association (ρ=-0.770; p=0.009); Critical Minerals shows an almost perfect positive association (ρ=0.988; p<0.001); and Data Center shows a moderate but non-significant positive association (ρ=0.328; p=0.354). Taken together, these results do not support a simple hypothesis that greater public attention automatically corresponds to a larger general GSERC.

The picture changes for AI-linked queries. In levels, the relationship between public attention and AI-linked GSERC is strong and positive for Semiconductor (ρ=0.903; p<0.001), Critical Minerals (ρ=0.963; p<0.001), and Data Center (ρ=0.906; p<0.001). Thus, while the estimated overall size of the fields does not uniformly track public attention, the explicit presence of AI within these fields grows in a way that is much more closely aligned with public-interest curves.

However, the first-difference analysis substantially reduces the strength of these associations. For Semiconductor, the correlation between annual changes is ρ=0.467 (p=0.205); for Data Center, ρ=0.477 (p=0.194); and for Critical Minerals it remains strong and significant, ρ=0.795 (p=0.010). The difference between correlations in levels and in annual changes indicates that part of the association for semiconductors and data centers is explained by shared upward trends rather than necessarily by year-to-year synchronization.

Dimension	Scholarly measure	ρ levels	p	ρ 1st difference	p	ρ lag +1 in levels	ρ lead +1 in 1st diff.
Artificial Intelligence	General GSERC	-0,079	0,829	-0,533	0,139	-0,117	0,214
Semiconductor	General GSERC	-0,770	0,009	-0,400	0,286	-0,883	-0,714*
Critical Minerals	General GSERC	0,988	<0,001	0,870	0,002	0,983	0,826*
Data Center	General GSERC	0,328	0,354	-0,664	0,051	0,042	-0,590
Semiconductor	AI-linked GSERC	0,903	<0,001	0,467	0,205	0,950	0,119
Critical Minerals	AI-linked GSERC	0,963	<0,001	0,795	0,010	0,983	0,874**
Data Center	AI-linked GSERC	0,906	<0,001	0,477	0,194	0,870	0,395

Table 3 – Spearman correlations between Google Trends and Google Scholar measures
*Source: author's own elaboration. * p<0.05; ** p<0.01 for the lead +1 test in first differences. Correlations in levels with a time trend should be interpreted with caution.*

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3.5 The temporal lag is not generalizable

Lagged correlations in levels are high for the three AI-linked series: 0.950 for Semiconductor, 0.983 for Critical Minerals, and 0.870 for Data Center. However, this result is insufficient to state that public attention precedes scholarly production because rising series tend to remain correlated after temporal shifts. When the procedure is repeated on first differences, only Critical Minerals maintains a positive and significant association between the change in attention in year t and the academic change in the following year (ρ=0.874; p=0.005). Semiconductor (ρ=0.119) and Data Center (ρ=0.395) do not show similar support.

This finding is methodologically important. The hypothesis of a simple chain—"public attention today, publication tomorrow"—does not receive general support. Critical minerals are the clearest exception: growth in public attention appears to precede increases in AI-linked scholarly visibility even after partially controlling for the trend through first differences. Even so, the small number of years and the estimated counts recommend treating the result as an exploratory signal to be tested in structured databases.

3.6 Evaluation of the hypotheses

Hypothesis	Result	Summary
H1	Not supported overall	General Scholar counts diverge by dimension; only Critical Minerals shows a strong positive association.
H2	Supported	The direction and strength of associations vary substantially across AI Core, compute, resources, and infrastructure.
H3	Supported for Semiconductor and Data Center	AILR rises from 2,62% to 28,62% for semiconductors and from 4,43% to 46,50% for data centers; there is no monotonic trend for Critical Minerals.
H4	Partially supported	Only Critical Minerals maintains a significant lead +1 relationship in first differences.

Table 4 – Summary of hypothesis evaluation
Source: author's own elaboration.

