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ORIGINAL ARTICLE

Global indicators and AI policy: Metrics, policy scripts, and narratives

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Abstract

Artificial intelligence (AI) has become a global policy issue that is actively governed by international actors producing governance indicators. This article argues that despite the arguments about disruptions to governance and policy due to AI, the global rankings increasingly constitute a strong path dependence on AI policy, leading to conformity with existing policies and institutional practices of economic competitiveness. By analyzing the composition and data sources of global indices in competitiveness, innovation, human capital, and artificial intelligence, I will show how the global rankings now evolve by sharing data and concepts. Consequently, these metrics and related policy scripts promote the seeming continuity of current activities of global competitiveness. AI is discussed as a "revolution" but framed as a matter of "competitiveness," "openness," and "talent competition," implying standard perceptions of economic competitiveness and innovation. There is also a narrative element in the policy script, as the future policies on AI are promoted with references to history that also project the past into the future. My article concludes that while path-dependent policy indicators and related future narratives give a sense of orientation, they are problematic as they portray a seeming continuity of activities in times of disruptions, delimiting policy alternatives such as AI ethics.

KEYWORDS
artificial intelligence (AI), competitiveness, data networks, global indicators, human capital, imaginaries, narratives, policy scripts

INTRODUCTION

Artificial intelligence (AI) has become a global policy issue, linked with major social challenges, as well as promises of unforeseen economic potential and enhanced wellbeing (Brynjolfsson & Mcafee, 2012; Feijóo et al., 2020; Mcafee & Brynjolfsson, 2017; Pencheva et al., 2020). Yet, there are critical observations about the "AI revolution" concerning qualitative shifts in capitalism and evolving power relations that are seen to pose significant, even existential challenges to democracy and economy (O'Donovan, 2019; Zuboff, 2019), involving accountability issues, systemic inequalities, and biases of algorithms (Barth & Arnold, 1999; Bucher, 2018; Eubanks, 2018; Pasquale, 2016). Scholars have pointed out the emerging issues in algorithmic regulation (Yeung & Lodge, 2019), while also acknowledging the limitations of existing accountability measures, as well as difficulties of creating new ones (Di Porto & Zuppetta 2021; Ahonen & Erkkilä, 2020; Ananny & Crawford, 2018). Principally, the regulation of AI is approached as an ethical issue (Council of Europe, 2018; Wong, 2020), with national strategies and policy documents highlighting AI "ethics" and "governance" (Radu, 2021; Sloane, 2022; Ulnicane et al., 2020, 2021). Yet, AI governance might also be demanding in practice due to the complexity and vague conceptualization of AI (Gahnberg, 2021; Taeihagh, 2021).

Along ethical aspects, AI is often framed as a matter of competition and innovation policy (Justo-Hanani, 2022; Kim, 2023; Murgia & Khan, 2019; Murphy & Waters, 2019; Schiff, 2022; Stacey, 2019). The perspective of economic competitiveness is particularly forcibly promoted by organizations such as the World Economic Forum, Institut Européen d'Administration des Affaires (INSEAD), and the World Bank that produce global rankings that they argue also indicate countries' ability to accommodate the "AI revolution." This "digital turn" in the work of established index producers coincides with and is linked to a more general ambit to measure the digital future, apparent in new actors launching global rankings that explicitly address the AI readiness of countries and cities. These are produced by smaller organizations that are hoping to make their entry into the field of global ranking. But as I will show, the composition of their indices closely resembles the previous rankings of competitiveness, innovation, and human capital, also drawing most of their data from existing metrics. Therefore, there is strong convergence between the rankings despite their nominally different focus.

This article holds that global indices are not neutral and carry policy prescriptions that steer national policies. It is therefore important to understand how they conceptualize AI policy and what kind of policy prescriptions they promote. This article asks, *how global rankings frame AI policy?*[1] My article argues that through conceptual and numerical objectification and narratives global indices, rankings in particular, lead to policy prescriptions on AI policy, associating it with human capital and competition over "talent," and narrowing out policy alternatives, such as governance and legal frameworks for regulating the pending ethical issues of AI (cf. Robles Carrillo, 2020). While there is no unified global discourse or narrative on AI, the rankings producers are nevertheless major information providers and potentially influential in shaping the debate on AI policy. I identify a path-dependent development in global indices that overlap conceptually and actively share data. This leads to similar policy prescriptions on AI, which are paradoxically static, given the arguably revolutionary character of this technology. My article is part of a special issue on politics and policy of AI.

The concept of policy script helps to understand how numerical objectification and narratives are used in policy prescriptions. A policy script can be understood as "a medium by which [an organization] frames its own definition of a reform issue: a diagnosis of problems followed by a set of prescriptions" (Halliday et al., 2010, p. 84). Unlike more general policy agendas or priorities, policy scripts define specific but generalizable measures to address a policy issue (Kentikelenis & Seabrooke, 2017, pp. 1086–1087), prescribing action through sequences of events that are based on storylines (Schank & Abelson, 1977).

In similar fashion, organizations producing so-called "composite indicators" that combine various existing data now aim for holistic analysis of AI readiness by merging data across policy domains and set seemingly generalizable goals for countries' AI policy, communicating these with narratives on an uncertain future. But the use of existing data creates a strong conformity with past assessments of competitiveness and innovation, which is problematic given the novel challenges of AI. The conformity is also present in the "storyline" that accompanies the indices, as ranking producers propose policy prescriptions based on historical narratives of "technological revolutions" that project past events to the anticipated future.

Next, I will present my theoretical framework, highlighting field development in global indicator production, as well as objectification and narratives carrying the economic imaginaries of the future. My research design covers data networks of major index producers, but I will focus more closely on those metrics that are explicitly linked with AI, analyzing them conceptually. I show how the field of global ranking is converging through intensive cross-referencing and sharing of concepts and indicator data. I argue that because of this ideational convergence, the index producers reduce AI policy to competitive institutional design and fostering of human capital, and effectively reproduce and strengthen previous policy prescriptions rather than propose policy alternatives in the face of "AI revolution."

NUMERICAL GLOBAL GOVERNANCE: RANKINGS, POLICY SCRIPTS, AND NARRATIVES

Field development and data networks of global ranking

Though quantification as a means of global governance has a longer history, there has been a surge in the use of global rankings in various policy domains over the past two decades. Comparing and identifying countries and cities as forerunners and laggards in innovation and digitization, the global rankings have also acquired governing functions, challenging traditional analysis of international relations (Broome & Quirk, 2015; Kelley & Simmons, 2015; Löwenheim, 2008; Porter, 2012). Previous assessments have highlighted numbers as policy instruments, the effects of which are not always consistent and even carry the potential to lead to unintended consequences (Espeland & Sauder, 2007; Pidd, 2005; Robinson, 2003; Smith, 1995; Van Thiel & Leeuw, 2002). Global governance indicators also carry normative Western-centered concepts (Malito et al., 2021). My approach complements the previous assessments of ranking mechanisms of influence by addressing the interplay of quantification and narrative elements of policy prescriptions. This is apparent in the indices on "AI revolution" that effectively uphold continuity in the policies on competitiveness.

Concerning quantification, this article builds on previous research on field development in global ranking, where the existing indices of competitiveness and good governance have been challenged by emerging data sets on innovation, human capital, and city competitiveness, compelling the old index producers to alter their methodology slightly or launch new indicators altogether (Erkkilä & Piironen, 2018, 2020). Despite the competition between ranking producers (Freistein, 2016), the new actors entering the field are compelled to validate their data sets against the existing ones concerning methodological choices and normative and causal beliefs (cf. Gieryn, 1983; Haas, 1992), leading to conformity through structuration (Giddens, 1986). I observe a similar convergence in global rankings on AI, in which the earlier measurements of competitiveness, innovation, human capital, and new AI rankings strongly resemble each other, also echoing ideational shifts around the concept of competitiveness (cf. Aiginger & Rodrik, 2020; Aiginger & Vogel, 2015; Ketels, 2006). Despite the emphasis on social and economic disruptions through AI and digitization by the index producers, the indices that claim to be relevant for AI policy have conceptually evolved only marginally from the earlier metrics and reproduce existing practices of measurement.

