

The background features a complex network graph with blue and grey nodes connected by thin lines, overlaid on a 3D molecular structure with blue and orange spheres. The text is centered and reads:

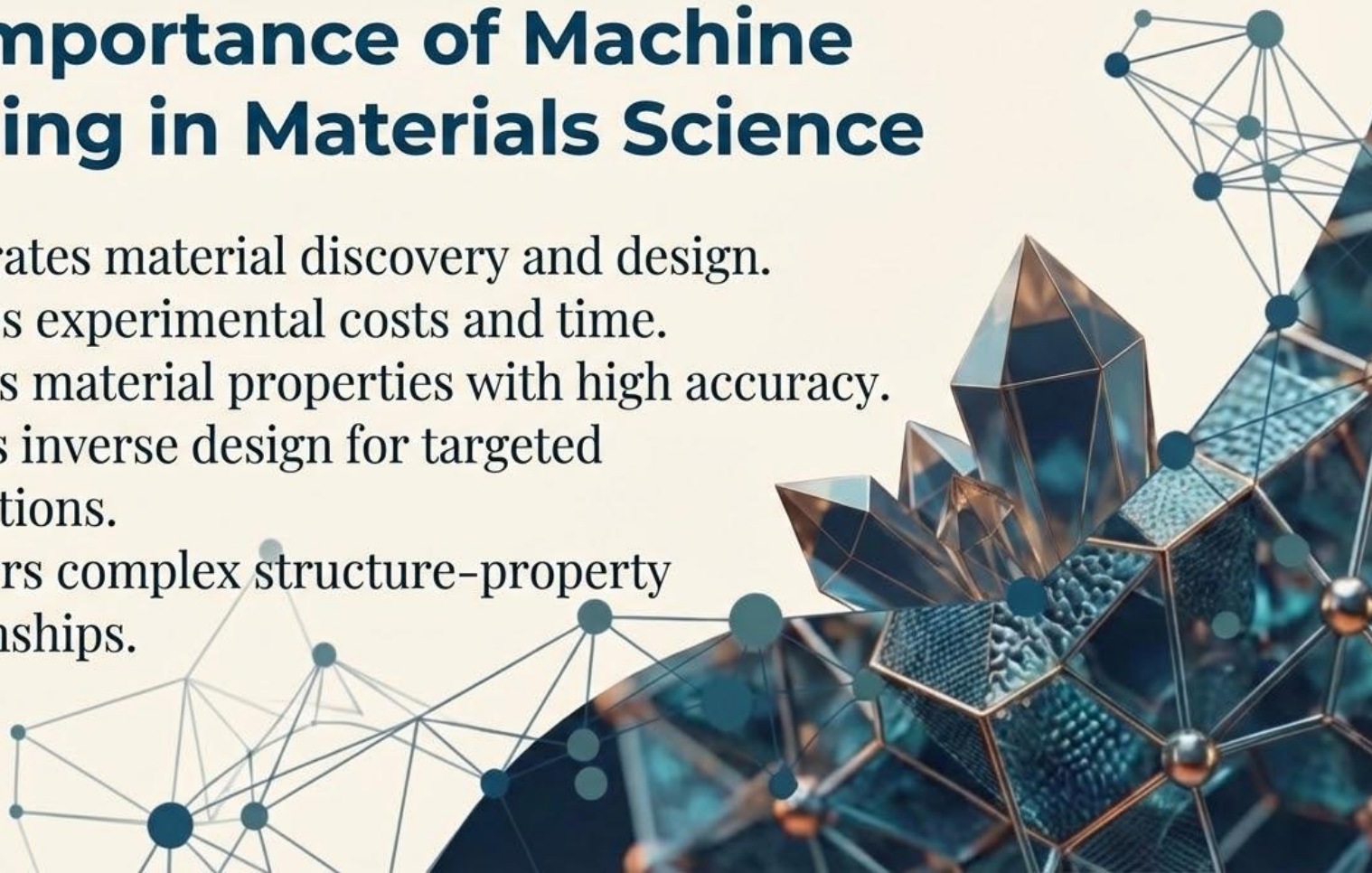
# ML meets Materials

## A Bibliometric Deep Dive

Ronaldo Cristiano Prati, Universidade  
Federal do ABC,  
[ronaldo.prati@ufabc.edu.br](mailto:ronaldo.prati@ufabc.edu.br)

# The Importance of Machine Learning in Materials Science

- Accelerates material discovery and design.
- Reduces experimental costs and time.
- Predicts material properties with high accuracy.
- Enables inverse design for targeted applications.
- Uncovers complex structure-property relationships.



