Mapping AI: Productivity, sustainability and employment

Taking Stock, Policy Relevance and Future Developments

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Plan of the discussion

1. **Introduction**: a brief summary of JRC-INNOVA findings and main take away messages
2. **Open issues** & suggested areas for improvement
3. **Positioning** of findings and policy implications in the context of AI debates
4. Potential directions for **future research**

Introduction: JRC-INNOVA findings and take away messages

Three main contributions

1. Trends in AI and robotics patenting: where and what
2. AI patenting and firm productivity: a positive relation, sometimes
3. Digital and environmental innovation: is there a relation?

Overall contributions:

- The studies cover a gap in the literature: lack of systematic evidence on the nature and behaviours of **AI innovators**
- Ensemble view on the AI landscape in relation to: firm productivity and regional digital-green

Trends in AI and robotics patenting: where and what

Setup

- The paper maps AI by matching patent and firm data (keywords vocabulary → AI patents/firms → matching with Orbis)
- global set of 155.000 AI patents for the period 2000-2016

Main findings

- sizeable growth from 2014, mostly driven by China (characterised by a prevalence of Univ patents, differently from other countries)
- underlying tech (IPC classes): mostly ‘transversally applicable tech’ (computing, measuring, etc); rapid growth in less high-tech fields
- sectoral distribution of AI firms: ICT, software, but also wholesale&retail trade/travel/e-commerce?
- increase in AI firms among SMEs and large firms
- increase in AI VC (but comparatively less in EU)
- <u>AI revolution is yet to come</u>

AI patenting and firm productivity: a positive relation, sometimes

- **Overall Research question**: does AI patenting lead to firm productivity? Two studies:
  - 1. AI patents (5200+ companies) → labour productivity
  - 2. AI patents in fintech and e-commerce → TFP / wages

- **Findings:**
  - AI patents application has a positive effect on labour productivity after controlling for non-AI patents (esp. SME & services)
    - Yet hard/early to disentangle AI & non-AI effects in larger companies
  - For fintech/e-commerce:
    - Productivity slowdown in TFP for AI firms in EU/US → more general pattern
    - High TFP ← → higher AI patenting, but costly transformation of that into profitability
    - (a bit of boost to wages is found)

Digital and environmental innovation: is there a relation?

Setup

- Construction of an original dataset comprising
  - Digital S&T, Green S&T, Emissions (GHG, CO2, PM10)
- Cross-mappings at NUTS2&3 regional level

Aim

- Is there cross fertilisation (reinforcing effect) between digital and environmental technologies (the 'twin transition')?
- Relevant to assess whether these technologies have potential to address societal challenges

Findings

- Growth of DT&GT overlapping patents → possible early trend (mostly additive manufacturing)
  - Preliminary result on positive relation between green and GHG, but negative with digital

Main open issues, suggested areas for improvement

1. **Definition**: what is AI and how to retrieve related STI
2. **Data:** what do publications and patents proxy for, in relation to the research questions?
3. **Sectors**: what aspect of sectors/firms’ does patenting capture?
4. **Impact**: what impact are we capturing, on what, at what level?

Definition: what is AI and how to retrieve related STI

What is AI?

- Major difficulty, even within computer science: “from there being, to this day, no agreed upon definition of intelligence within the AI community of researchers”. (Franklin, 2014)
- Various definition of AI exists (e.g. Artificial General Intelligence vs Narrow AI; collective forms of intelligence, or fields such as robotics or embedded systems, or embodied systems (Boden, 2016))
- AI is a general label for a cluster of technologies. Rather than considering AI as a single entity, it can be studied by more coherent groups of technologies within the field of AI, such as ‘machine learning’, ‘intelligent robots’...

→ **this has implications for the study of AITs’ impact:** assessing effects (e.g. productivity) of AI as a bundle of techniques can lead to misunderstandings of which technology drives which impact, in which sectors/firms

Definition: what is AI and how to retrieve related STI

- Open definition, together with other properties of AI, suggest AI is an emerging technology (Rotolo et al. 2015), and should be studied as such
- Emerging technologies due to their properties of novelty, coherence (convergence of technologies or research streams) and uncertainty (impact lies in the future and is uncertain) have methodological implication especially for <u>keywords</u> searches:
  - Need to enable the identification of activities across sectors/domains of applications
  - Need to rely on an accurate definition of the components of AI taking into account, historical effect, language changes, varying importance/emergence of constituting technologies
  - Keyword list can be further extended by machine learning

→ Bibliometricians take therefore great care in defining search terms for proxying technologies (Porter et al. 2008) as differing keyword use can lead to dramatic differences in findings (Armitage et. al. 2020)