Though this evolution might be incremental in methodological terms, it is important for the new policy issues such as AI, as they are objectified as subjects of governance through quantification that gives them attributes and limits (Desrosières, 1998, p. 9; Miller & Rose, 1990; Robson, 1992). As the focus of global rankings is shifting towards measuring AI readiness, the rankings effectively also come to frame and make prescriptions for AI policy. Despite their seeming neutrality, governance indicators are by no means apolitical but often privilege certain perceptions and normative ideas over others, prescribing policy actions (Dahler-Larsen, 2014; Espeland & Sauder, 2007; Hansen & Porter, 2012).

This article holds that to understand how rankings frame AI policy, and potentially narrow policy alternatives, one needs to understand how the focus of the metrics is shifting and how they objectify AI readiness and subjectify responsible actors through narratives and discourses calling for action (cf. Erkkilä & Piironen, 2018). This also links to the debate on policy scripts that can be understood as specific but generalizable measures to address a policy issue prescribed, according to a storyline (Kentikelenis & Seabrooke, 2017; Schank & Abelson, 1977).

I study the framing of AI policy through conceptual shifts and convergence in global rankings. I am particularly interested in the indicator data networks consisting of relationships between organizations producing and repositing indicator data and global indices that use these data in their metrics that arguably measure AI readiness in a meaningful way. Using indicator data from a range of sources allows for bridging assessments of various policy domains, as global rankings are mainly composite indicators that borrow data and concepts from existing data sets. As my empirical analysis shows, this is leading to ideational convergence in the global rankings that now frame AI as an issue of economic competitiveness and human capital, or "talent competitiveness." The use of existing numerical data not only constitutes these associations but also constitutes "robust visions" of future, referring to an attempt to foresee future based on (past) evidence, instead of trying to reimagine it (Berten & Kranke, 2022, p. 160). This also means that certain alternative visions and policy frames are not actively being considered.

Numbers tell stories

As a response to disruptive technology, AI policy is often constructed through narratives on the uncertain future (af Malmborg, 2022; cf. Jasanoff & Kim, 2015). Global rankings also contain narrative elements and my empirical analysis shows how numerical objectifications of AI policy are being promoted with future narratives. Global rankings carry economic imaginaries that shape and limit governance approaches to innovation and AI (cf. Alasuutari & Qadir, 2016; Jessop, 2010; Sum, 2009). The rankings are used to construct policy narratives based on imaginaries of global competition, where countries, regions, and cities are out to compete with their like units. Moreover, the global rankings colonize the future (cf. Robertson, 2017) through their rigid assessment criteria, predictions based on countries' past performance, and by framing AI policy as a matter of economic competitiveness. They hence come to rule out effective policy alternatives and political horizons, such as global regulation of AI.

Policy scripts prescribe generalizable policy measures based on storylines (cf. Schank & Abelson, 1977). My analysis of policy narratives that accompany AI metrics shows how claims about future are done through references to past, as various "traditions" are evoked to justify the policy measures proposed. Such historical narratives coincide with conceptual shifts that happen in a context in which past concepts of governance no longer fully fit the horizons of expectation of the anticipated future (Koselleck, 2004). This also resonates with a more general trend of anticipatory governance by international organizations (Berten & Kranke, 2022), in which the struggles over imagined future(s) tend to be heightened during times of crisis (Robertson, 2022). Despite the uncertainty of our digital future, the narratives of global competition and "arms race" in AI promote seeming continuity by creating a future vision that merges invented traditions and contemporary ideas of economic competitiveness.

Consequently, AI is framed as one technological revolution in a series of many, and a matter of economic competitiveness, leaving states to alleviate its anticipated social costs. The global policy model for AI becomes a race for talent and data. But describing history as continuity or progress is problematic, as the narratives can narrow the horizon for policy alternatives (cf. Arendt, 1973, p. 137, 143; Hyvönen, 2016; Skinner, 1989). There are indications of this concerning democratic and ethical issues of AI, as they do not readily fit the talent competitiveness frame.

Research design, data, and methodology

Analyzing the technical annexes and reports of the major ranking producers, in this article I explore how global rankings address AI and digitization and how they frame AI policy through conceptual and numerical objectification and narratives. To analyze how the ideational shifts and data sharing in global index production influence the framing of AI policy, my data selection is conceptually and temporally motivated, covering the indicators and reports by established index producers who argue for the relevance of their metrics in tracking countries' ability to cope in the "AI revolution," as well as more recent indices that specifically claim to measure "AI readiness." *Global Competitiveness Index* (GCI), *Global Innovation Index* (GII), *Global Talent Competitiveness Index* (GTCI), and *Human Capital Index* (HCI) represent more traditional data sets, which are prominent metrics of competitiveness, innovation, and human capital. With the exception of HCI, these indices are all rankings, meaning that they represent their results as a ranking list. In addition, I analyze novel rankings that are specifically crafted for measuring AI: *Global AI Index* (GAI), *Government AI Readiness Index* (AIRI), and *Global City AI Readiness Index* (GCAIRI). All the above indices explicitly claim to analyze countries' AI readiness in a meaningful way.

To analyze convergence in objectifications of AI policy through sharing of data, I use Gephi network visualization tool to analyze the linkages between selected global indices and their data sources, that is, organizations producing or repositing the data used. The data sources are further classified by the type of organization as (1) corporations (including consultancies), (2) inter-governmental organizations, (3) the European Union (EU), (4) nonprofit organizations (think tanks, NGOs, foundations), (5) educational institutions, and (6) national institutions. In addition, I conduct a comparative conceptual analysis on the composition of these indices to uncover how concepts are operationalized in their selected indicators and objectify AI policy (cf. Daly, 2003; Erkkilä, 2020; Sartori, 1970). The reports accompanying the indices further construct AI policy with narratives on navigating uncertain future (cf. af Malmborg, 2022). I study how they frame AI as a policy problem (cf. Bacchi, 1999) through conceptual and numerical objectification (Miller & Rose, 1990) and related future narratives that often refer to past experiences (Koselleck, 2004). Here peer concepts (Koselleck, 2004) of AI are also important, as concepts such as "competitiveness," "talent," and "openness" now frame index producers' AI policy prescriptions (Skinner, 1989).

NUMERICAL GLOBAL GOVERNANCE AND AI POLICY

Global rankings and objectification of AI

I will next show how the global indices are evolving through indicator data networks with new indices being launched based on existing indicator data, and how this affects the objectification of AI as a policy issue. When entering the global field of ranking (Erkkilä & Piironen, 2018), new actors have to conform to the existing norms and rites of verification (Haas, 1992), while also trying to carve their own niche (Gieryn, 1983). Table 1 shows how the global ranking field has evolved with indices in good governance, competitiveness, innovation, and wellbeing emerging over time. The number of indices has grown in all the policy fields, while they have also become geographically more contextualized, studying cities and regions, and become thematically more nuanced, analyzing items such as innovation and talent competition. There are also links between the global indices, as good governance indicators have been used by rankings of economic competitiveness, as well as innovation metrics that also draw data from global university rankings.