3.7 Implications for the geopolitics of AI

The central result is not a simple correspondence between "public interest" and "number of publications." The most consistent pattern is different: as semiconductors and data centers gain public attention as components of AI infrastructure, the frequency with which these fields appear explicitly associated with the expression "artificial intelligence" in Google Scholar also increases. This is consistent with literature describing AI, chips, computing facilities, energy, and minerals as elements of the same strategic system (STACCIARINI & GONÇALVES, 2025; REINHOLD, 2026).

In the case of semiconductors, the divergence is particularly revealing. General GSERC falls during the second half of the period, while AI-linked GSERC and the AILR grow strongly. Rather

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than indicating decline in the field, the data suggest that AI occupies a growing share of the visibility retrieved within a much broader domain of materials science, electronics, photonics, sensors, and manufacturing. This interpretation is consistent with the increasing centrality of chips in technological and security competition.

For data centers, the trend is even clearer: AILR rises every year, reaching 46.5% in 2025. This does not mean that nearly half of actual data-center publications concern AI, because Scholar counts are estimates; it means that, under a constant protocol, the query combining AI and data centers gained substantial relative weight compared with the general query. The literature on data-center energy consumption and the expansion of data-intensive workloads helps contextualize this convergence (MASANET ET AL., 2020).

Critical minerals form a distinct case. The general field is already growing rapidly, and the AI-linked search also expands. The relative ratio, however, does not increase monotonically, suggesting that the recent explosion of scholarly interest in critical minerals is driven by a broader set of agendas—energy transition, supply security, electric vehicles, defense, and geoeconomic rivalry—within which AI is only one connection. The fact that Critical Minerals is the only dimension with a significant association both in first differences and in the lead +1 test reinforces its singularity during the period analyzed.

4 - CONSIDERATIONS

This article examined the relationship between public attention and scholarly visibility across four dimensions of the geopolitics of artificial intelligence between 2016 and 2025. The design extends a previous institutional report based only on Google Trends by introducing Google Scholar as a second source and distinguishing general scholarly visibility from visibility explicitly linked to AI.

The main conclusion is that there is no universal relationship between public attention and the estimated raw size of the literature. General Google Scholar counts produced heterogeneous and, in some cases, counterintuitive trajectories. By contrast, AI-linked scholarly visibility showed a strong monotonic association with public attention for semiconductors, critical minerals, and data centers. The result suggests that the most relevant process is not necessarily expansion of the academic field as a whole, but rather the growing incorporation of AI into strategic fields that sustain its material base.

The methodological contribution consists of proposing a three-layer architecture: Google Trends as a signal of public attention; general GSERC as a signal of broad scholarly visibility; and AI-linked GSERC as a signal of thematic intersection with AI. AILR complements this architecture by measuring the relative intensity of linkage, always as an exploratory indicator. Comparing levels, first differences, and lags shows why time-series correlations must be treated carefully: very strong relationships in levels can weaken when only annual changes are observed.

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The findings also have substantive implications for the geopolitics of technology. Semiconductors and data centers become progressively associated with AI both in public attention and in the retrieved literature, reflecting a shift in the debate from a purely algorithmic view to an infrastructural one. Critical minerals, in turn, form a broader agenda in which AI, the energy transition, supply security, and international rivalry overlap. This infrastructural shift occurs in parallel with the strengthening of AI governance, explainability, and accountability agendas (ALVES CORREIA ET AL., 2026; SANTANA ET AL., 2026).

The main limitation remains Google Scholar. The article does not claim that GSERC corresponds to actual publication counts and does not use the results as substitutes for bibliometrics in controlled databases. Future replication should reconstruct the same series in Scopus, Web of Science, Dimensions, or OpenAlex, preferably using title, abstract, and keyword queries, to validate whether the AI-linkage pattern observed here persists. It is also advisable to repeat Google Scholar extractions on different dates and in different environments, store screenshots, and, when possible, compare samples of individual records.

In summary, the data support a reading of the geopolitics of AI as a phenomenon of convergence among public attention, computing, infrastructure, and material resources. This convergence is more visible when the growing presence of AI within strategic fields is measured than when only the estimated raw volume of those fields is observed. The result provides an initial empirical basis for later studies of how infrastructure topics simultaneously enter the public, academic, and geopolitical agendas.

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