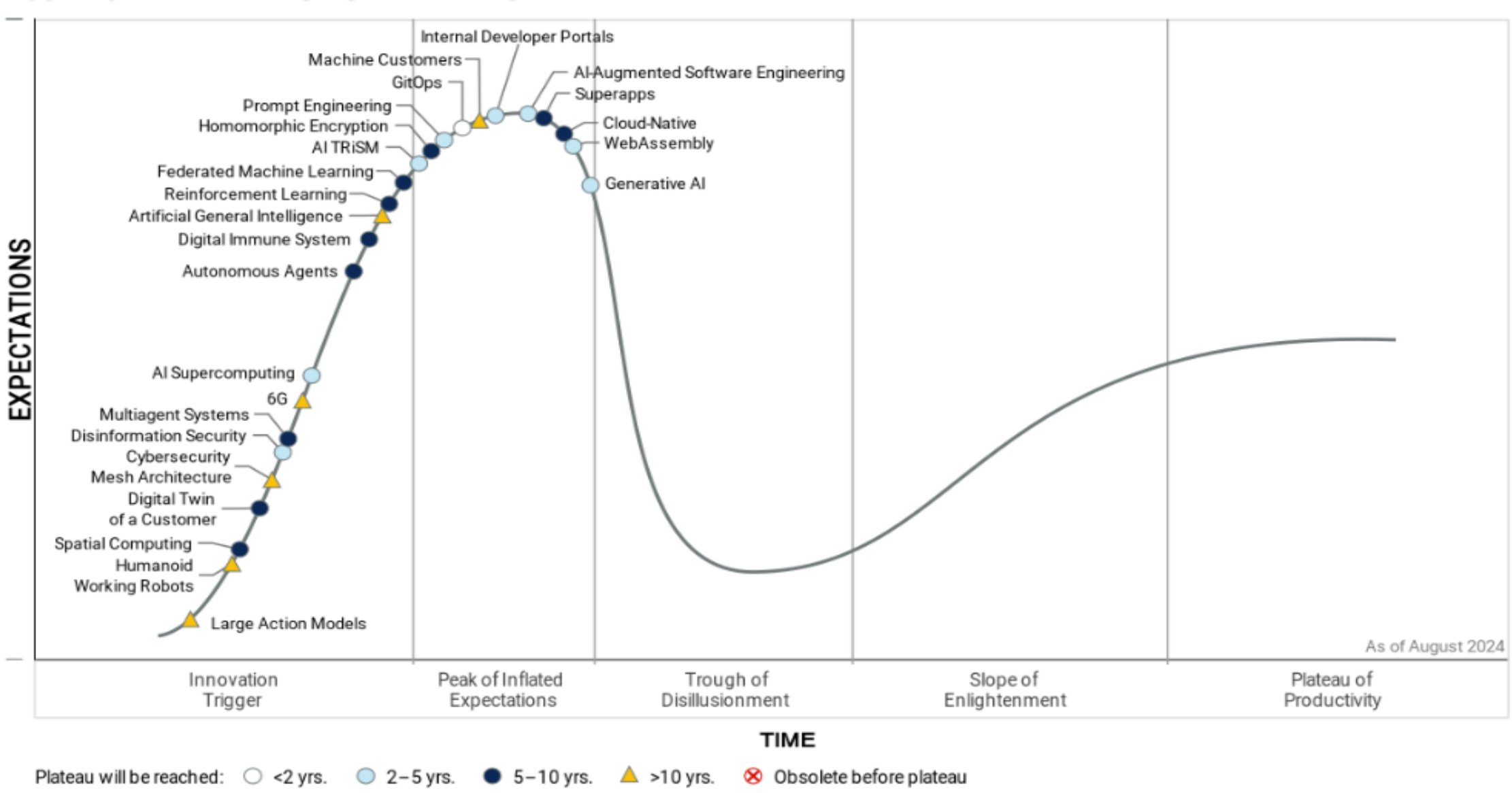
Más allá de los algoritmos:

El humano en la ecuación en un mundo impulsado por tecnologías emergentes

Ing. Henry Lizano Mora, PhD.C, MTI

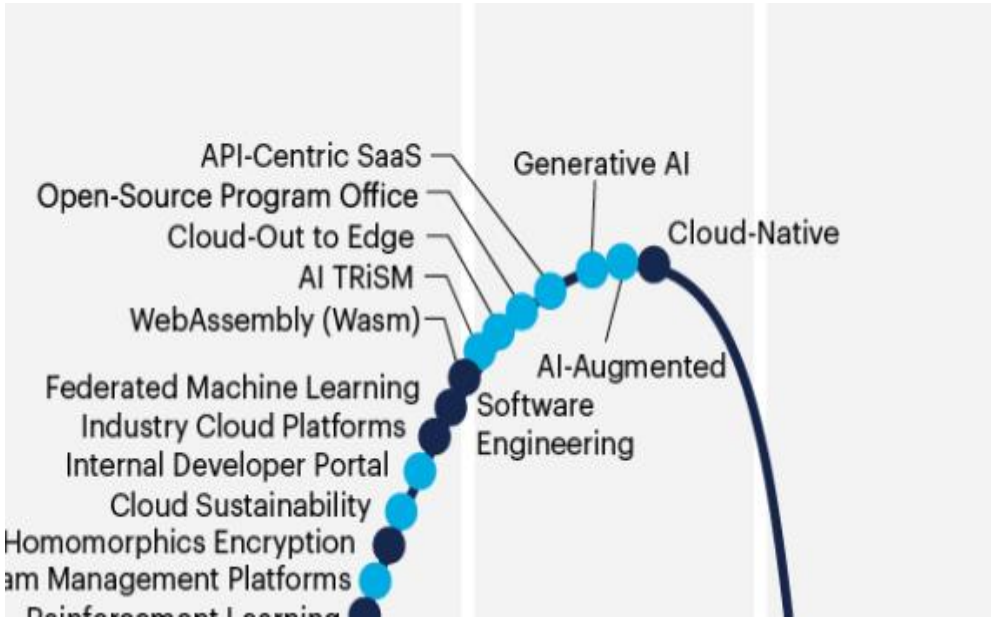
Ciclo de Sobreexpectación (Hype Cycle) para Tecnologías Emergentes 2024



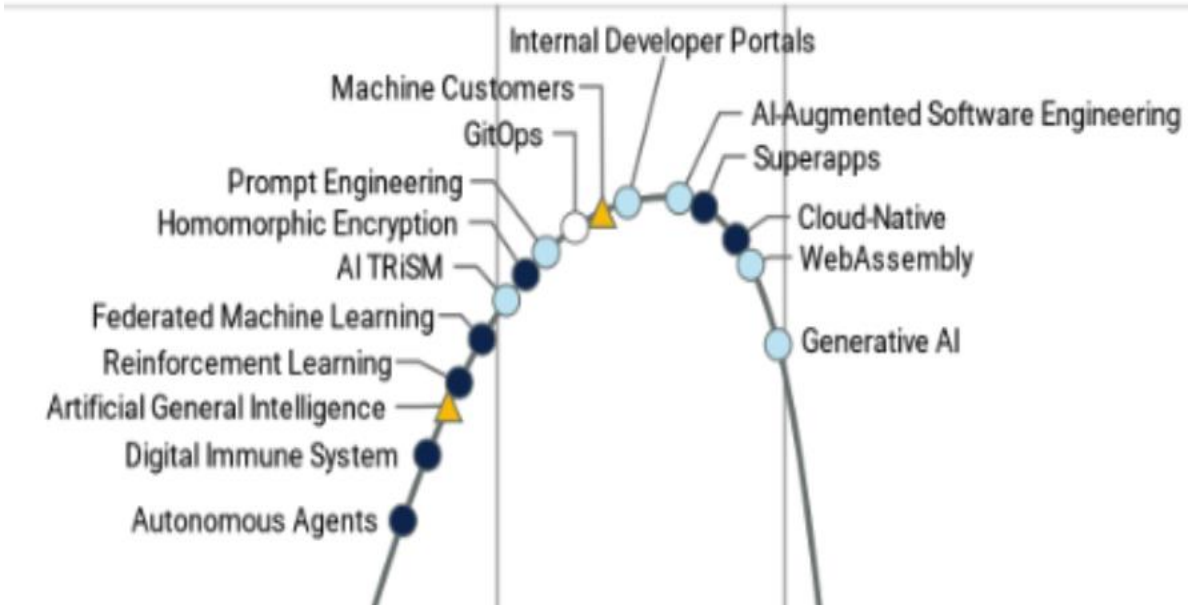
Gartner

...