The field development of ranking is highly relevant to the global policies on AI as the major ranking producers—also selected for analysis in this article—are explicitly revising their indicators to analyze the social transformations anticipated through automation and AI (INSEAD, Adecco Group, and Google Inc., 2020; World Economic Forum, 2019c) or using AI as a motivation for launching a new index (World Bank, 2019). However, though the number of indices has increased, and their nominal focus has expanded, there is nevertheless strong convergence between them, both conceptually and in terms of the use of data between different indicator sets. They are now coming together under the notion of AI.

Another recent trend of innovation and city rankings has emerged to complement the existing measurements of competitiveness, visible also in Table 1. In addition, highlighting the critique of GDP as a standardized measure (Stiglitz et al., 2009), there has been a shift towards

TABLE 1 Selected global indices: good governance, competitiveness, higher education, innovation, human capital, and AI governance.

	Before 1999	2000–2009	Year 2010 onwards
Good governance	Freedom in the World (1972) Freedom of the Press (1980) Corruption Perception Index (1995) Worldwide Governance Indicators (1996)	Fringe Special (2001) Press Freedom Index (2002) Global Integrity Report/Index (2006) Open Budget Index (2006) Bertelsmann Transformation Index (2006) Ibrahim Index of African Governance (2007) Open Net Initiative (2007) Actionable Governance Indicators (2008) Government at a Glance (2009)	Global Integrity Report—Integrity Scorecard (2010) Global Right to Information (RTI) Rating (2011) Implementation Assessment Tool (IAT) (2011)
Competitiveness	Global Competitiveness Report (1979) World Competitiveness Yearbook (1989)	Global Business Competitiveness Index (2000) Growth Competitiveness Index (2000) Global Competitiveness Index (2004) Worldwide Centers of Commerce Index (2007) Rich States, Poor States (2007) A.T. Kerneys Global Cities (2008) Global Power City Index (2008)	EU Regional Competitiveness Index (2010) Hot Spots 2025 (2013) The Competitiveness of Cities (2014)
Higher education		Academic Ranking of World Universities (2003) Times Higher Education Supplement (2004) Webometrics Ranking of World Universities (2004) Affordability and Accessibility Comparison of Global Higher Education Rankings (2005) Performance Ranking of scientific papers for world universities (2007) The Leiden Ranking (2008) The SCImago Institutions Ranking (2009)	QS World University Ranking (2010) Times Higher Education—Thomson Reuters (2010) High Impact Universities (2010) The U-Multirank (2011) The Assessment of Higher Education Learning Outcomes (AHELO) (2012)

(Continues)

TABLE 1 (Continued)

	Before 1999	2000–2009	Year 2010 onwards
Innovation		European Innovation Scoreboard (2001) Global Innovation 1000 (2005) Global Innovation Index (2007) Innovation Cities Index (2007) Innovation Union Scoreboard (2008) International Innovation Index (2009)	The Bloomberg Innovation Index (2011) The Startup Ecosystem Report (2012) Thomson Reuters Top 100 Global Innovators (2011) The Global Cleantech Innovation Index (2012) Global Talent Competitiveness Index (2014) Top 100 Innovative Universities (2015) Contributors and Detractors (2016) Top 25 Global Innovators—Government (2016)
Human capital/ Wellbeing	Human Development Index (1990)	GLOBECO World Happiness Index (2000) Happy Planet Index (2006) Gallup-Sharecare Well-Being Index (2008)	OECD Better Life Index (2011) UN World Happiness Report and Index (2012) Bloomberg Healthiest Countries Index (2013) Indigo Wellbeing Index (2016) Human Capital Index (2018)
Digital/AI Governance		UN E-Government Readiness/Development Index (2003) UN E-Participation Index (2003)	Government AI Readiness Index (2017) Global Cities AI Readiness Index (2019) Digital Government Index (2019) Global AI Index (2019)

measurements of wellbeing. It is noteworthy that the "digital turn" in the focus of the World Economic Forum's *Global Competitiveness Index* (GCI) occurs in the same timely context where the World Bank (2019) ties its *Human Capital Index* (HCI) to the changing nature of work through automation and the *Global Talent Competitiveness Index* (GTCI) promotes its ranking as a companion for "the age of AI" (INSEAD, Adecco Group, and Google Inc., 2020). Also, AI-specific indices are emerging, such as *Government AI Readiness Index* (2017) by Oxford Insights, *Global Cities AI Readiness Index* (2019) by Oliver Wyman Forum, and Tortoise media company's *Global AI Index* (GAI) that arguably are the first rankings to assess countries and cities readiness and capacity for artificial intelligence (Oliver Wyman Forum, 2019a; Oxford Insights, 2017; Tortoise, 2019a, p. 1).

Conceptual shifts and data networks

While the WEF's GCI data set is under pressure to accommodate the new ideas of economic competitiveness and is challenged by emerging data sets, it serves as a model for other rankings, many of which also use its underlying Executive Opinion Survey data. This is apparent in Figure 1 showing a visualization of network analysis of the data sources of *Global Competitiveness Index* (GCI), *Global Innovation Index* (GII), *Global Talent Competitiveness Index* (GTCI) *Human Capital Index* (HCI), *Government AI Readiness Index* (AIRI), *Global Cities AI Readiness Index* (GCAIRI), *Global AI Index* (GAI).

Figure 1 shows a general visualization of the above indices and all their indicator data sources (organizations producing or repositing data) using Gephi's Fruchterman-Reingold layout.[2] The

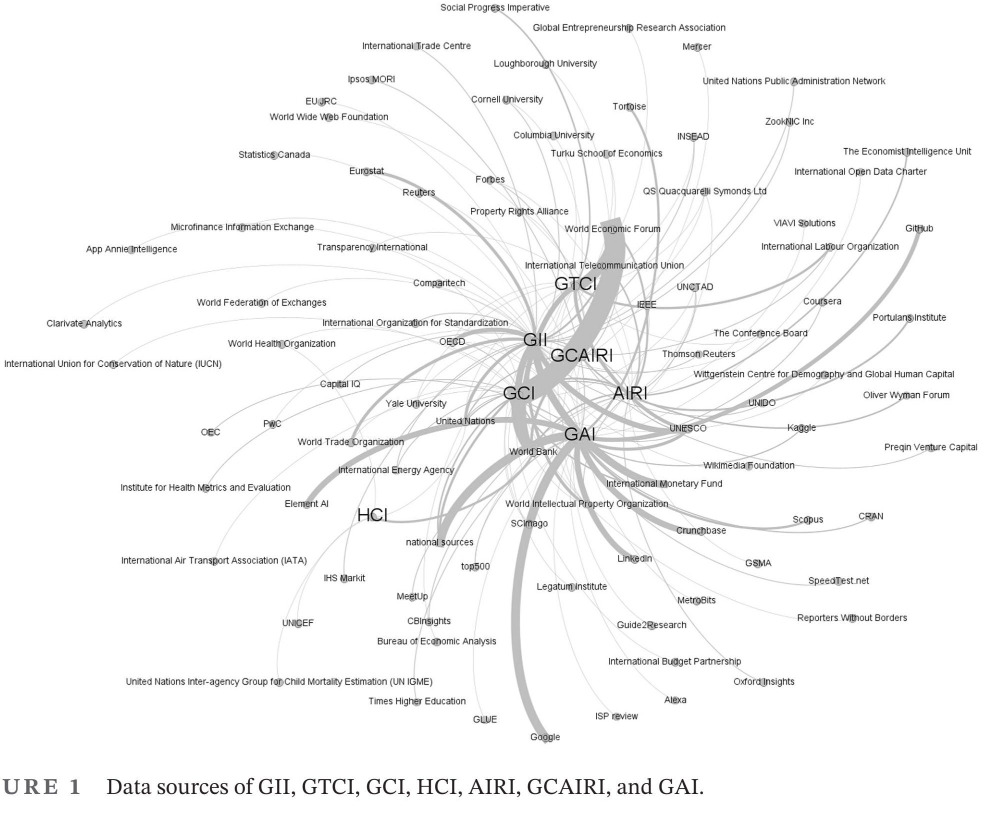

FIGURE 1 Data sources of GII, GTCI, GCI, HCI, AIRI, GCAIRI, and GAI.