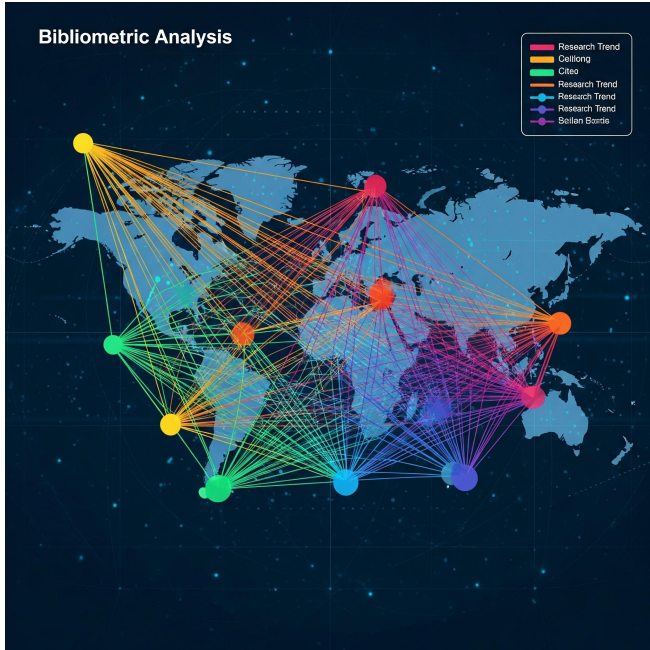
# The 4th Paradigm

- Data-intensive science is the fourth paradigm
- It involves exploration through massive datasets
- The paradigm integrates theory, experiment, and simulation
- Scientific discovery is increasingly driven by data



## THE FOURTH PARADIGM

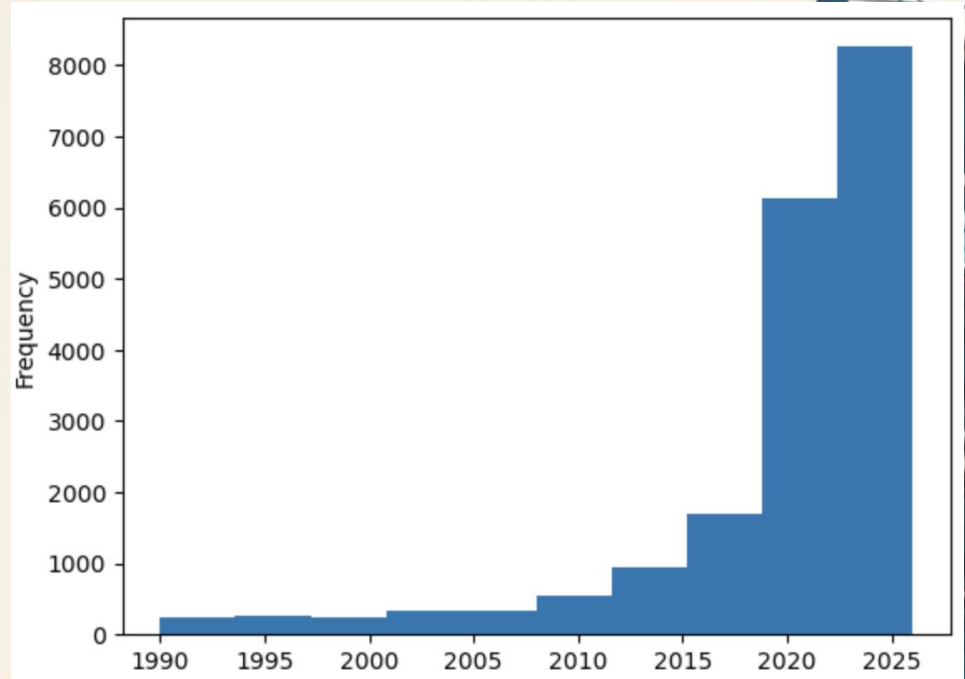
# Bibliometric Analysis Essentials



- Bibliometric analysis helps identify important research trends
- It reveals the geopolitics of scientific production globally
- The analysis assists in mapping collaboration networks effectively
- It is crucial for understanding the landscape of science

# Exponential Growth of Publications

- Dramatic increase in research output in recent years.
- Reflects growing interest and adoption of ML techniques.
- Driven by data availability and computational power.



# Data Source and Methodology

- Data source: OpenAlex database.
- Scope: Papers categorized under Machine Learning in Materials Science.
- Focus: Journal papers with an Impact Factor.
- Timeframe: Published after 1990.
- Total volume: 20,127 papers analyzed.