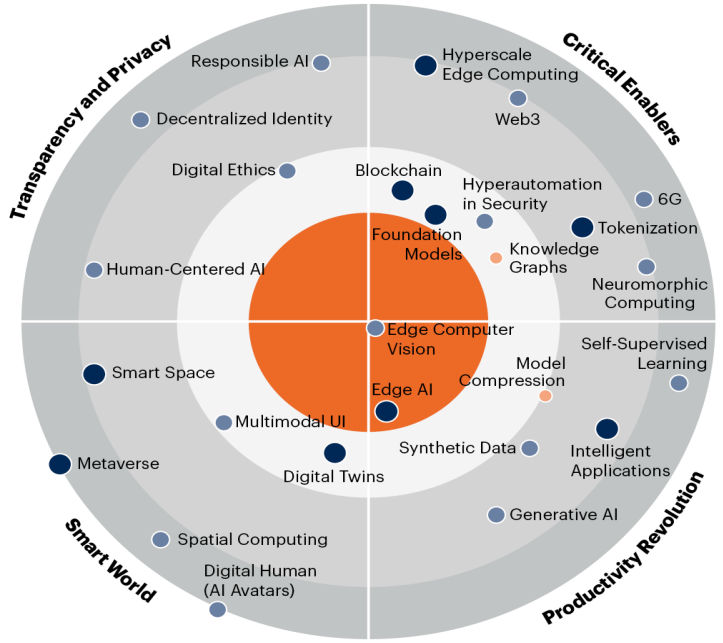
2023


API-Centric SaaS
Open-Source Program Office
Cloud-Out to Edge
AI TRiSM
WebAssembly (Wasm)
Federated Machine Learning
Industry Cloud Platforms
Internal Developer Portal
Cloud Sustainability
Homomorphics Encryption
Generative AI
Cloud-Native
AI-Augmented
Software
Engineering

2024


Internal Developer Portals
Machine Customers
GitOps
Prompt Engineering
Homomorphic Encryption
AI TRiSM
Federated Machine Learning
Reinforcement Learning
Artificial General Intelligence
Digital Immune System
Autonomous Agents
AI-Augmented Software Engineering
Superapps
Cloud-Native
WebAssembly
Generative AI

2023 Gartner Emerging Technologies and Trends Impact Radar



Range
- 6 to 8 Years
- 3 to 6 Years
- 1 to 3 Years
- Now (0 to 1 Year)

Mass
- Low
- Medium
- High
- Very High

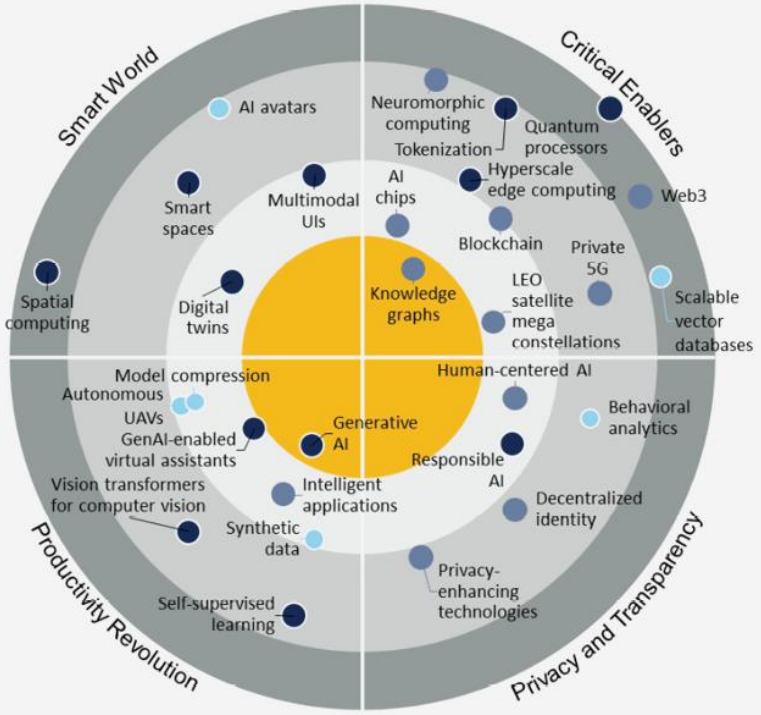
gartner.com

Note: Range measures number of years it will take the technology/trend to cross over from early adopter to early majority adoption. Mass indicates how substantial the impact of the technology or trend will be on existing products and markets.

Source: Gartner

Gartner

Impact Radar for 2024



Range
- 6 to 8 Years
- 3 to 6 Years
- 1 to 3 Years
- Now (0 to 1 Years)

Mass
- Low
- Medium
- High
- Very High

Source: Gartner

Gartner

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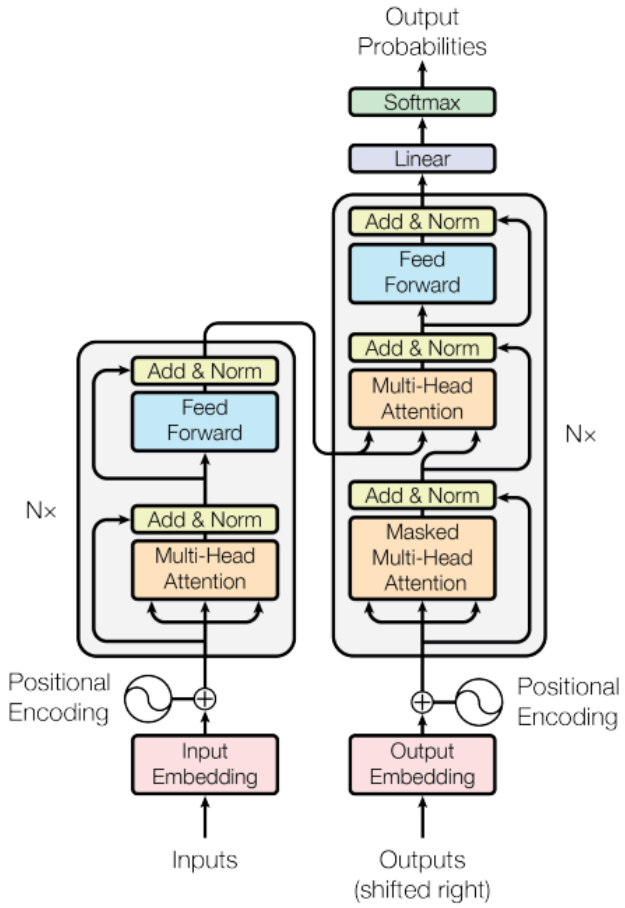


Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com
Noam Shazeer* Google Brain noam@google.com
Niki Parmar* Google Research nikip@google.com
Jakob Uszkoreit* Google Research usz@google.com
Llion Jones* Google Research llion@google.com
Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu
Łukasz Kaiser* Google Brain lukaszkaiser@google.com
Illia Polosukhin* ‡ illia.polosukhin@gmail.com

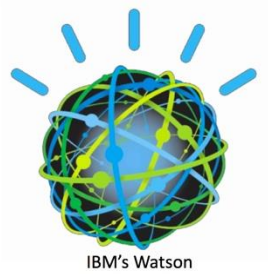
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). *Attention Is All You Need* (arXiv:1706.03762). arXiv. http://arxiv.org/abs/1706.03762

Antropomorfismo

DALL-E 2



Efecto Eliza de Joseph Weizenbaum

Skjuve, M., Følstad, A., & Brandtzæg, P. B. (2023). A Longitudinal Study of Self-Disclosure in Human–Chatbot Relationships. Interacting with Computers, iwad022. https://doi.org/10.1093/iwc/iwad022

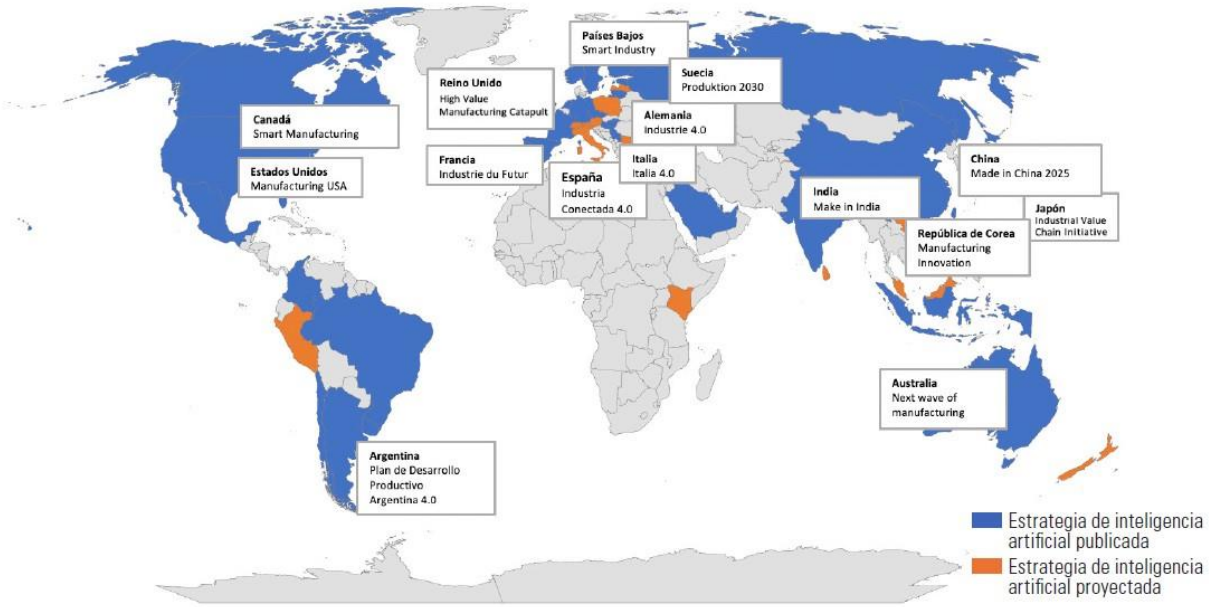
Digitalización y dinámica del empleo

Fuente: Comisión Económica para América Latina y el Caribe (CEPAL), sobre la base de CEPAL, *Estudio Económico de América Latina y el Caribe, 2021* (LC/PUB.2021/10-P/Rev.1), Santiago, 2021.