nodes (i.e., connecting points) of the graph are indices using indicator data or organizations producing or repositing it. The edges (i.e., links) between these nodes indicate that the indices analyzed (in capitalized acronyms) are using data from the organization or other index that they are linked to. The line strength of the edges indicates the number of indicator data points between an index and the organization from which the data were sourced.[3] Individual data producers may provide significant amounts of data for several indices. While organizations producing and repositing data might influence the development of global rankings differently, it is empirically difficult to differentiate between them, as the documentation of data sources in technical annexes of indices often does not explicitly state if the named indicator data source actually produced the data or rather reposited it, and if so, where did the original data come from and was it somehow modified. World Bank is a case in point, as many indices name it as their indicator data source, while the Bank often merely acts as a repository for data produced by other organizations. However, it is important for my argument to analyze if the organizations producing global indices on AI produced their own indicators or merely used existing indicator data instead.

But along with the use of indicator data, the similarities in the composition of the indices and their conceptual underpinnings are important for understanding the construction of traditional indices of competitiveness and human capital, as well as the new AI metrics. Table 2 shows GCI, GII, GTCI, and HCI that are prominent measurements of competitiveness, innovation, and human capital and whose producers have explicitly claimed that they are also relevant for assessing countries' ability to accommodate transformations related to the "AI revolution" (INSEAD, Adecco Group, and Google Inc., 2020; Persson, 2016; World Bank, 2019; World Economic Forum, 2019c).

The World Economic Forum has been one of the most prominent organizations arguing for the challenges to society as a result of AI. Since its publication in 2004, the World Economic Forum's *Global Competitiveness Index* (GCI) has been influential in making economic competitiveness an active policy concern for countries. While the concept has been around for longer than that (Cerny, 1997; Krugman, 1994), the World Economic Forum's ranking has made "competitiveness" a knowledge brand that can be copied across contexts (Sum, 2009). The launching of the fourth version of GCI in 2018 happens in the context in which the WEF forcibly promotes its view of AI, bringing this also to national governments' policy agenda.

Discussing AI as the "Fourth Industrial Revolution," the WEF frames the related policy problems with a discourse emphasizing discontinuities and disruptions. WEF also revises the GCI, calling it "a new economic compass for the Fourth Industrial Revolution," while highlighting "human capital, innovation, resilience, and agility" as drivers of competitiveness amid the technological revolution (World Economic Forum, 2018, v, 1–2). While human capital—understood as health and skills (education)—had already been part of the measure, the fourth generation of GCI now also includes assessments of countries' "innovation ecosystem," exploring business dynamism and innovation capability.

On one hand, the change in the measurement reflects recent debates on competitiveness that now highlight regained interest in industrial policy amid technological change and AI, arguing for a broader understanding of economic activities and collaboration between enterprises, academia, and the public sector, while taking into account regional policy, employment, migration, and sustainability issues (Aiginger & Rodrik, 2020, pp. 191–193, 202–203; Ketels, 2006, pp. 116–118; cf. Porter, 1990, 2003). On the other hand, the shift in the WEF measurement is part of a larger development in global ranking, in which new indices are constantly emerging to challenge the previous ones.

TABLE 2 Composition of global indices on competitiveness, innovation, and human capital.

	Global competitiveness index	Global innovation index	Global talent competitiveness index	Human capital index
Producer	World Economic Forum (WEF), 2004-	Cornell University, INSEAD Business School for The World, World Intellectual Property Organization (WIPO), 2007-	INSEAD Business School, Human Capital Leadership Institute, Adecco Group, 2013-	World Bank, 2018-
Focus	Economic prospects of countries	Innovation capacity of countries	Countries' ability to grow, attract and retain talent	Newborn's expected amount of human capital by age 18
Assessment	12 pillars Enabling environment 1. Institutions 2. Infrastructure 3. ICT adoption 4. Macroeconomic policy Human capital 5. Health 6. Skills Markets 7. Product market 8. Labor market 9. Financial system 10. Market size Innovation ecosystem 11. Business dynamism 12. Innovation capability	Innovation input sub-index 1. Institutions 2. Human capital and research 3. Infrastructure 4. Market sophistication 5. Business sophistication Innovation output sub-index 6. Knowledge and technology outputs 7. Creative outputs	Six pillars Input sub-index: 1. Enable 2. Attract 3. Grow 4. Retain Output sub-index 5. Vocational and technical skills 6. Global knowledge skills	Three components: 1. Survival 2. School 3. Health

The Global Innovation Index was first published in 2007, claiming to extend the conceptualization of global ranking to "innovation." The Global Talent Competitiveness Index was launched in 2013, claiming to measure countries' ability to attract and retain human capital, necessary for competitiveness and innovation. It is noteworthy that the GCI, GII, and GTCI rankings bear great similarities in their composition, despite being published over a timespan of 10 years and measuring the broad topics of competitiveness, innovation, and human capital, respectively. This has particularly been the case since 2018, when GCI incorporated the innovation environment into its measurement and emphasized drivers of competitiveness in the context of AI and digitization.

There is also a striking overlap in their sources of data. In the network graph (Figure 1) there is a strong link between the World Economic Forum and the GCI, GTCI, and GII; World Economic Forum's Executive Opinion Survey not only makes the core of the GCI but also provides the bulk of data for the GTCI, while also used by the GII. Moreover, while the three indicator sets might not have exactly the same data, 87% of their data is produced by the same 10 organizations (Erkkilä & Piironen, 2020), most notably by the WEF (42%), the World Bank (15%), and UNESCO (10%).

This demonstrates how the existing data sets prompt numerical knowledge production both conceptually and at the level of data. The persistent use of existing data in composite indicators limits and conditions what can be measured, leading to only incremental steps in the development of global indices of AI. The focus of measurement has moved towards assessments of human capital in terms of research and development, using data from university rankings. As is visible in the network graph (Figure 1), GCI, GTCI, and GII use data from university rankings providers such as Thomson and Reuters, QS, and Times Higher Education. In addition, new metrics on human capital have been launched, such as the World Bank's *Human Capital Index* (first published in 2018), which conceptually overlaps with the human capital component of *Global Competitiveness Index* but is narrower in its analysis, focusing on education and health based on UN and World Bank data.

Though artificial intelligence has not been the main focus of the global indices outlined in Table 2, these prominent index producers have nevertheless explicitly claimed (see above) that their indicator sets are also capable of assessing countries' ability to adapt to AI-driven changes. Along with the composition, methodology, and indicator data used in these indices, there is also strong convergence in their underlying causal and normative beliefs (cf. Haas, 1992). Consequently, these indices provide a uniform view of innovation-driven economic performance, contributing to future narrative and policy script on AI as global competition over talent, world-class education, and well-performing institutions.

New metrics of AI, old ideas of competitiveness

Recently, the indices of competitiveness, innovation, and human capital have been complemented by new rankings that claim to focus specifically on artificial intelligence. Table 3 shows the composition of *Government AI Readiness Index* (AIRI), *Global AI Index* (GAI), and *Global Cities AI Readiness Index* (GCAIRI) that are new metrics that have been crafted to analyze countries' and cities' readiness and capacity for AI. To answer the research question of this article—how global rankings frame AI policy—it is interesting to study their added value to the previous indicator sets.