# Topic distribution

|                                           |                                          |                                                        |                                                   |                                                  |                                             |                                           |                                              |
|-------------------------------------------|------------------------------------------|--------------------------------------------------------|---------------------------------------------------|--------------------------------------------------|---------------------------------------------|-------------------------------------------|----------------------------------------------|
| Alloy Modeling<br>(4.4%)                  | Ai Battery<br>Discovery (2.5%)           | X-Ray<br>Spectroscopy<br>Analysis (1.8%)               | Deep Materials<br>Learning (1.5%)                 | Bayesian<br>Materials<br>Discovery (0.9%)        | MI Adsorption<br>Prediction<br>(0.9%)       | Kinetic Monte<br>Carlo (0.9%)             | Uncertainty<br>Quantification<br>(0.7%)      |
|                                           |                                          |                                                        | Machine-Learned<br>Phase<br>Transitions<br>(1.5%) | Clinical Imaging<br>Studies (1.0%)               | Band-Gap<br>Prediction<br>(0.9%)            |                                           | Ai-Driven Solar<br>Discovery (0.8%)          |
| Materials<br>Science Research<br>(5.8%)   | Ai-Driven<br>Nanotechnology<br>(2.6%)    | Electronic<br>Structure MI<br>(2.0%)                   |                                                   |                                                  |                                             | Machine-Learning<br>Magnetism (0.9%)      | Machine-Learning<br>Perovskites<br>(0.9%)    |
|                                           |                                          |                                                        | LLMs For<br>Materials (1.5%)                      | Ai Microscopy<br>Analysis (1.4%)                 | Computational<br>Chemistry MI<br>(1.4%)     |                                           | Ai-Driven<br>Synthesis (1.2%)                |
|                                           | Atomic Machine<br>Learning (2.7%)        | Machine-Learned<br>Interatomic<br>Potentials<br>(2.1%) | Generative<br>Inverse Design<br>(1.8%)            | Machine-Learning<br>Thermodynamics<br>(1.6%)     | Thermal<br>Conductivity<br>Discovery (1.6%) |                                           | MI Force Fields<br>(1.5%)                    |
| Ai-Driven<br>Catalyst<br>Discovery (6.0%) | Quantum<br>Chemistry<br>Computing (2.8%) | Graph Neural<br>Networks (2.5%)                        |                                                   | Ai Molecular<br>Property<br>Prediction<br>(2.4%) |                                             | Ai-Driven<br>Molecular<br>Dynamics (2.2%) | Nitride<br>Semiconductor<br>Materials (2.1%) |
|                                           |                                          |                                                        |                                                   |                                                  |                                             |                                           |                                              |
| Ai Materials<br>Discovery (7.6%)          | Neural Network<br>Potentials<br>(3.5%)   |                                                        | Machine Learning<br>Methods (3.3%)                |                                                  | Organic-Metal<br>Interfaces<br>(3.2%)       |                                           | Density<br>Functional<br>Theory (2.9%)       |
|                                           | Ai Reaction<br>Prediction<br>(3.8%)      |                                                        | Crystal<br>Structure<br>Prediction<br>(3.6%)      |                                                  | MI Energy<br>Surfaces (3.6%)                |                                           | Ai-Driven<br>Polymer Design<br>(3.5%)        |

# Key Trends: AI in Materials Science Research



- **Dominance of 'Ai Materials Discovery':** The largest research category (7.6%), emphasizing the search for novel materials.



- **Foundational Role of ML Methods:** 'Graph Neural Networks' and general 'Machine Learning Methods' are key enabling techniques.



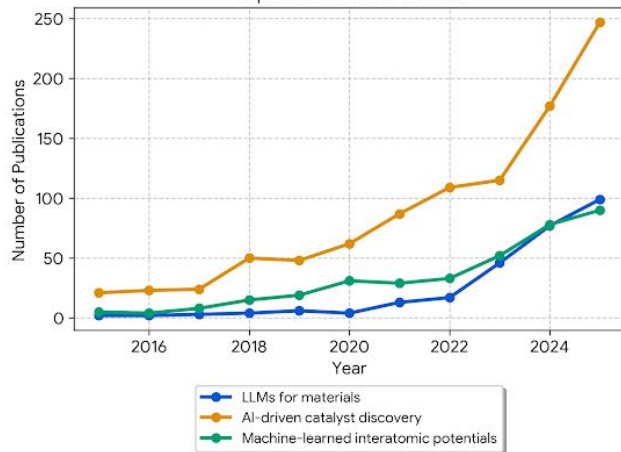
- **Focus on High-Impact Applications:** Significant research in 'Catalyst Discovery', 'Battery Discovery', and 'Polymer Design'.



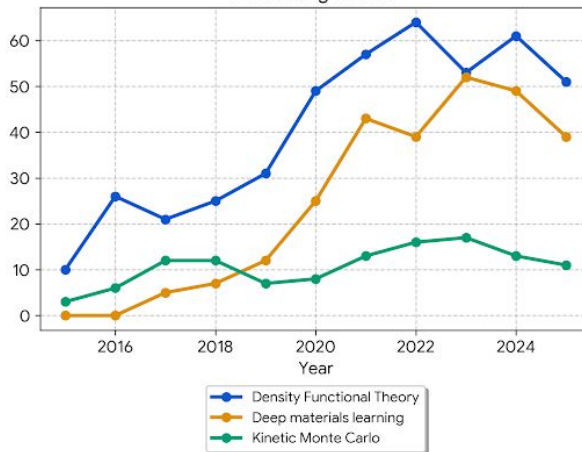
- **Widespread Adoption:** AI is integrated across diverse fields, from 'Alloy Modeling' to 'Quantum Chemistry'.