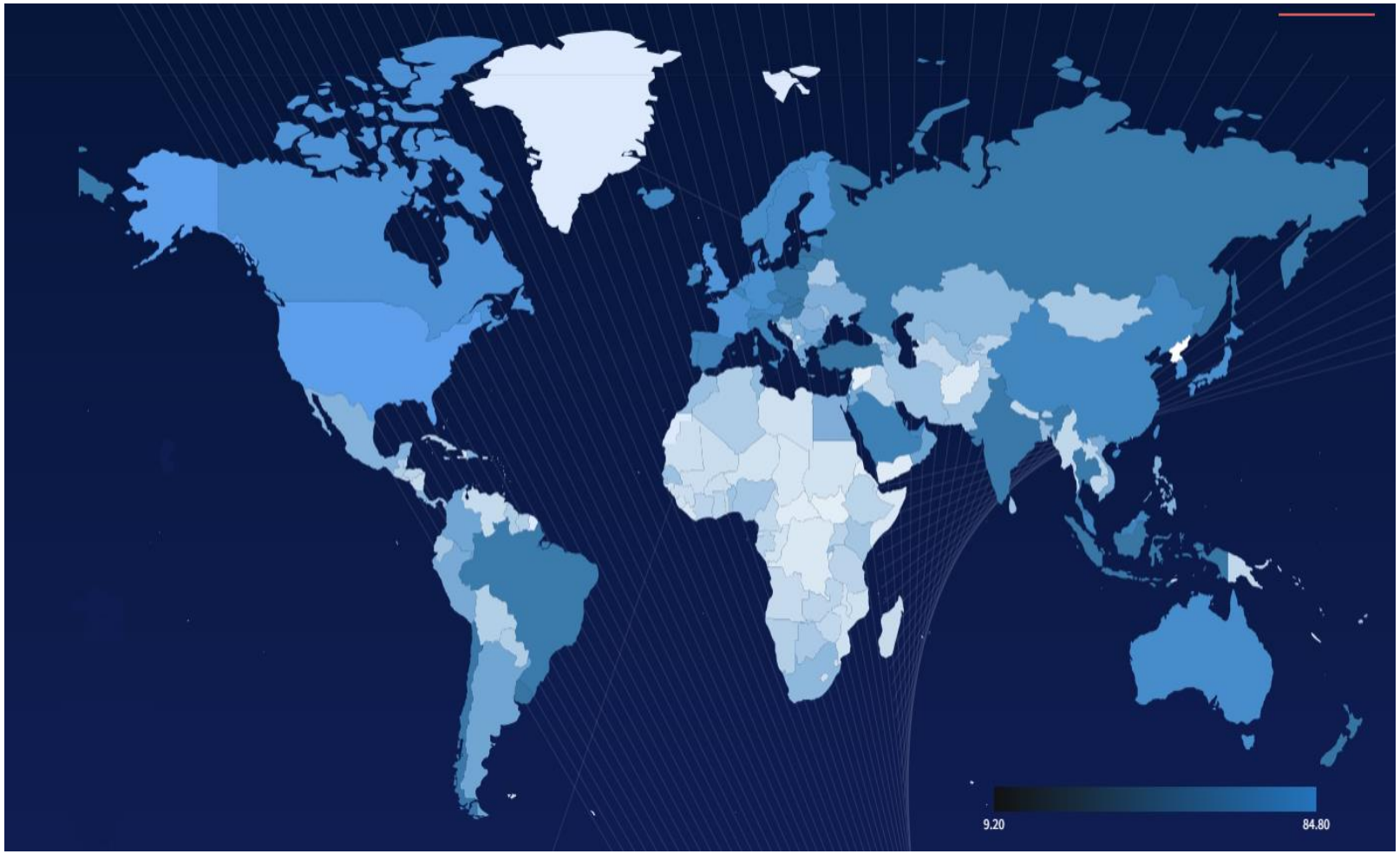

TESLA

Políticas públicas de IA

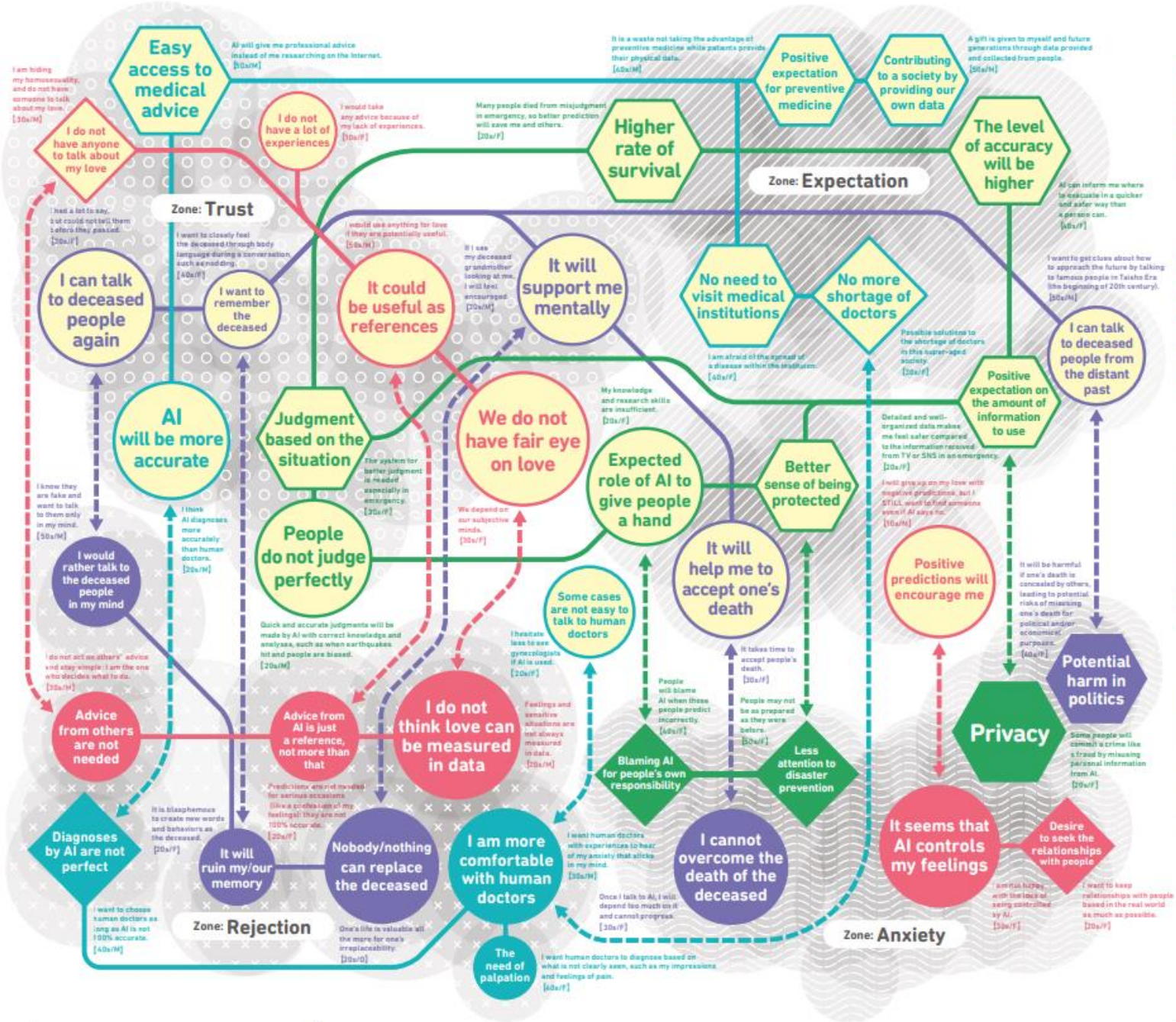
Políticas industriales digitales y estrategias de inteligencia artificial, mayo de 2022

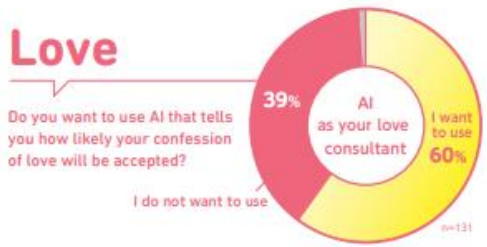


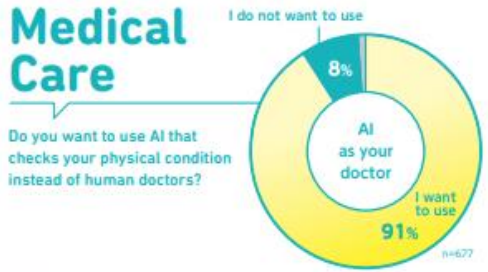
Fuente: Comisión Económica para América Latina y el Caribe (CEPAL).

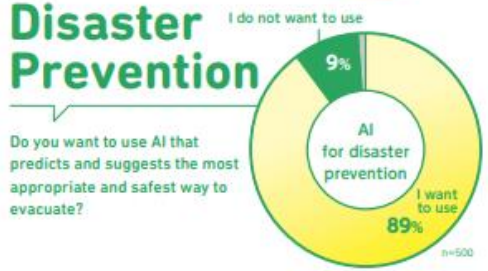


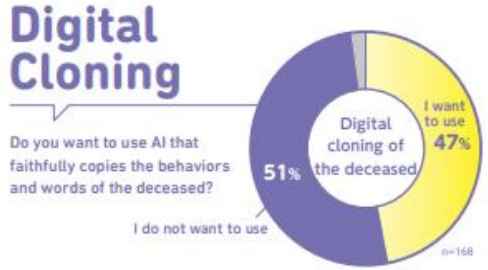
Oxford. (s. f.). *2023 Government AI Readiness Index*. https://oxfordinsights.com/ai-readiness/ai-readiness-index/











Mirakan, M. (2020). *AI Map: From Everyone, for Everyone*. https://www.miraikan.jst.go.jp/en/resources/provision/aimap/

Caso UCR - NICSP

Transformación Digital en Instituciones de Educación Superior con Gestión de Procesos de Negocio

Modelo de mediación de Automatización Robótica de Procesos

Digital Transformation in Higher Education Institutions with Business Process Management

Robotic Process Automation mediation model

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San José, Costa Rica
henry.lizano@ucr.ac.cr