TABLE 3 Composition of AI indices.

Index	Government AI readiness index	Global cities AI readiness index	Global AI index
Producer (year)	Oxford Insights (2017-)	Oliver Wyman Forum (2019)	Tortoise Intelligence (2019-)
Focus	Governments' preparedness to use AI in public services	Cities' AI readiness	Countries' capacity for artificial intelligence
Assessment	Government 1. Vision 2. Governance & Ethics 3. Digital capacity 4. Adaptability Technology sector 5. Human capital 6. Innovation capacity 7. Size Data and infrastructure 8. Infrastructure 9. Data availability 10. Data representativeness	Vision 1. Vision, priorities, mindset Activation 2. Quality of life and diversity 3. Demographic enablers 4. Legal and governmental enablers Asset base 5. Companies 6. Workforce 7. Funding 8. Education and research 9. Infrastructure Development and trajectory 10. Activation (development over time) 11. Asset base (growth over time)	Implementation 1. Talent 2. Infrastructure 3. Operating environment Innovation 4. Research 5. Development Investment 6. Government strategy 7. Commercial ventures

AIRI is an intermediary between the traditional governance indicators and the new AI metrics. It has strong links to a range of UN data, but it also makes direct use of GCI and GII data. In its initial 2017 version, AIRI covered three "factors": public service reform, economy and skills, and digital infrastructure. But with a clear conceptual reference to the GCI, the AIRI currently consists of three "pillars": government, technology sector, and data and infrastructure. The government pillar covers four "dimensions": vision, governance and ethics, digital capacity, and adaptability.[4] The aim of the technology sector pillar is to assess the size of the sector that supplies governments with AI technologies but also its "innovation capacity" and citizens' skill set (human capital). Here the AIRI contains elements of both digital governance metrics and innovation indicators.[5] The data and infrastructure pillar of AIRI again draws data from various existing IT assessments (particularly ITU and Economist Intelligence Unit), comparing countries' technological and data infrastructures. It is of generic nature and includes few AI-specific elements.[6]

The AIRI builds on data from established index producers. It draws 26% of its data from UN organizations, but the Portulans Institute (which coproduces the GTCI) is also well-represented with 16% of its data coming from its Network Readiness Index and GII (coproduced by WIPO). The World Economic Forum (12%) and the Economist Intelligence Unit (10%) are also significant data sources. In many ways, AIRI contains conceptual elements and data from previous measurements of competitiveness, innovation, and digital/e-government indicators, but there is little about AIRI that is AI-specific.

In fact, only three of AIRI's 42 indicators are AI-specific: (1) the assessment of whether the country has an AI strategy in place (government pillar), (2) the number of AI Unicorns (technology sector pillar), and (3) the number of research papers published in AI (human capital pillar). Though AIRI's conceptual dimensions such as the availability of data for training AI models or representativeness of data do nominally address issues relevant to AI policy, the actual metrics borrowed from standard digital governance indices do not specifically operationalize the concepts. And as AIRI fully relies on existing data, there is a strong sense of continuity with previous metrics of competitiveness, innovation, and digital governance.

The *Global Cities AI Readiness Index* (GCAIRI) arguably analyses the AI readiness of urban areas. However, a closer look shows that it shares the typical problem of city rankings, namely it does not really measure cities but is mostly composed of existing country data. Moreover, a closer look at the GCAIRI shows limitations in measuring AI. The GCAIRI is composed of four categories—vision, activation, asset base, and development and trajectory—that are called "vectors" (see below). The vision category basically assesses the strategic work done in the cities, concerning smart city plans, city strategies, and economic development plans, which are complemented by data from the World Economic Forum.

The activation vector covers dimensions such as quality of life and diversity, demographic enablers, and legal and governmental enablers. The metrics of "quality of life" (Mercer data) and "diversity" (UN data) are typical in city rankings that assess the attractiveness of urban spaces. However, in the GCAIRI the diversity element is conceptually very narrow and refers to the openness of immigration policy for high-skilled individuals, carrying the idea of global talent competition. The demographic enablers refer to wealth and its distribution in society.[7] The legal and government enablers again nod towards the existing rankings of good governance, building on the World Bank's Worldwide Governance Indicators and Doing Business rankings.

The aim of the asset base vector is to assess whether the city has the necessary "assets" to fulfill its vision. Focusing on companies, workforce, funding, education and research, and infrastructure, this "vector" resembles the idea of "innovation ecosystem" that is also present in other metrics of economic competitiveness, including the *Global Competitiveness Index* by the WEF. Asking if a city has "a reservoir of talent in colleges and universities, an educated workforce, high-quality STEM education in primary and tertiary education, a track record for innovation and attracting pioneering companies, and the necessary infrastructure" (Oliver Wyman Forum, 2019b), the category also firmly echoes the talent competition paradigm, while containing elements of university and innovation rankings.

The development and trajectory vector of GCAIRI contains items selected from its activation and asset base vectors, now assessing change within them "in recent years." Focusing on changes in government effectiveness, business environment, wealth, flows of venture capital, number of firms, ranked universities, and quality of infrastructure, the vector further conceptualizes the "AI readiness" as economic competitiveness. Overall, the GCAIRI's perception of AI is quite limited, understood in terms of economy and human capital ("talent"). The regulatory and ethical aspects relevant to AI governance are not measured. In fact, the GCAIRI does not include any AI-specific metrics but is solely based on existing indicators of good governance, economic competitiveness, education, and innovation.

The *Global AI Index* (GAI) is conceptually similar to the earlier indices depicted in Table 2. Like the World Economic Forum's GCI, the GAI calls its conceptual elements "pillars." The implementation dimension of GAI contains sub-pillars on "talent," owing to the talent competition paradigm, as well as "infrastructure" and "operating environment" that are linked with the institutional aspects of governance and economic competitiveness. The innovation ecosystem perspective is also present, visible in the emphasis on the research and development sub-pillars. The investment dimension contains sub-pillars of government strategy and commercial ventures. However, while the composition of the GAI builds on the earlier competitiveness and innovation metrics such as the GCI, GTCI, and GII, it differs from them in terms of indicator data sources. As is apparent in Figure 1, the GAI builds on varied data, much of which has been derived from platforms such as GitHub, CrunchBase, LinkedIn, and Google.

This also allows the GAI to include AI-specific data. For example, the Talent pillar builds on LinkedIn data, counting the numbers of AI engineers, data scientists, and machine learning engineers in a country. It also counts AI-related R and Python programming language downloads (sources: CRAN and Google), the GitHub IT development site's ratings and activities for software packages on artificial intelligence, machine learning, and data science by country, as well as the use of Amazon Alexa's AI MOOC. In addition, GAI uses platform data (Meetup, Kaggle) to count the number of AI experts and to assess the size of the associated community. Like the other AI metrics, GAI also contains conventional assessments of skills levels by using UNESCO data for counting countries' science, AI, and IT graduates and undergraduates.

On the other hand, the infrastructure pillar is similar to the ones seen in the AIRI and GCAIRI data sets, combining generic technological infrastructure indicators from international organizations such as the OECD and the World Bank with more specific IT metrics from private actors (ISP review, Top500, Speedtest). The operating environment pillar contains conceptual elements of talent competition (residency and visa arrangements), gender diversity (based on UNESCO and Kaggle data), trust in AI (Ipsos MORI), open data (International Open Data Charter, OECD), and data protection (UNCTAD). This resonates with the notion of "openness" that is also present in the policy script on AI policy that the rankings carry.