Definition: what is AI and how to retrieve related STI

- AI assumed to be a **General Purpose Technology (GPT)**: ‘mantra’ repeated in every AI paper
- Is that so? GPTs are (i) pervasive, (ii) improving technologically, and (iii) inducing innovation in downstream industries
- As for AI
  - (i) AI is not so pervasive (yet): narrowly defined AITs are used where prediction algorithms can be implemented: advertisement/search engines, logistics, HRM, quality control, industries performing vision tasks → not adoption at scale as for e.g. integrated circuits
  - (ii) AITs improvement is a complex cycle: algorithms/techniques improve (DL case in point), but strong pull from hardware/computing power needs (today’s algorithms still do what perceptrons were designed for in the 60s)
  - (iii) AI induces innovation, but mostly it changes the logic of innovation: addressing ‘needle-in-a-haystack’ problems. Hard for patents to capture innovation in downstream industries.

Data: what do publications and patents proxy for?

- What do patents and publications tell us?
  - Publications: characterise how science have developed AI techniques (basic and applied). Can be used to look at technological emergence, the corporate involvement in R&D, identifying coherent bodies of literature (citation analysis), diffusion from AI producers and AI users in science.
  - Patents: capture the moving frontier of technological advance (invention), but also strategic moves of key actors (e.g. preemptive patenting)
- Current points of concern:
  - Partial picture of AI innovators and even more so for AI users. The broader impact of AI may be difficult to identify.
  - Keywords: well-designed lists require a deep understanding of the technology; more ubiquitous tech tend to ‘disappear’ and the related words might not be mentioned in patents’ abstracts/texts; vocabularies need continuous updating as the tech evolves;
  - Patent classification: yet in formation, AITs scattered across different codes (see WIPO report 2019)

Data: what do publications and patents proxy for?

- Can we move beyond patent and publication data?
  - Does the evidence between patent and publication data match? Are AI technologies discussed in the same way?
  - extensions/triangulation with additional data sources and indicators, **in particular text-as-data and Web-based indicators**
    - crawling of companies' descriptions & product information from websites (→ to identify covariates at a granular level and taxonomise actors)
    - social media on sentiment/adoption (→ to capture e.g. ethical issues and perception)
    - ongoing-projects data (e.g. GitHub) (→ to capture non-patented products/software and works in progress)
    - grant application information (e.g. Horizon) (→ to capture scientific exploration and trajectories)
    - Jobs-ads (→ to identify characteristics of labour demand)

Sectors: what aspect of sectors/firms' does patenting capture?

- What are we capturing with patenting sectors? Patents used in the industry or produced for other industries?
  - Pavitt (1984), Malerba and Orsenigo (1995):
    - Different sectors innovate in different ways (patents overcount some sectors)
    - Technological balance of payments: buyers and suppliers
      - Robots: both producers and adopters (Montobbio et al, 2020) -- but what share?
  - Technologies need to diffuse -- ≠ between invention and innovation
    - Import (e.g. IFR)
    - GVC; I/O
- Overall better understanding of who uses which technology
  - See discussion on keywords and GPT
- What do AITs transform in firms: production, organisation, products?
  - Implications on sectors?

Sectors: what aspect of sectors/firms' does patenting capture?

- What does this tell us about the impact on economic variables?
  - The impact of producing a new intermediate good
  - Mixed with the impact on the process of those firms that inn
    internally
  - Mixed with some market stealing effect
  - Mixed with spillovers (at regional level)

- Different timeframes for observing different impacts?
  - Innovation shorter term impact than adoption (Solow paradc
    - But, depending on how we define it, AI has been around for a while (
    - And yet far from optimised -- when will adopters be confident (Roge

Vodafone

Impact: what "impact" are we identifying, on what, at what level?

- The "big data" streetlight effect

Source: [The New Republic]

Impact: what “impact” are we identifying, on what, at what level?

- Level: Skills, Worker, Production process, Firm, Systemic (local labour market, region, country)
  - Beyond productivity: Entry? Survival? Non-AI innovation (enabling effect of AI)? Talent (employees) inflow and outflow?
- Irrespective of level, we need evidence on adoption/use
- Skewed distribution of patenting adopting: need to consider effects along the distribution (e.g. large companies vs start-ups?)
- Need for more granular modelling of the channels from AI to performance/employment/sustainability
  - Productivity: Innovation brings rents, if successful; increases capabilities, knowledge stock; first mover advantage; path dependency
  - Unpack the complementarities enabling AI to produce effects (other technologies? Organisation of the firm? Skills?)
  - Impact on environment positive or negative?