Pedro Palos Sánchez
Universidad de Sevilla
Sevilla, España
ppalos@us.es

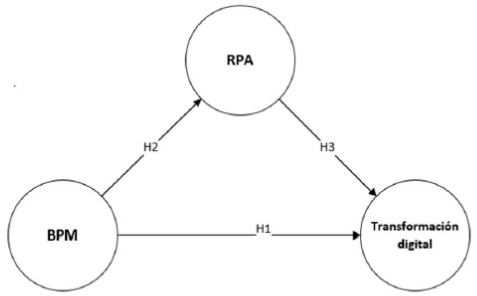


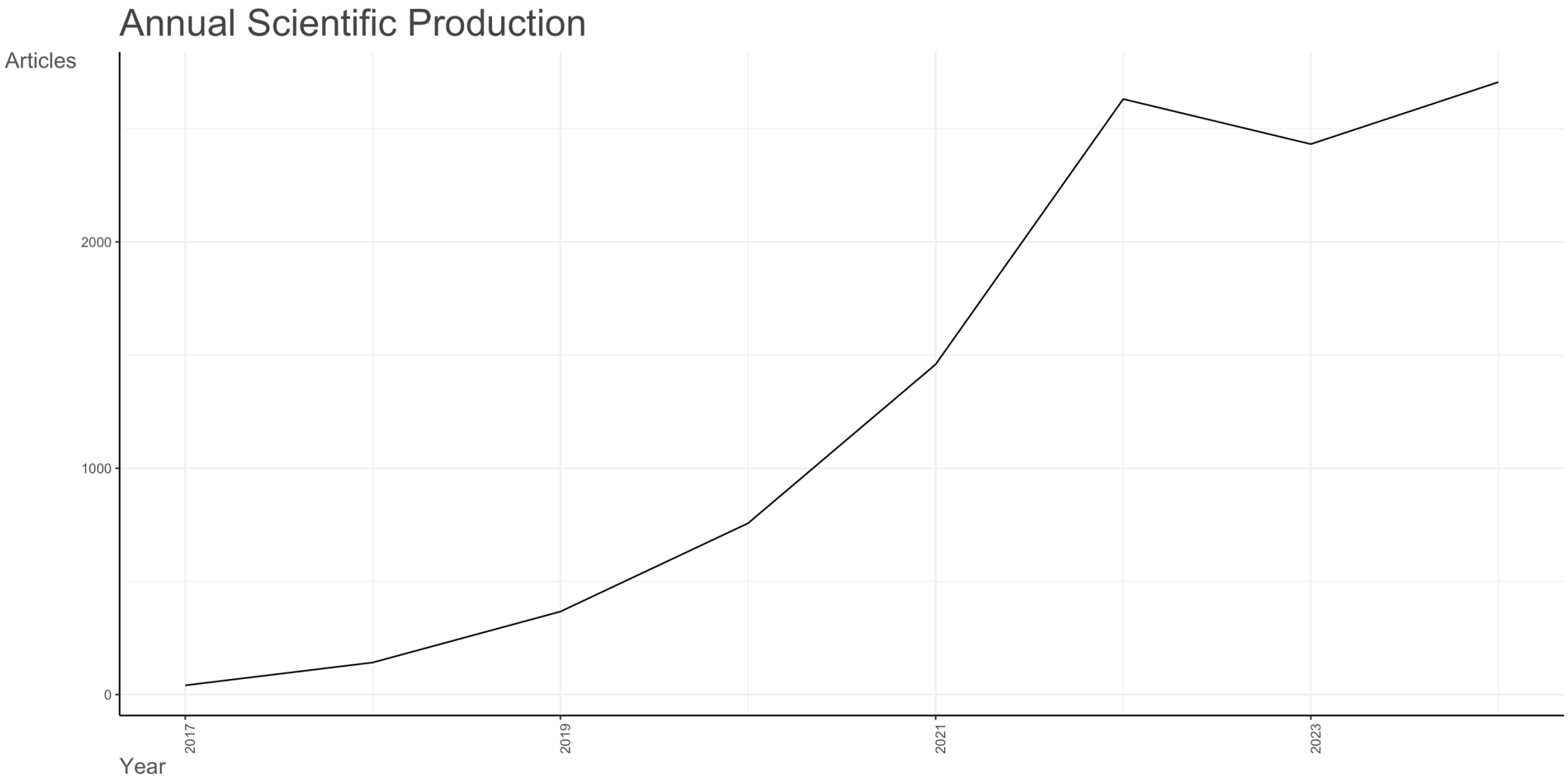
Figura 2 Modelo de transformación digital con BPM y RPA en IES, adaptado de Almaraz [1]

H. L. Mora and P. P. Sánchez, "Digital Transformation in Higher Education Institutions with Business Process Management : Robotic Process Automation mediation model," *2020 15th Iberian Conference on Information Systems and Technologies (CISTI), Seville, Spain, 2020, pp. 1-6*, doi: 10.23919/CISTI49556.2020.9140851.

Estado Situación de la Investigación en IA

Periodo	**2017:2024**
Origen (Revistas, Libros, entre otros)	**2468**
Documentos	**10 535**
Tasa de crecimiento anual	**81.9%**
Referencias	**393 592**
Términos	**20 981**
Autores	**46 677**

Elaboración propia con R y Bibliometrix desde WoS y Scopus de 2102 artículos científicos relevantes sobre AI


Annual Scientific Production
Articles
2000
1000
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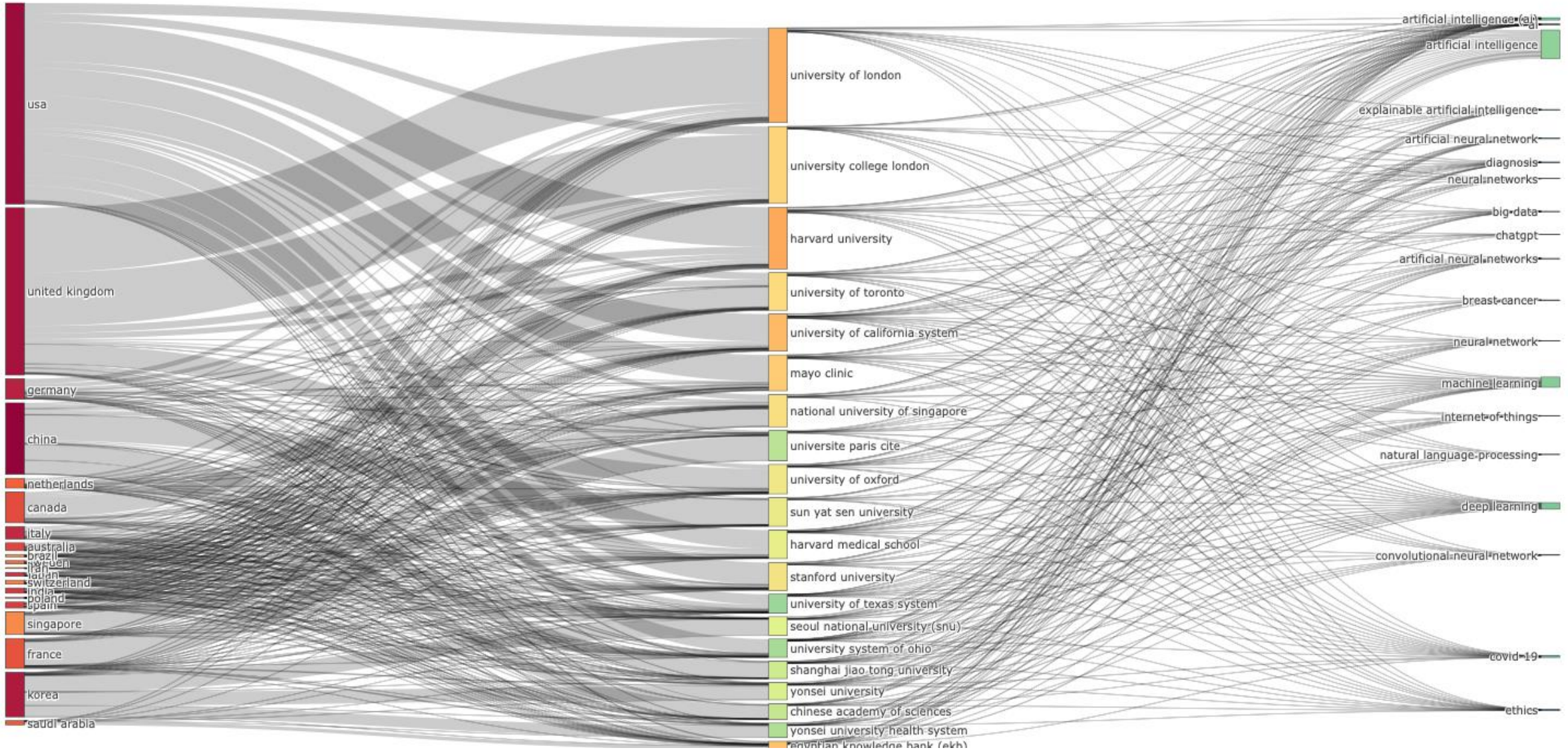
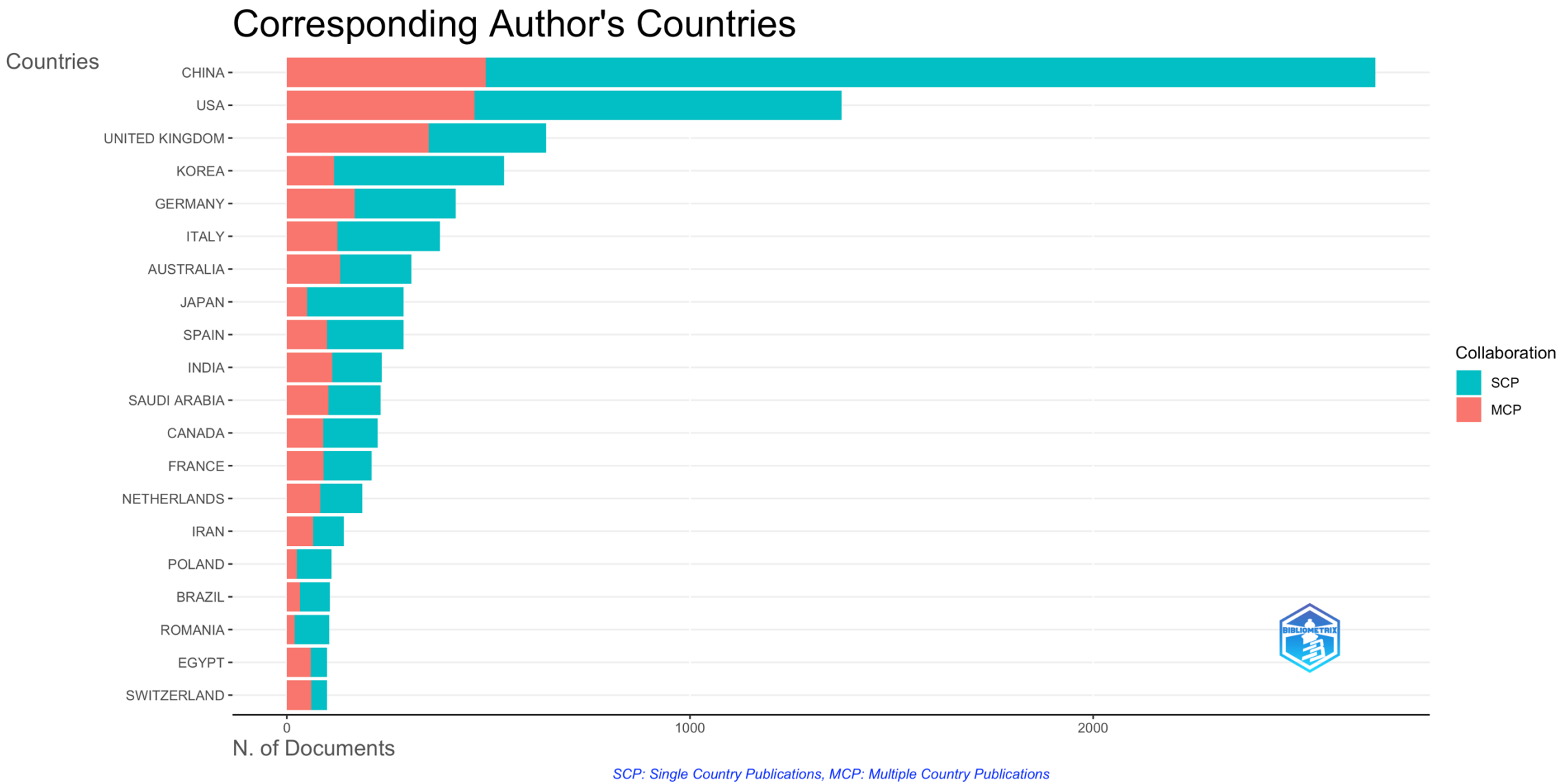
2017
2019
2021
2023
Year