# Interesting trends

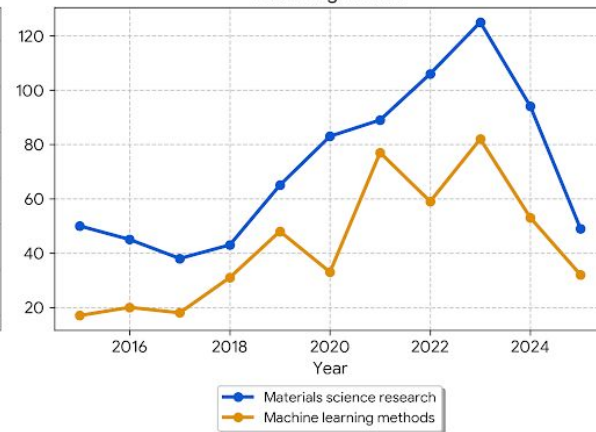
Explosive Growth Trends



Plateauing Trends



Declining Trends

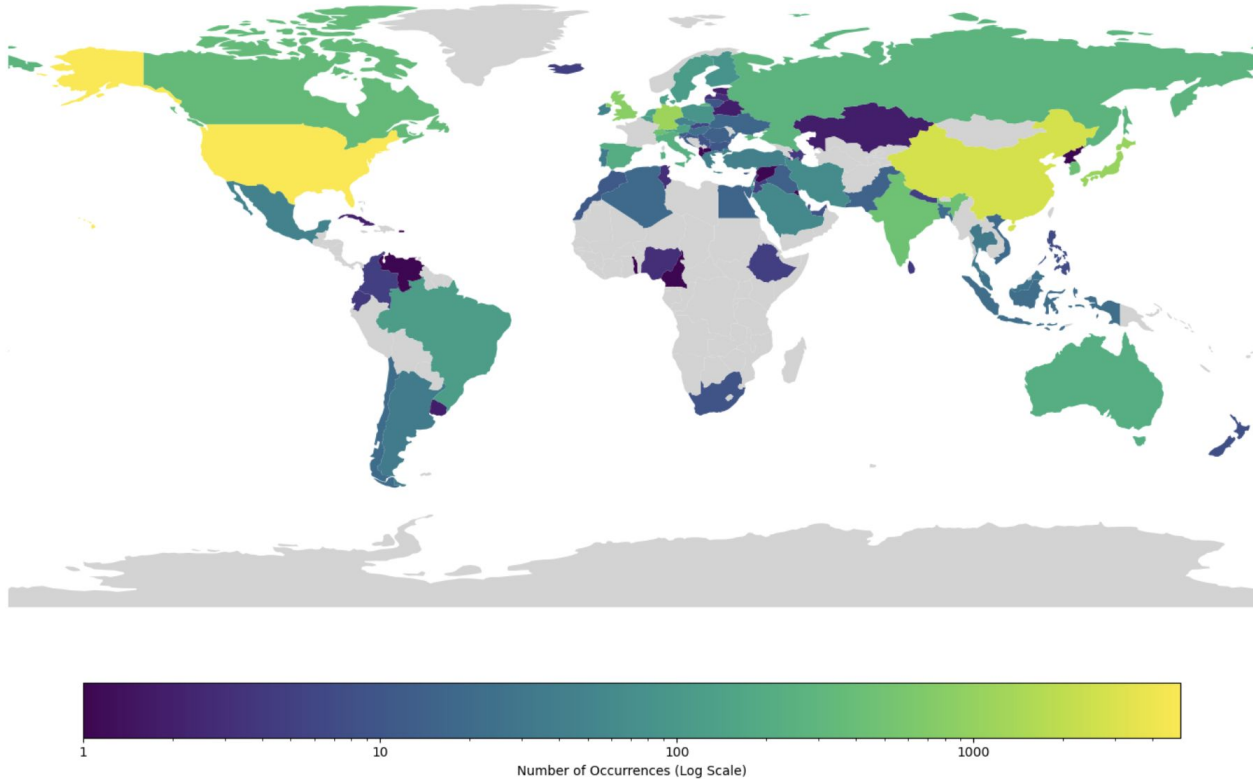


# Highlights: Trends in Materials Science Research Topics

-  **Explosive Growth in AI-Driven Fields:** Topics like “LLMs for materials,” “AI-driven catalyst discovery,” and “Machine-learned interatomic potentials” are experiencing a rapid surge in publications, particularly since 2022.
-  **Plateauing of Established Methods:** Traditional computational methods such as “Density Functional Theory” and “Kinetic Monte Carlo,” along with earlier “Deep materials learning” approaches, appear to have reached a **saturation point** in research output.
-  **Shift Towards Specialization:** Broader categories like general “Materials science research” and “Machine learning methods” are seeing a **decline**, suggesting a research focus shift towards more **specific**, applied AI and ML techniques in materials science.