The GAI's research and development pillars are conceptually similar to the ones seen in other rankings, building on university rankings and citations data (Times Higher Education, SCOPUS) combined with R&D spending data and researcher counts (the World Bank, UNESCO) and the number of patents (GitHub and Google data). Though the global regulatory aspects are underrepresented in all the AI rankings discussed, this is at least acknowledged in the GAI development pillar that assesses countries' participation in the ISO's standardization work through its AI committee.

With its specific focus on AI, the GAI stands out from the other AI rankings through its broad use of national sources. This is particularly visible in the government strategy pillar, which builds on the comprehensive analysis of national-level data. Another element that distinguishes the GAI from the other metrics is the extensive use of platform data, apparent also in the commercial pillar that contains an assessment of AI startup activity and funding based on Crunchbase data.

Patterns of data production and measurement

As the above analysis shows, there are significant similarities between the various indices concerning their composition and concepts. There are also strong overlaps and cross-references in data sources, but for a more systematic view, one needs to compare them for the type of organization that produced the data. The dominant role of intergovernmental organizations in producing indicator data is also visible in Figure 2, in which the global indices selected and their data sources are presented with Gephi Radial Axis layout with nodes grouped by organization type of data sources (corporations, intergovernmental organizations, the EU, nonprofit organizations, educational institutions, and national institutions). The number and percentage shares of indicator data sources by producer type are presented in Table 4.

As becomes apparent from Figure 2, intergovernmental organizations as data producers (placed at the bottom of the graph and indicated in turquoise) produce the bulk of data for all indices concerned, particularly for the GII and HCI (see Table 4). National sources[8] (placed on the right and colored yellow in Figure 2) are rarely used apart from the AI-specific metrics GAI and GCAIRI. The EU data sources (placed on the left in blue) are only used by GII. As seen from Table 4, most of the indices analyzed used indicator data from nonprofit organizations such as the WEF, Transparency International, and Reporters Without Borders (placed on the top right in green in Figure 2). Educational institutions (lower left side, in pink) provide data for GCAIRI, GII, GTCI, and GCI (see Table 4).

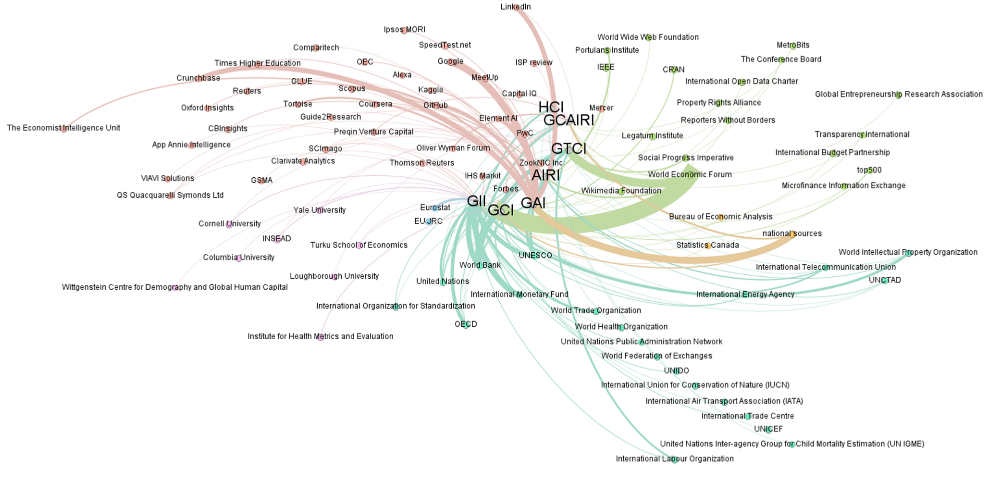

FIGURE 2 Data sources of GII, GTCI, GCI, HCI, AIRI, GCAIRI, and GAI by type of producer.

TABLE 4 Number and percentage of indicator data by type of data source.

	AIRI		GCAIRI		GAI		GII		GTCI		GCI		HCI	
Nonprofit	12	29%	4	12%	7	4%	8	6%	34	48%	58	51%	0	0%
EU	0	0%	0	0%	0	0%	9	7%	0	0%	0	0%	0	0%
IGO	17	40%	12	35%	16	10%	96	72%	32	45%	46	41%	10	100%
Corporations	13	31%	11	32%	113	72%	11	8%	2	3%	1	1%	0	0%
National institutions	0	0%	6	18%	22	14%	2	2%	0	0%	4	4%	0	0%
Educational	0	0%	1	3%	0	0%	7	5%	3	4%	4	4%	0	0%
Total	42	100%	34	100%	158	100%	133	100%	71	100%	113	100%	10	100%

As I have argued above, the new AI-specific rankings in many ways echo the policy script of talent competitiveness and innovation of the earlier indices. But their composition does differ from previous metrics due to their use of corporate data. Marked in Figure 1 with red color in the top left corner, the corporate data sources make a significant share of the new AI metrics AIRI (31%), GCAIRI (32%), and in particular GAI (72%). This use of platform data brings a more dynamic element to the study of AI governance, but as the above conceptual analysis shows, the ideational elements of the AI rankings are surprisingly similar to the existing indices of competitiveness, innovation, and human capital.

Though all the indices analyzed are brought together under the label of AI, with the exception of Global AI Index (GAI), there is very little content that would specifically link to artificial intelligence. Rather, the metrics are reproducing old patterns of measuring competitiveness and innovation, with renewed interest in human capital and education. Seen through the metrics, AI policy is framed as a matter of competitiveness, talent mobility, digital infrastructure, open data, and research and innovation.

Limitations: The problem of AI ethics

Numerical objectification not only gives shape to policy problems but also effectively decides what is excluded (Bacchi, 1999; Miller & Rose, 1990). There is a discrepancy between the ranking producers' policy script on competitiveness and existing national strategies that along competitiveness also highlight AI "ethics" (Radu, 2021; Sloane, 2022; Ulnicane et al., 2020, 2021). The issue of AI ethics is addressed in the new AI rankings but in limited scope or with proxies that are not AI-specific. Interestingly, the developers of Government AI Readiness Index (AIRI) in 2020 pilot tested a separate Responsible Use sub-index, acknowledging the work by governments and international organizations attempting "to articulate principles by which we can prevent AI from doing harm" (Oxford Insights, 2020, p. 9).

Building on OECD principles on AI (inclusivity, accountability, transparency, and privacy), the pilot test covered 34 countries but was not included in the 2021 edition of the Government AI Readiness Index that simply states that the Responsible AI sub-index will be published again in 2022 as a "standalone project" (Oxford Insights, 2021, p. 5). This is problematic, as some countries leading the AIRI ranking, for example, the USA and UK, actually ranked poorly in the responsible use sub-index (Oxford Insights, 2021, p. 22), which could have influenced the general ranking scores significantly had it been included in the actual ranking.

The 2020 AIRI report describes problems in establishing measurements on AI ethics:

> "Many of the values and conditions needed for responsible use are hard to quantify, and global datasets are hard to come by" (Oxford Insights, 2020, p. 9).

This underlines the difficulties of making new AI indices of global scope, which often are done with limited resources leading to great dependency on existing data. Sartori famously stated that comparative analyses "travel on their concepts" (Sartori, 1970). The current comparative assessments in policy indicators rather seem to travel on the availability of existing data, as the global rankings are often composite indicators, drawing their data from a range of existing sources.[9] Consequently, several ranking producers have come to intimately share normative and causal beliefs (cf. Haas, 1992), reproducing the prevailing practices in the measurement field while creating seemingly novel solutions, a typical effect of structuration (cf.