Correlación de tópicos de IA

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SPAIN
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CANADA
FRANCE
NETHERLANDS
IRAN
POLAND
BRAZIL
ROMANIA
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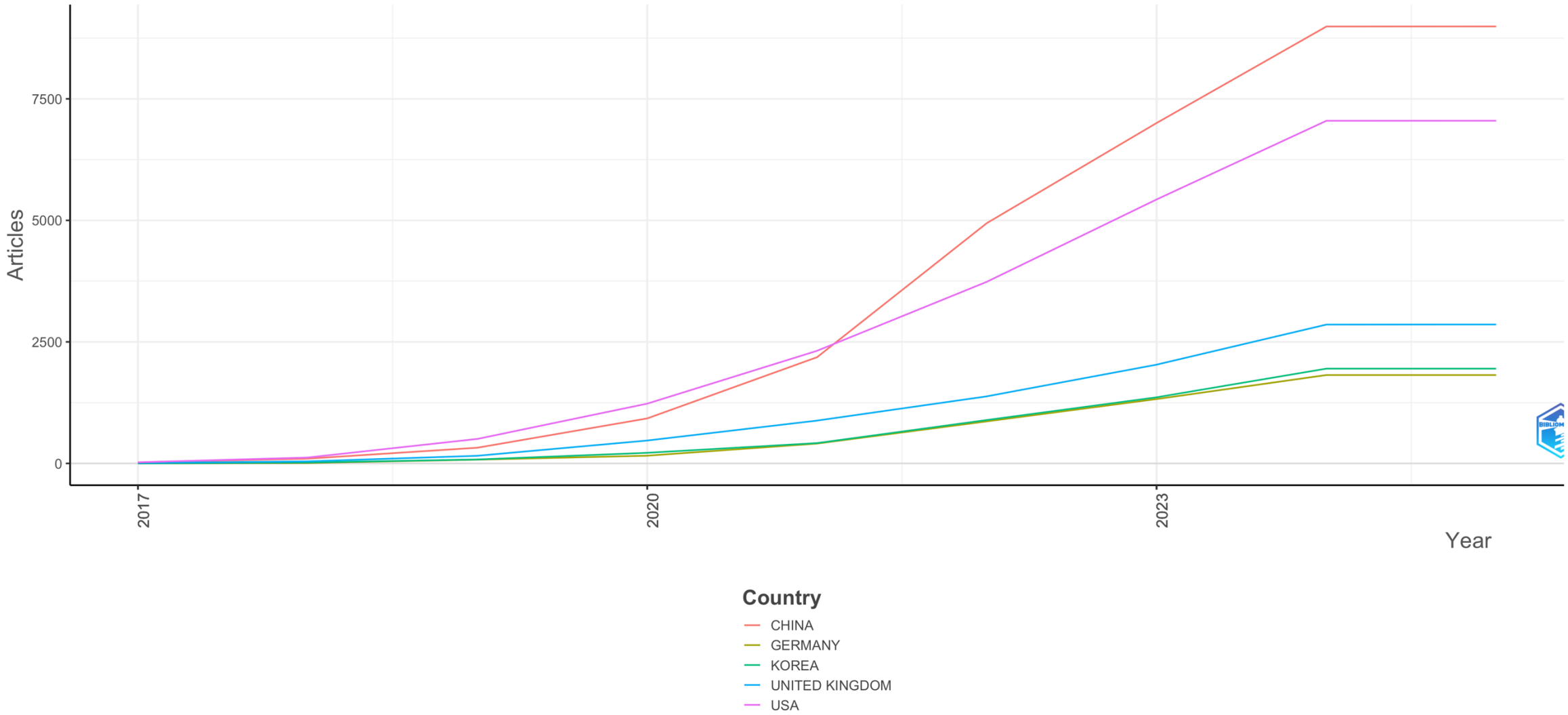
Collaboration
SCP
MCP
SCP: Single Country Publications, MCP: Multiple Country Publications

Country Production over Time



Information Fusion 58 (2020) 82–115

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI

Alejandro Barredo Arrieta[a], Natalia Díaz-Rodríguez[b], Javier Del Ser[a,c,d,*], Adrien Bennetot[b,e,f], Siham Tabik[g], Alberto Barbado[h], Salvador Garcia[g], Sergio Gil-Lopez[a], Daniel Molina[g], Richard Benjamins[h], Raja Chatila[f], Francisco Herrera[g]

[a] TECNALIA, Derio 48160, Spain
[b] ENSTA, Institute Polytechnique Paris and INRIA Flowers Team, Palaiseau, France
[c] University of the Basque Country (UPV/EHU), Bilbao 48013, Spain
[d] Basque Center for Applied Mathematics (BCAM), Bilbao 48009, Bizkaia, Spain
[e] Segula Technologies, Parc d'activité de Pissaloup, Trappes, France
[f] Institut des Systèmes Intelligents et de Robotique, Sorbonne Université, France
[g] DaSCI Andalusian Institute of Data Science and Computational Intelligence, University of Granada, Granada 18071, Spain
[h] Telefonica, Madrid 28050, Spain

ARTICLE INFO

Keywords:
Explainable Artificial Intelligence
Machine Learning
Deep Learning
Data Fusion
Interpretability
Comprehensibility
Transparency
Privacy
Fairness
Accountability
Responsible Artificial Intelligence

ABSTRACT

In the last few years, Artificial Intelligence (AI) has achieved a notable momentum that, if harnessed appropriately, may deliver the best of expectations over many application sectors across the field. For this to occur shortly in Machine Learning, the entire community stands in front of the barrier of explainability, an inherent problem of the latest techniques brought by sub-symbolism (e.g. ensembles or Deep Neural Networks) that were not present in the last hype of AI (namely, expert systems and rule based models). Paradigms underlying this problem fall within the so-called *eXplainable* AI (XAI) field, which is widely acknowledged as a crucial feature for the practical deployment of AI models. The overview presented in this article examines the existing literature and contributions already done in the field of XAI, including a prospect toward what is yet to be reached. For this purpose we summarize previous efforts made to define explainability in Machine Learning, establishing a novel definition of explainable Machine Learning that covers such prior conceptual propositions with a major focus on the audience for which the explainability is sought. Departing from this definition, we propose and discuss about a taxonomy of recent contributions related to the explainability of different Machine Learning models, including those aimed at explaining Deep Learning methods for which a second dedicated taxonomy is built and examined in detail. This critical literature analysis serves as the motivating background for a series of challenges faced by XAI, such as the interesting crossroads of data fusion and explainability. Our prospects lead toward the concept of *Responsible Artificial Intelligence*, namely, a methodology for the large-scale implementation of AI methods in real organizations with fairness, model explainability and accountability at its core. Our ultimate goal is to provide newcomers to the field of XAI with a thorough taxonomy that can serve as reference material in order to stimulate future research advances, but also to encourage experts and professionals from other disciplines to embrace the benefits of AI in their activity sectors, without any prior bias for its lack of interpretability.

https://doi.org/10.1016/j.inffus.2019.12.012

IEEE Access

Received August 5, 2018, accepted September 4, 2018, date of publication September 17, 2018, date of current version October 12, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2870052

Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)

AMINA ADADI AND MOHAMMED BERRADA
Computer and Interdisciplinary Physics Laboratory, Sidi Mohammed Ben Abdellah University, Fez 30050, Morocco
Corresponding author: Amina Adadi (amina.adadi@gmail.com)

ABSTRACT At the dawn of the fourth industrial revolution, we are witnessing a fast and widespread adoption of artificial intelligence (AI) in our daily life, which contributes to accelerating the shift towards a more algorithmic society. However, even with such unprecedented advancements, a key impediment to the use of AI-based systems is that they often lack transparency. Indeed, the black-box nature of these systems allows powerful predictions, but it cannot be directly explained. This issue has triggered a new debate on explainable AI (XAI). A research field holds substantial promise for improving trust and transparency of AI-based systems. It is recognized as the sine qua non for AI to continue making steady progress without disruption. This survey provides an entry point for interested researchers and practitioners to learn key aspects of the young and rapidly growing body of research related to XAI. Through the lens of the literature, we review the existing approaches regarding the topic, discuss trends surrounding its sphere, and present major research trajectories.