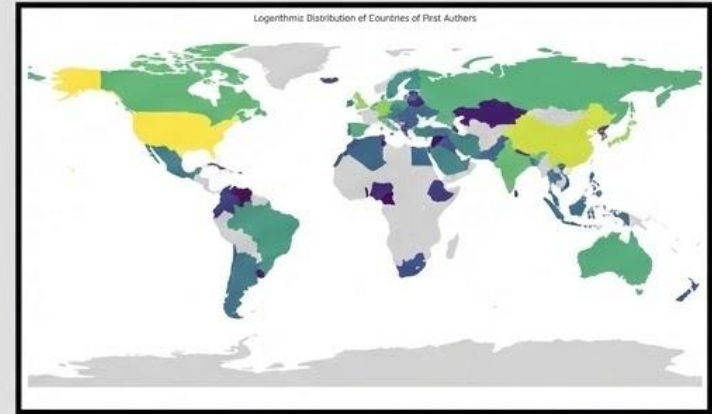
# Distribution of first authorship

Logarithmic Distribution of Countries of First Authors

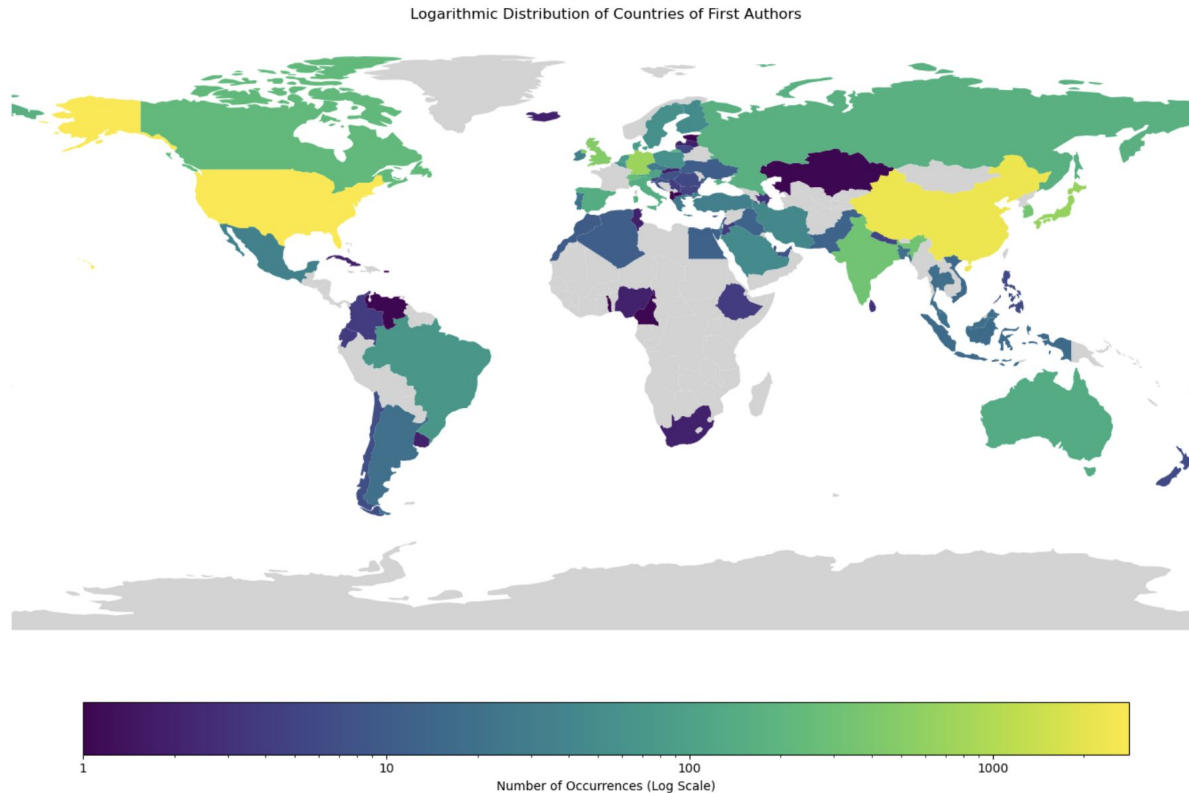


# Analysis of Global First Author Distribution

- **Dominant Research Hubs:** The USA, China, and Western Europe (e.g., Germany, UK) exhibit the highest concentrations of first authors, reflecting their leading global research positions.
- **Key Regional Contributors:** Significant contributions are also evident from nations like India, Japan, South Korea, Brazil, and Australia, indicating strong regional research activity.
- **Global Disparities:** A marked inequality in research output is observable, with lower participation rates across much of Africa, South America, and Central Asia.
- **Logarithmic Scale Effect:** The logarithmic coloring highlights the massive order-of-magnitude differences between top-tier publishing countries and others.



# Distribution of authorship (last 5 years)



# Comparative Analysis: Authorship Distribution (Since 1990 vs. Last 5 Years)

- **Since 1990 (Long-Term Trend):**
  - Historical dominance by traditional research hubs (USA, Western Europe).
  - Gradual growth in contribution from emerging economies.
- **Last 5 Years (Recent Trend):**
  - Rapid acceleration of China's authorship, establishing it as a top-tier contributor.
  - Increased prominence of countries like India, Brazil, and South Korea.
  - Persistent global disparities remain, with limited change in many developing regions.
- **Key Shift:**
  - A discernible shift in the center of gravity of scientific production towards Asia.
  - High-volume output remains concentrated in a relatively small number of nations, despite broader global participation.

# Key Bibliometric Indicators: FWCI & SJR

## Field-Weighted Citation Impact (FWCI)

- Measures citation impact compared to world average (1.0) for the same field, publication year, and document type.
- A value  $> 1.0$  indicates higher than average impact;  $< 1.0$  indicates lower than average.
- Accounts for variations in citation practices across different disciplines.



## SCImago Journal Rank (SJR)

- Reflects the scientific prestige and influence of a journal based on citations.
- Higher SJR values represent greater prestige, considering both the number of citations and the prestige of the citing journals.
- Often used to rank journals within specific subject areas.