Giddens, 1986, p. 5). This produces a uniform view of AI-related metrics in which the seemingly neutral and apolitical (cf. Porter, 1996) indices come to hide the particularistic choices and value judgments made in the process of quantification, as well as the complexity in the issues compared.

Paradoxically, the discourse of AI revolution accommodates only incremental changes to the global indices, both existing ones and their new emerging challengers. Nevertheless, through objectification (Desrosières, 1998; Miller & Rose, 1990), global rankings now define the content and scope of AI policy, associating it with "competitiveness," "openness," and "talent." These concepts are also present in the ranking producers' narratives on AI-driven future analyzed in the next section.

Policy scripts and narratives of AI: Competitiveness, openness, and talent

Narratives are part of the policy scripts that describe the causal beliefs, the agency, and the aim of policies (Kentikelenis & Seabrooke, 2017; Schank & Abelson, 1977) amid an uncertain future (af Malmborg, 2022; cf. Beckert, 2016; Robertson, 2017). Also, numbers tell stories: rankings imply a social ontology of competition (cf. Alasuutari & Qadir, 2016; Sum, 2009), point out issues of concern, and motivate policy interventions (cf. Bacchi, 1999), while identifying weak performance, models to follow, and goals to reach, as well as the means for obtaining them. Because of the ideational convergence in global indices discussed above, AI is firmly linked to the semantic field (Koselleck, 2004) of economic competitiveness on the one hand and to human capital and mobility on the other. Through sharing of indicator data and conceptual overlap, global indices bridge policy domains of good governance, economic competitiveness, innovation, and urban development that come together under the concepts of competitiveness, openness, and talent.

In the reports that accompany the global rankings analyzed for this study, the index producers explicitly argue for the revolutionary character of AI (World Economic Forum, 2019c, p. 25), and even stress its global regulation as a justification for publishing their metrics (Tortoise, 2019b). AI governance is framed in terms of economic competition between countries and innovation clusters. The atomist perception of competition gives responsibility to all actors concerned; individuals, businesses, and governments are the "grand designers of [their] own destinies" (Lanvin & Monteiro, 2019, p. 39) but only as actors in economic competition. Seeing innovative firms as disruptors and governments as the actors responsible for promoting the innovation ecosystem (World Economic Forum, 2019b, p. 10), the governments' role is reduced to fostering the disruptive "superstar" companies and alleviating the pain of reskilling (World Bank, 2019, p. 9, 10, 12, 19; World Economic Forum, 2017, p. 4, 2019b, p. 10).

Ethical and democratic aspects, such as bias, fairness, and accountability of AI, are hardly addressed by the prominent index producers. The WEF mentions that the global governance of AI should take into account "diversity of values," though EU fundamental rights and UN declaration of human rights are mentioned as examples (World Economic Forum, 2019a, p. 9, 12, 15). The World Bank and WEF argue that global agreements on digital taxation and anti-trust policies are needed, thereby allowing revenues for investments in social protection, wellbeing, and human capital (World Bank, 2019, p. 9; World Economic Forum, 2019c, p. 9), which are also aligned with the shifting ideas of competitiveness. However, AI ethics and democracy are not self-evidently part of the competitiveness paradigm.

While all ranking producers have adopted a future-oriented approach, WEF explores the idea of a global "formula for innovation" with digitalization and AI altering the "sequences" of economic development (World Economic Forum, 2018, v, 1–2, 6). Future prosperity is also linked to countries' scores on "openness," with Singapore being ranked as the world leader (World Economic Forum, 2018, p. 6, pp. 18–20). Rankings also give a seeming sense of orientation; WEF even measures countries' future readiness and rates them with a "progress number," constructing a "robust vision" of the future (Berten & Kranke, 2022). Today's competitive economies are seen as having a smooth transformation to the digital future (World Economic Forum, 2019c, p. 28).

In a similar vein, the Global Cities AI Readiness Index refers to its conceptual dimensions as vectors, arguing that "[a] vector has direction as well as magnitude, which makes it useful in determining relative positioning. Cities are in motion as they meet new technologies—and our research has tried to balance present standing with potential progress." (Oliver Wyman Forum, 2019b). Here the rankings again function as tools of prediction.

As a normatively appealing concept of governance (cf. Skinner, 1989), *openness* resonates with the proposed policy model on AI. The ranking producers' narratives on AI stress talent competition, understood as the ability of countries or cities to attract and foster "*talent*" (World Economic Forum, 2019c, p. 8; cf. Lanvin & Monteiro, 2019, p. 5; Oliver Wyman Forum, 2019b; World Bank, 2019, p. 10, 70). Openness is also associated with access to data ("open data") as a raw material of services and applications and efficiency of government (Cornell University, INSEAD and WIPO, 2019, p. 22, 123; INSEAD, Adecco Group, and Google Inc., 2020, p. 92, 93, 102; Tortoise, 2019a) or as a requirement for "training AI models" (Oxford Insights, 2021, p. 72).

The narrative on the future governance of AI is riddled with references to the past. Index producers see AI as bringing social turmoil and job losses, but the historical cases of industrial revolutions and innovation, ranging from the Spinning Jenny to the Telegraph, are presented as analogies for tackling future challenges (World Bank, 2019, pp. 20–22, 50, 124; World Economic Forum, 2019a, p. 6; Tata Communication, 2018, p. 9, 15). The Nordic governments' "AI readiness" is largely explained by their administrative traditions and entrepreneurial culture (Oxford Insights, 2021, p. 10). These references to the past help to communicate the policy prescriptions on AI. German conceptual historian Reinhart Koselleck argues that in times of crisis and social turmoil, actors become reflexive about the past vis-à-vis the expectation horizons of the future (Koselleck, 2004). The narratives on the "AI revolution" now accommodate a strong continuity in the ideas and measurements of economic performance, while also projecting past experiences to an anticipated AI-driven future. As a rhetorical means (cf. Skinner, 1989), references by ranking producers to traditions also narrow the political horizon for AI policy, framing it as "race" for AI innovation, talent, and data.

CONCLUSIONS

This article has presented an analysis on how global rankings frame AI policy. As rankings are becoming a lingua franca for global governance, it is important to understand how they objectify and frame AI as a policy problem through their composition and prescribe action through narratives (Miller & Rose, 1990; Schank & Abelson, 1977). The above analysis has shown how the field development of ranking has led to strong conformity with current institutional practices as index producers intimately share concepts and data. The concepts of "competitiveness" "openness" and "talent competition" succinctly summarize the ranking producers' prescription for AI policy, signifying deregulation, a liberal open society and transparent government, an open labor market and talent mobility, as well as open data, and research and innovation.

The underlying imaginary of global competition potentially limits AI ethics, as well as global regulation of AI. While the index producers do acknowledge the potential social costs of AI, they have largely overlooked the ethical aspects that do not readily fit the frame of talent competitiveness or are subsumed by it. The indicators of AI ethics included in the newer data sets tend to be limited in number or scope (non-AI-specific proxies), indicating the lack of existing data and the smaller index providers' limited resources to produce it, also acknowledged by the producers of *Government AI Readiness Index*. This further underlines the path dependencies of data production in the field of global ranking, in which large intergovernmental organizations and prominent index producers such as the WEF have a dominant role.

The case of AI policy also points out the implications of rankings for global governance in more general sense, showing how metrics, policy scripts, and narratives are intimately related. In the standing literature on global indices, the focus is often on the aggregate number, the ranking score, and rankings' subject's reflexivity over this. But equally important is the composition of the measurements and their shifting focus, as this allows one to understand the dynamics behind the objectification of policy problems.