INDEX TERMS Explainable artificial intelligence, interpretable machine learning, black-box models.

https://doi.org/10.1109/ACCESS.2018.2870052

Artificial Intelligence 267 (2019) 1–38

Contents lists available at ScienceDirect

Artificial Intelligence

www.elsevier.com/locate/artint

Explanation in artificial intelligence: Insights from the social sciences

Tim Miller

School of Computing and Information Systems, University of Melbourne, Melbourne, Australia

ARTICLE INFO

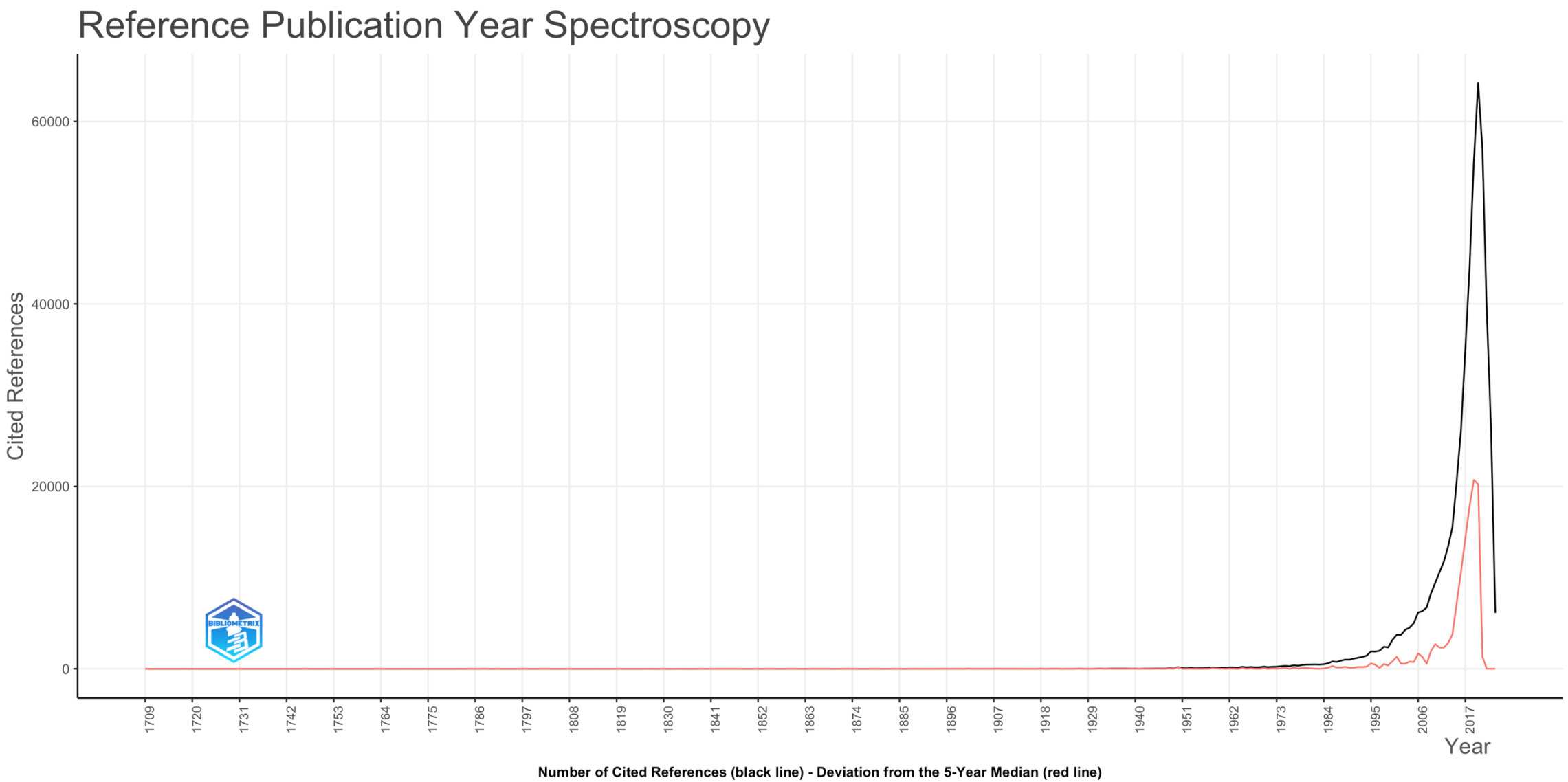
Article history:
Received 22 June 2017
Received in revised form 17 May 2018
Accepted 16 July 2018
Available online 27 October 2018

Keywords:
Explanation
Explainability
Interpretability
Explainable AI
Transparency

ABSTRACT

There has been a recent resurgence in the area of explainable artificial intelligence as researchers and practitioners seek to provide more transparency to their algorithms. Much of this research is focused on explicitly explaining decisions or actions to a human observer, and it should not be controversial to say that looking at how humans explain to each other can serve as a useful starting point for explanation in artificial intelligence. However, it is fair to say that most work in explainable artificial intelligence uses only the researchers' intuition of what constitutes a 'good' explanation. There exist vast and valuable bodies of research in philosophy, psychology, and cognitive science of how people define, generate, select, evaluate, and present explanations, which argues that people employ certain cognitive biases and social expectations to the explanation process. This paper argues that the field of explainable artificial intelligence can build on this existing research, and reviews relevant papers from philosophy, cognitive psychology/science, and social psychology, which study these topics. It draws out some important findings, and discusses ways that these can be infused with work on explainable artificial intelligence.

https://doi.org/10.1016/j.artint.2018.07.007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1951
1962
1973
1984
1995
2006
2017
Year
Number of Cited References (black line) - Deviation from the 5-Year Median (red line)

AN

ESSAY

Towards a

New Theory

OF

VISION.

By GEORGE BERKELEY, M. A.
Fellow of *Trinity College, Dublin.*

The Second Edition.

DUBLIN:
Printed by AARON RHAMES, for JEREMY PEPYAT, Bookseller in *Skinner-Row*, 1709.

To the Right Honourable
Sir *John Percivale*, Bar.t
ONE OF
Her Majesty's
Most Honourable
PRIVY COUNCIL
IN THE
Kingdom of *Ireland.*

SIR,

I Cou'd not, without doing Violence to my Self, forbear upon this Occasion, to give some publick Testimony of the Great and Well-grounded Esteem