FWCI Distribution by Number of Unique Countries



### Number of Unique Countries

# International Collaboration Premium: How Country Diversity Impacts FWCI

## 1. Correlation Between Diversity and Impact

- Generally, as number of unique countries increases, Mean and Median FWCI tend to rise.
- Why? Papers benefit from wider networks, diverse expertise, and higher visibility across geographic regions.
- The 'Global Reach' Effect: A paper with 5 countries (e.g., , , , , ) is more likely cited in all five regions compared to a single-country paper.





# SJR Distribution by Number of Unique Countries

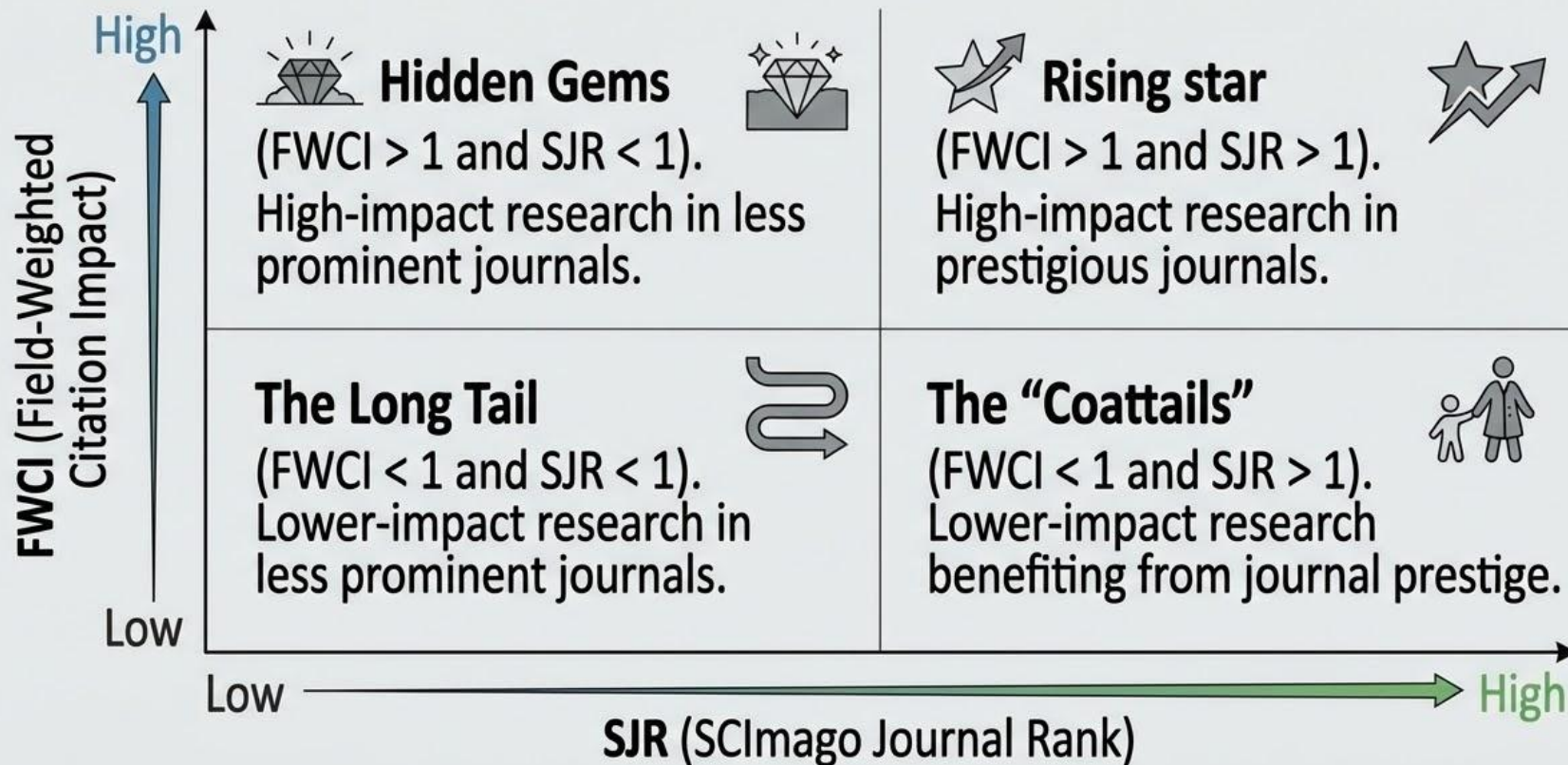


## Key Insights

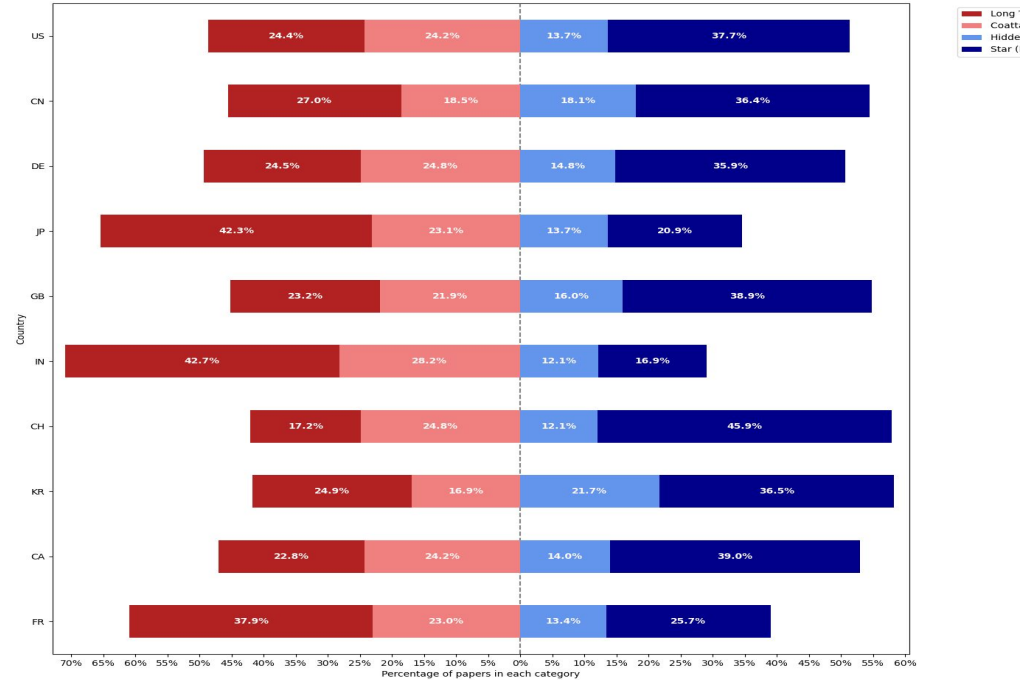


- **Clear Trend:** Higher country diversity correlates with higher median SJR.
- **Multi-national teams** are more successful in publishing in top-quartile (Q1) journals.
- **‘Prestige Floor’:** High collaboration groups have fewer low-impact venues.
- **Single-country** papers show a wider, more volatile range of journal quality.