Rather than "traveling on their concepts" (Sartori, 1970), the global indices seem to travel on the availability of existing indicator data. The global indices analyzed here are mainly composite indicators building on existing data, creating path dependence and conformity with past choices, as the metrics on AI are evolving through existing data and concepts that owe much to the WEF's ranking of economic competitiveness. Even if the metrics evolve only slowly and incrementally, they nevertheless frame AI policy by objectifying AI readiness as a policy problem.

Reflecting on future research agenda on politics and policy of AI set out in this special issue, my article has shown how the numerical objectification and narratives that frame AI policy also delimit the causal beliefs, agency, and aim of policies. The concerns over AI ethics and democracy (Zuboff, 2019), and issues of bias and accountability (Barth & Arnold, 1999; Bucher, 2018; Eubanks, 2018; Pasquale, 2016) are not addressed in detail in the rankings or related policy narratives, though the new AI-specific rankings contain indicators to cover this, which is part of their added value. AI ethics is nevertheless subsumed to competitiveness, as the concepts and data of earlier indices heavily influence the later entries to the field of ranking. Narratives of uncertain digital future and their underlying imaginaries now further communicate the policy prescriptions on AI. The temporal aspects of these narratives imply references to the past in attempts to address future expectations (cf. Koselleck, 2004).

Consequently, the global rankings frame AI policy as a race for talent and data. Despite uncertainties related to AI technologies, these metrics and related policy scripts promote seeming continuity by creating a robust future vision (Berten & Kranke, 2022) that merges invented traditions and contemporary ideas of competitiveness. While such framings and narratives might give a sense of orientation and help to communicate normative and causal beliefs on complex issues, they are problematic as they portray a seeming continuity of activities in times of disruptions, while delimiting policy alternatives.

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ENDNOTES

[1] Empirically, this article analyses the use of indicator data in global indices. I analyze seven indices, Global Competitiveness Index (GCI), Global Innovation Index (GII), Global Talent Competitiveness Index (GTCI), Human Capital Index (HCI), Global AI Index (GAI), Government AI Readiness Index (AIRI), and Global City AI Readiness Index (GCAIRI), most of which are also so-called composite indicators (drawing data from existing sources) and rankings (presenting their findings as an aggregate figure allowing ranking of measured entities). The primary focus of the article is on the actual indicators that the indices are using as their building blocks, which provides a view on how the indices operationalize the concepts that they claim to measure. The indicator data typically consist of statistics, assessments (perception data or survey), or counts of something.

[2] The full names of data sources are presented in Appendix 1. This applies to both Figures 1 and 2.

[3] For example, Global Innovation Index (GII) uses one data point from Statistics Canada, but nine data points from Eurostat, which is indicated in the visualization by line width that is nine times thicker for Eurostat.

[4] The "vision" is an assessment of the country having an AI strategy in place (yes/no). Governance ethics covers assessments of data protection and privacy (based on UNCTAD data), cybersecurity (ITU data), national ethics framework (various sources), and legal framework (WEF GCI data). The digital capacity dimension draws its data from the Network Readiness Index, the UN e-Government Survey, and the Economist's Inclusive Internet Index. Here, the Network Readiness Index is particularly interesting, as it was initially launched with the World Economic Forum but was relaunched in 2019 by the Portulans Institute which also coproduces the GTCI. The adaptability dimension measures government effectiveness, responsiveness to change, and e-procurement capacity, drawing its data from the World Bank (Worldwide Governance Indicators), the World Economic Forum (GCI), and the Govtech Maturity Index.

[5] Apart from the count of AI unicorns, the metrics used are generic assessments of the IT branch. In similar fashion, the innovation capacity dimension focuses on the conditions supporting innovations, covering entrepreneurial culture and business administrative requirements (source: WEF/Global Competitiveness Index), R&D spending (UNESCO), and investments in emerging technologies (Portulans / Network Readiness Index). Finally, the human capital dimension draws its data from university rankings concerning the quality of higher education institutions in engineering (QS) and number of AI-related research papers (Scimago), as well as UNESCO counts of graduates in science, technology, engineering, and mathematics, and assessments of digital skills (WEF/Global Competitiveness Index), "knowledge-intensive employment" (Portulans/Global Innovation Index), and activities in GitHub code hosting platform (Portulans/Network Readiness Index).

[6] The data availability and representativeness dimensions are at least conceptually aligned with the key issues of AI development—the data that AI algorithms are trained on and how "representative" of the population is the data, also to avoid biases. But actual data are again somewhat generic, reducing data availability to open government data and policies (Open Data Barometer, EIU), statistical capacity (World Bank), and mobile phone and internet access coverage (ITU), while representativeness is assessed in terms of gender gaps in internet and mobile access (EIU) and socio-economic gaps in internet usage and ability to purchase an internet-enabled device. Here, the data dimension becomes blurred, as the metrics are rather focused on internet access and ownership of digital devices and not the actual data.

[7] This is based on standard metrics of wealth such as GDP per capita, dependency ration (UN), and Gini coefficient (OECD).

[8] These consist of Statistics Canada and US Bureau of Economics as well as undefined 'national sources'.

[9] On methodological development in global indices, see Erkkil (2020).

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APPENDIX 1

LIST OF DATA SOURCES (ORGANIZATIONS)

Amazon Alexa
App Annie Intelligence
US Bureau of Economic Analysis
Capital IQ
CBInsights
Clarivate Analytics
Columbia University
Comparitech
Cornell University
Coursera
The Comprehensive R Archive Network (CRAN)
Crunchbase
Element AI
European Union Joint Research Center (EU JRC)
Eurostat
Forbes
GitHub
Global Entrepreneurship Research Association
General Language Understanding Evaluation (GLUE)
Google
GSMA, Mobile Connectivity Index
Guide2Research
Institute of Electrical and Electronics Engineers (IEEE)
Information Handling Services (IHS) Markit
Institut Européen d'Administration des Affaires (INSEAD)
Institute for Health Metrics and Evaluation
International Air Transport Association (IATA)
International Budget Partnership

(Continues)

APPENDIX 1 (Continued)

International Energy Agency
International Labour Organization
International Monetary Fund
International Open Data Charter
International Organization for Standardization
International Telecommunication Union
International Trade Centre
International Union for Conservation of Nature (IUCN)
Ipsos MORI (Market and Opinion Research International)
Internet Service Provider (ISP) review
Kaggle
Legatum Institute
LinkedIn
Loughborough University
Meetup
Mercer
MetroBits
Microfinance Information Exchange
National sources (undefined)
The Observatory of Economic Complexity (OEC)
Organization for Economic Co-operation and Development (OECD)
Oliver Wyman Forum
Oxford Insights
Portulans Institute
Preqin Venture Capital
Property Rights Alliance
PricewaterhouseCoopers (PwC)
QS Quacquarelli Symonds Ltd
Reporters Without Borders
Reuters
SCImago
Scopus abstract and citation database
Social Progress Imperative
speedtest.net
Statistics Canada
The Conference Board
The Economist Intelligence Unit
Thomson Reuters
Times Higher Education
Top500—The List

APPENDIX 1 (Continued)

Tortoise Media
Transparency International
Turku School of Economics
United Nations (undefined)
United Nations Conference on Trade and Development (UNCTAD)
United Nations Children's Fund (UNICEF)
United Nations Industrial Development Organization (UNIDO)
United Nations Educational, Scientific and Cultural Organization (UNESCO)
United Nations Inter-agency Group for Child Mortality Estimation (UN IGME)
United Nations Public Administration Network
VIAVI Solutions
Wikimedia Foundation
Wittgenstein Centre for Demography and Global Human Capital
World Bank
World Economic Forum
World Federation of Exchanges
World Health Organization
World Intellectual Property Organization
World Trade Organization
World Wide Web Foundation
Yale University
ZookNIC Inc