segmentation
identification
association
neural-networks
regression
machine
innovation
diagnosis
models
mortality
knowledge
future
validation
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challenges
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prediction
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classification
health
disease
information
behavior
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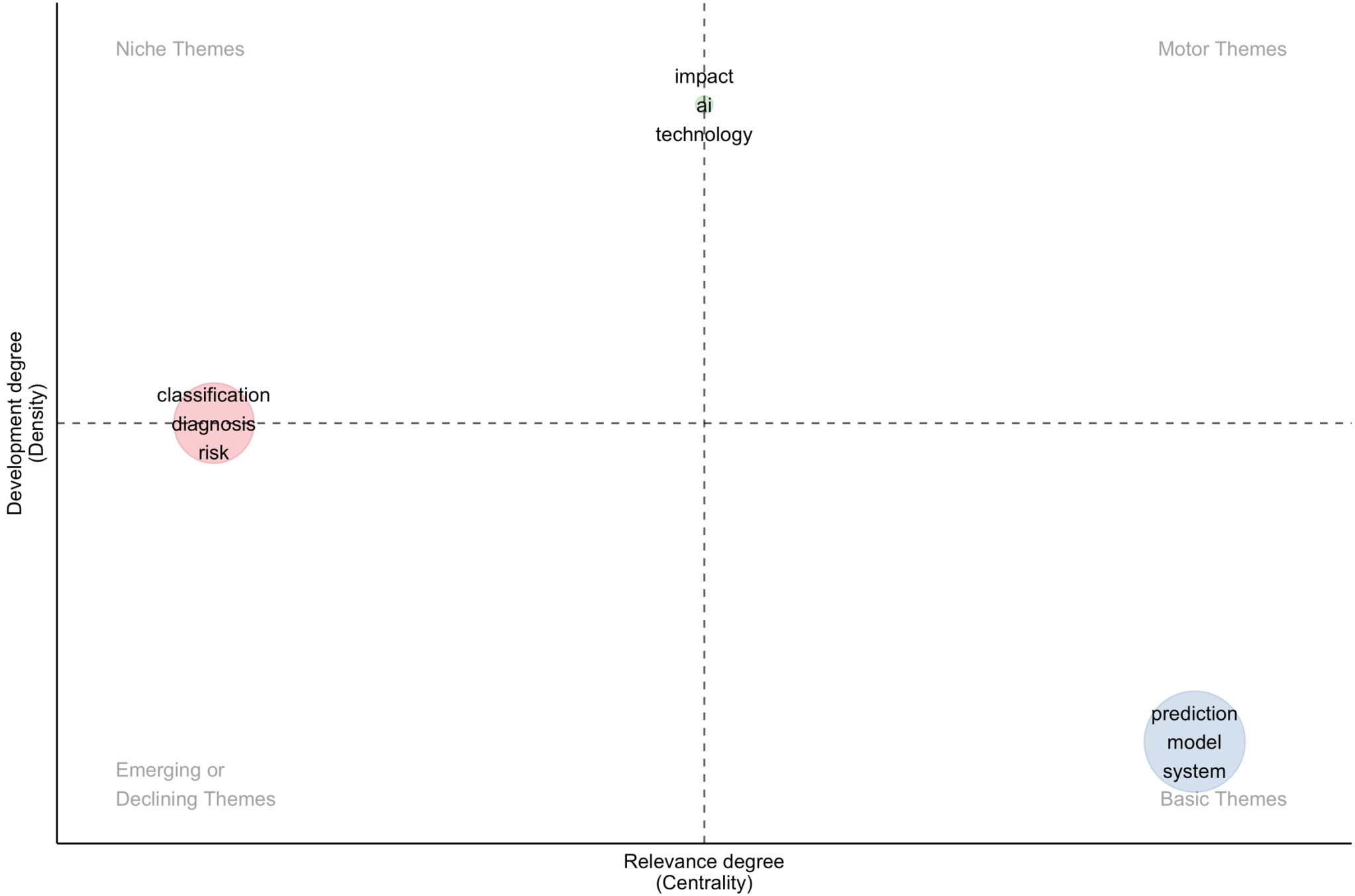
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prediction
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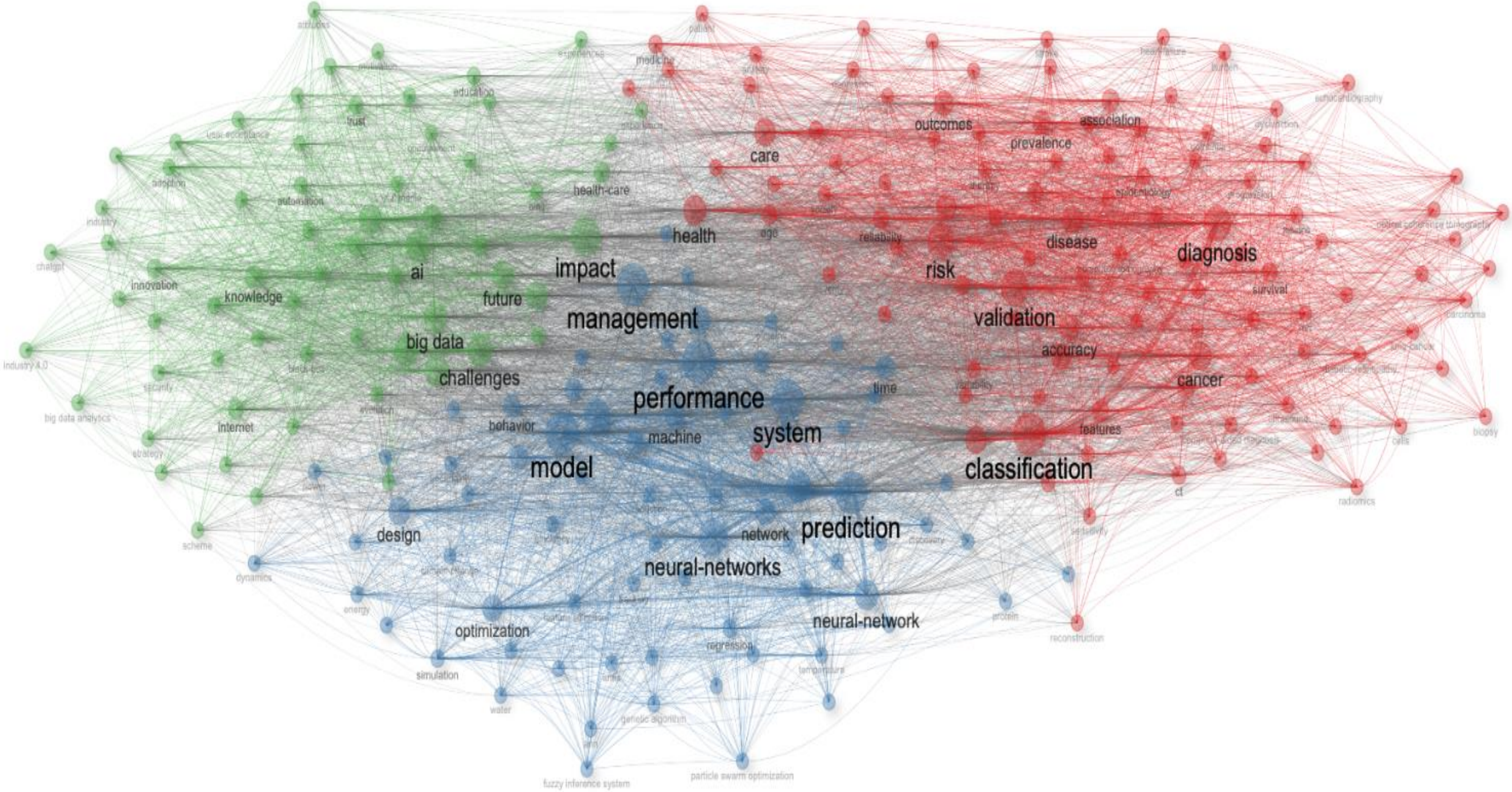
Declining Themes
Basic Themes
Development degree
(Density)
Relevance degree
(Centrality)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sensitivity
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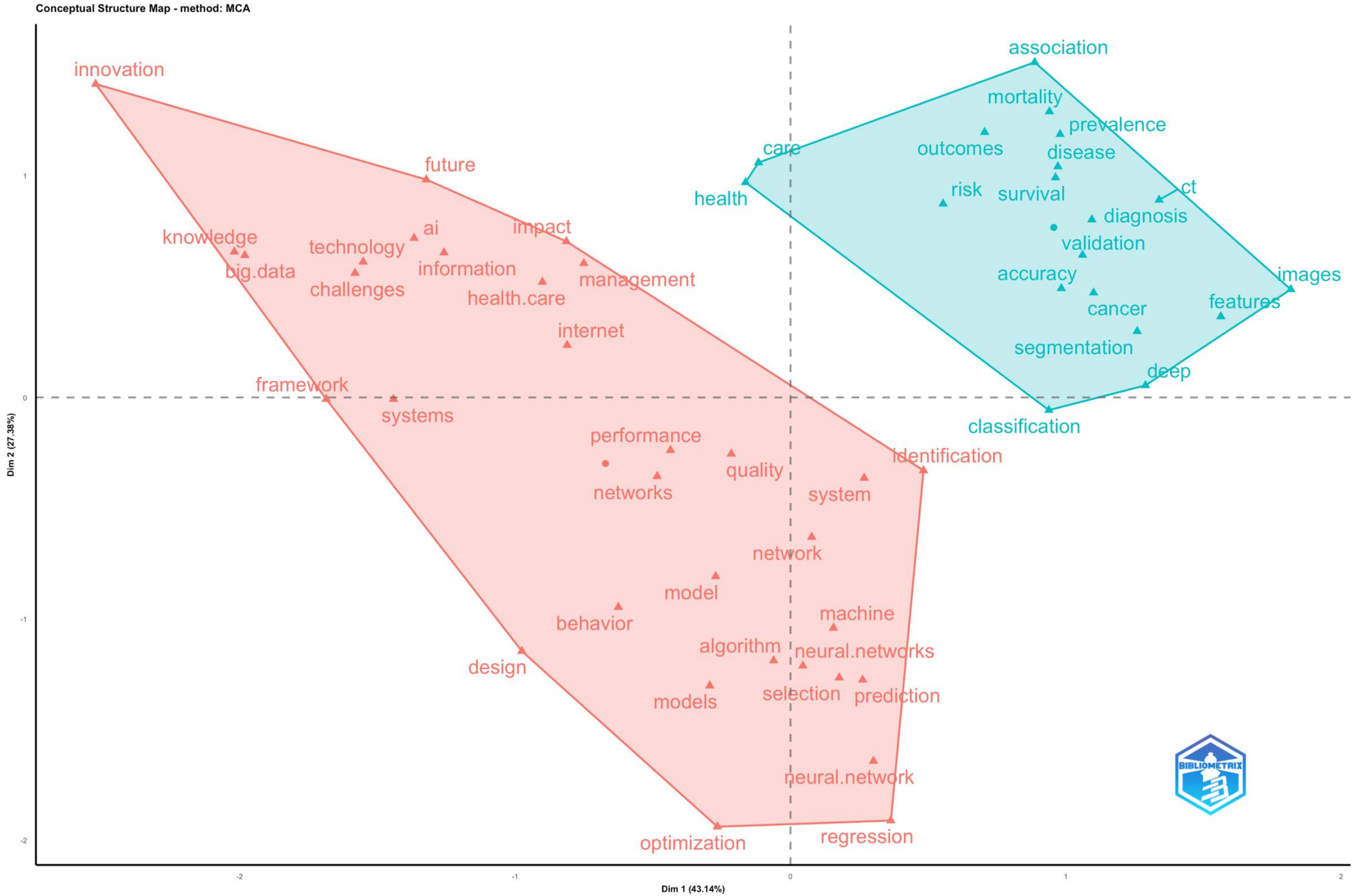
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models
neural.network
optimization
regression
association
mortality
prevalence
outcomes
disease
care
health
risk
survival
ct
diagnosis
validation
accuracy
images
cancer
features
segmentation
deep
classification
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Dim 1 (43.14%)
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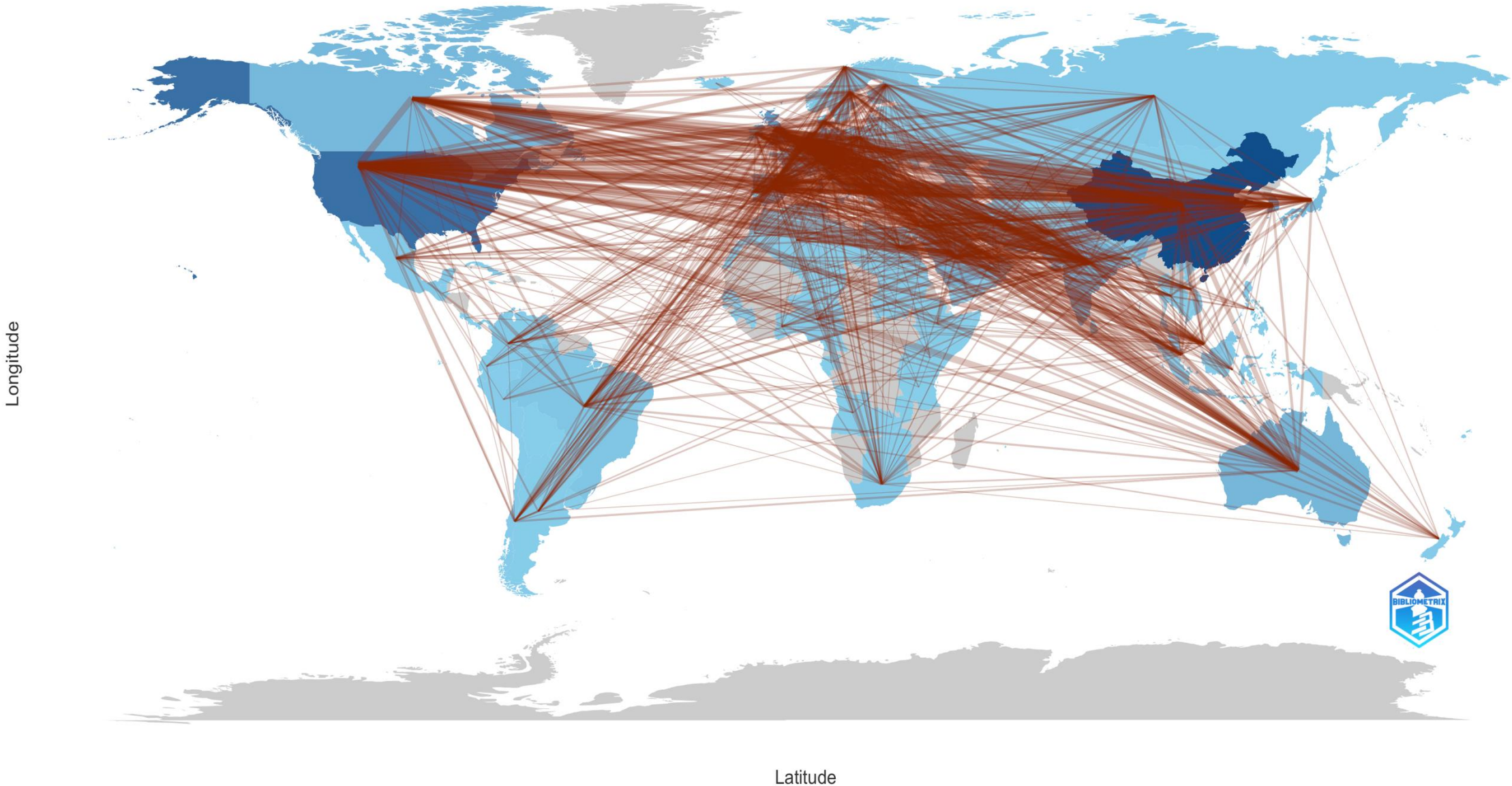
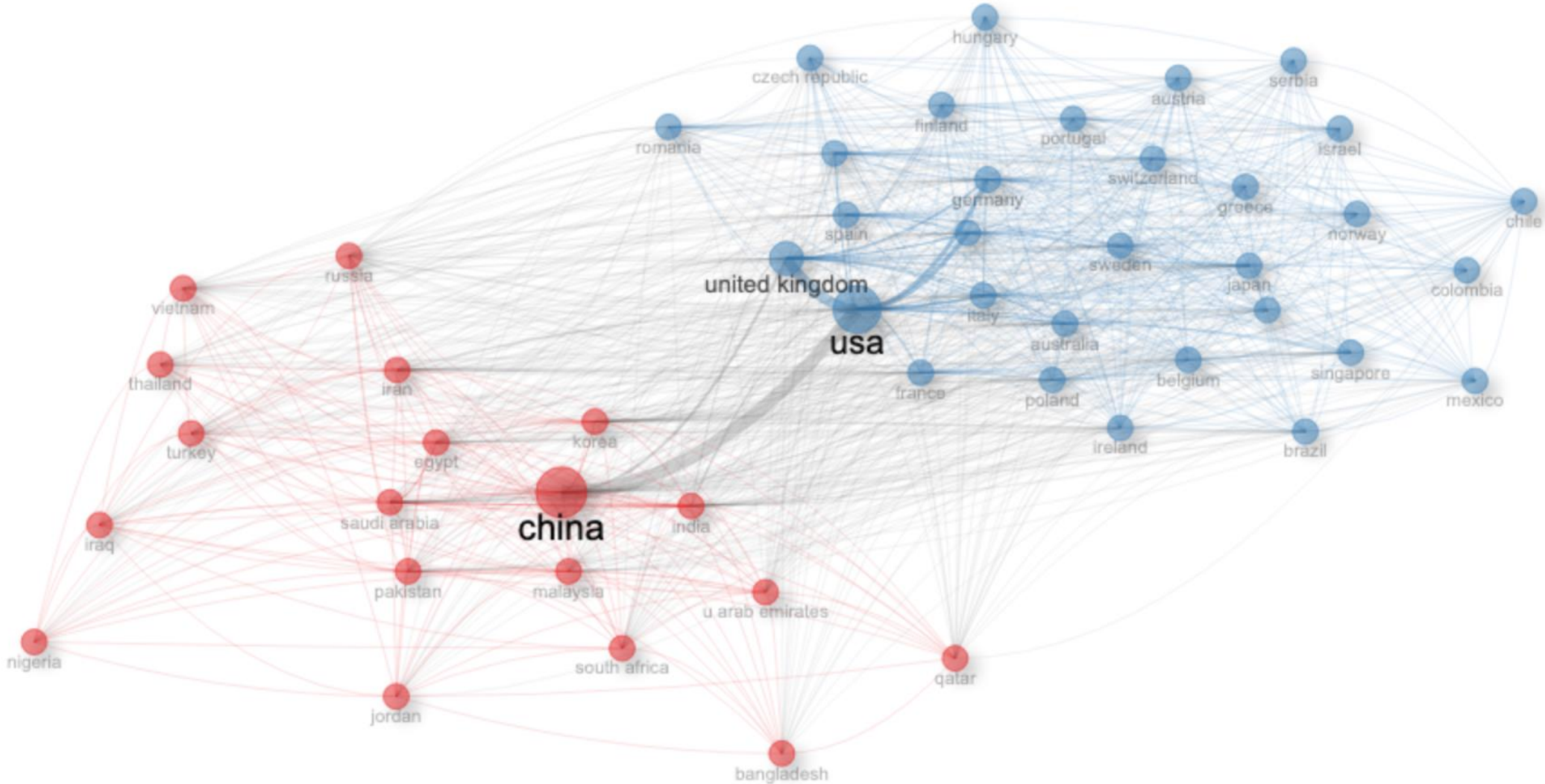
-1
-2
-2
-1
0
1
2