# Journal Classification Matrix: FWCI vs. SJR



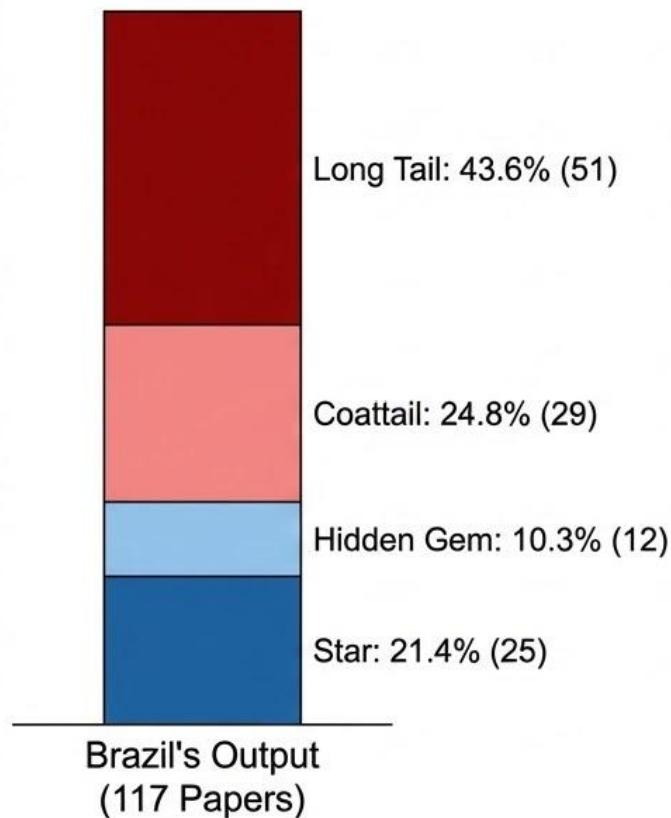
# Quality indicators by country



# Highlights: Quality Indicators by Country

- **China (CH)** leads in high-quality "Star" publications (**45.9%**) and has the lowest proportion of "Long Tail" papers (**17.2%**).
- The **United States (US)** and **United Kingdom (GB)** also demonstrate strong performance with high percentages of "Star" publications (**37.7%** and **38.9%**, respectively).
- **India (IN)** has the highest proportion of "Long Tail" publications (**42.7%**) and the lowest percentage of "Star" papers (**16.9%**), indicating a challenge in publication quality.
- **Japan (JP)** shows a similar profile to India, with a high "Long Tail" (**42.3%**) and relatively low "Star" percentage (**20.9%**).
- **South Korea (KR)** is notable for having the highest proportion of "Hidden Gems" (**21.7%**), suggesting high-impact research in less prominent journals.

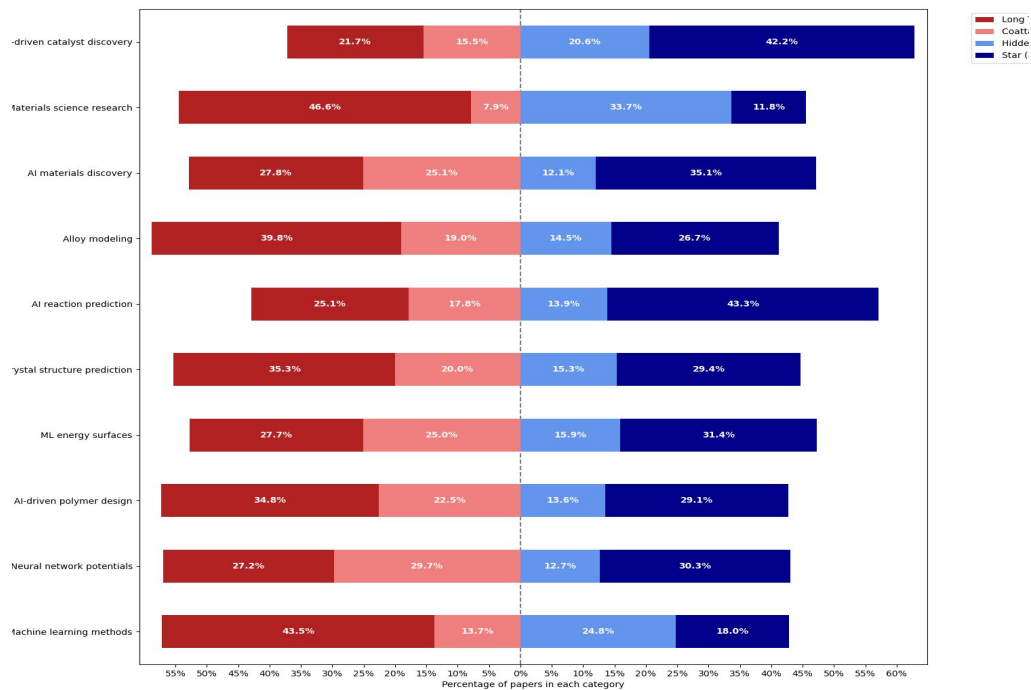
# Brazil's Research Profile



## Key Comparisons & Summary

- **High Concentration in 'Long Tail' (~44%):** Significant portion in lower-tier journals. Nearly double the US (~24%) or China (~27%). Similar to India and Russia.
- **Gap in 'Star' Papers (~21%):** Lower than leaders like the US (~38%) and China (~36%), and volume peers like Belgium (41%).
- **'Coattail' Rates (~25%) are Globally Consistent:** Similar to the US, Russia, and Denmark, indicating a universal challenge in converting prestigious placements into high citations.
- **Summary Assessment:** Represents a volume-driven, developing research ecosystem, similar to India and Russia, but distinct from highly efficient European nations.

# Quality index by topic



# Highlights: Quality Index by Topic



**AI-Driven Topics Lead in "Star" Papers:** Topics like "AI reaction prediction" and "AI-driven catalyst discovery" show the highest proportion of "Star" papers (over 40%), indicating high impact.



**Broader Topics Have Longer "Tails":** General categories like "Materials science research" and "Machine learning methods" have a larger share of "Long Tail" papers, suggesting a wider range of quality.



**Modeling and Prediction Show Balance:** Topics such as "Alloy modeling" and "Crystal structure prediction" exhibit a more even distribution across all quality categories.



**Niche AI Applications Yield "Hidden Gems":** Specialized areas like "AI-driven polymer design" and "Neural network potentials" have a significant portion of "Hidden Gem" papers, highlighting their potential.

# LLMs for Materials: The Quality Index Leader

Highest-performing topic in impact & prestige, drastically outperforming global averages.

## 1. The Undisputed Leader in “Star” Papers & Shrinking “Long Tail”

 **47.9%** (LLMs) vs. 30.8% (Global Avg.) Star Papers.  
Rank #1/44 topics for highest concentration.

 **18.6%** (LLMs) vs. 31.0% Rare (Global Avg.) Long Tail Papers.  
publication in low-impact venues.

## 3. Comparison Table: LLMs vs. Global & Other Topics

| Topic                        | ★ Star (Gold) | 💎 Hidden Gem | 📄 Coattail (Pink) | 📉 Long Tail |
|------------------------------|---------------|--------------|-------------------|-------------|
| LLMs for materials           | 47.9%         | 14.5%        | 19.0%             | 18.6%       |
| AI-driven catalyst discovery | 42.2%         | 20.6%        | 15.5%             | 21.7%       |
| GLOBAL AVERAGE               | 30.8%         | 17.5%        | 20.6%             | 31.0%       |
| Materials science research   | 11.2%         | 33.7%        | 16.5%             | 38.6%       |

### Summary Conclusion

The data reveals a compounding ‘gold rush’ effect. Fast volume growth combined with aggressive community reward (high acceptance & citations).

# Conclusion: The Power of Bibliometric Insight



**Bibliometric analysis** is crucial for mapping scientific landscapes, identifying emerging trends, and understanding research impact.



Data reveals a significant shift towards AI-driven research, with distinct quality profiles across different topics, as seen in the 'Star' and 'Long Tail' distributions.



**Specialized fields** like 'LLMs for Materials' are experiencing explosive growth and high community recognition, highlighting a 'gold rush' effect in science.

**Leveraging these insights enables strategic decision-making in research and development.**

# Thank You!

- Thank you to PhD student Luis Cesar Azevendo
- Grateful for the support from the CINE CMD team for the valuable contributions and discussion provided
- Presentation made possible through this collaboration