Country Collaboration Map

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austria
finland
portugal
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germany
greece
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spain
norway
russia
sweden
japan
colombia
united kingdom
vietnam
italy
usa
australia
thailand
iran
singapore
belgium
france
poland
mexico
korea
turkey
egypt
ireland
brazil
saudi arabia
china
india
iraq
pakistan
malaysia
u arab emirates
nigeria
south africa
qatar
jordan
bangladesh

Aplicaciones Prácticas

AI-CFT		CODIGOS		
		1	2	3
Aspectos		Progresión		
		Aquire	Deepen	Create
1	Centrado en el humano	Human Agency	Human Accountability	Social responsibility
2	Etica de la IA	Ethical principles	Safe and responsible use	Co-creating ethical rules
3	Fundamentos y aplicaciones de la IA	Basic AI techniques and application	Application skills	Creating with AI
4	Pedagogía de la IA	Ai-asisited teaching	AI-pedagogy integration	AI-enhance pedagogical transformation
5	IA para el desarrollo profesional	AI enabling lifelong profesional learning	AI to enhance organizxational learning	AI to support professional transformation

Mapeo de Objetivos Inteligencia Artificial en el aula: una guía para la educación innovadora							
CODIGOS	Objetivos	1	2	3	4	5
		Indicador (KPI)				
		Conoce	Usa	Capacitado	Mejora	Guía
1	Diagnostico de competencias IAG	O1K1	O1K2	O1K3	O1K4	O1K5
2	Programa pedagógico de IAG	O1K1	O2K2	O2K3	O2K4	O2K5
3	Cierre de brechas digitales	O3K1	O3K2	O3K3	O3K4	O3K5
4	Evaluación de experiencia con IAG	O4K1	O4K2	O4K3	O4K4	O4K5
5	Guía de uso IAG	O5K1	O5K2	O5K3	O5K4	O5K5