Positioning findings and policy implications in the context of AI debates

1. What are the many policy findings? Can we raise policy suggestions at this stage of the research?

2. What is relevant now in the AI debate? An how can JRC work contribute to this?

3. What may be the next policy priority?

What are the many policy findings?

- Policy suggestions from JRC studies
  - Supporting development of AI ecosystems
  - Continuous monitoring of AI landscape to inform strategic planning
  - Easing implementation lag (e.g. licensing AI technologies)
- We may need more research for substantive policy implications:
  - Findings may be too embryonic to underpin any policy conclusion (see points of concerns raised earlier on)
  - Definitions yet too coarse might mislead policy design and resources allocation
  - ext round of findings will have to identify stylised facts and directions of the impact of AI, aiming at forecasting economic effect as systematically as possible
  - The impact on productivity is relevant, though the effects on jobs and inequality are a priority, given the historical moment

What is relevant now in the AI (policy) debate? And how can JRC work contribute to this?

- **Technological level**
  - Addressing the debate on which fine-grained technology should be studied: DL (Klinger et al., 2019; Bianchini et al., 2020), ML (Goldfarb et al., 2020), Robotics, Software-hardware interaction (Prytkova and Vannuccini, 2020)

- **Economic level**
  - Distribution of gains/losses from AI adoption: who controls AI systems?
  - Ownership of AI systems scarce resources (<u>data</u>)
  - Distinction of the labour market impacts between Automation (Bessen et al., 2019) and AI (Webb, 2020)
  - Impact on inequality & exclusion, due to labour market transformations and biases built-in in the technology

What may be the next policy priority?

- *Anticipating* directions of AI development to tackle inequality
  - e.g. defending vulnerable workers (Gig AI work as in Tubaro et al., 2020)
    - → address current AI debate wrt economic impacts
- *Providing* publicly the input to AI systems (public data repository, Gaia-X?)
    - → address current AI debate wrt the ownership of data, AI systems and distribution of power to build the technology
- *Monitoring* market power asymmetries (and effective ways to regulating it)
    - → address current AI debate wrt to how different modes of control produce rents and distributional asymmetries
- *Guaranteeing* fairness of outcomes (especially for algorithmic policy-making)
    - → address current AI debate wrt the inclusiveness of AI impacts

Potential directions for future research

1. How can we better understand/forecast future AI trajectories?
2. How do ethical and social aspects arise surrounding AI research and applications?
3. Future of work
4. Who are AI firms, what are they doing, and what are the implications for market structure/industrial organisation?
5. Implications for the SDGs?
6. How can we better understand data value chains, data value and the implications on market structure?

Better understanding of future trajectories

AI trajectories can take many forms:

- Convergence of socio-technical features developed independently (software and hardware)
- Diffusion of AI technologies:
  - ML techniques diffuse between type of cognitive tasks (neural network is being used for visual and now also for natural language processing tasks)
  - AI technologies is increasingly used in different sectors of applications (e.g. energy efficiency, healthcare / diagnostics, transport, etc.)
  - Are there particular actors driving specific change (research groups, corporate actors, countries)
  - Do countries or actors specialise in specific AI technologies, or do they develop capabilities across AIT and domains of applications?

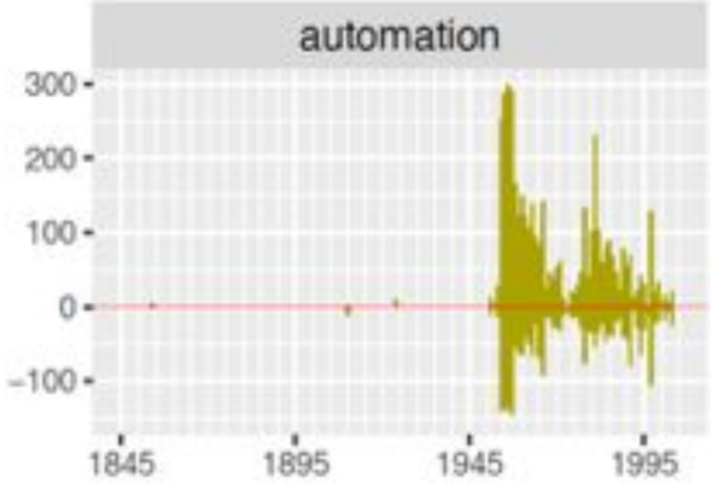
Exploring ethical and social issues

Social and ethical concerns:

- Ethical concerns can arise from the introduction of AI systems (e.g. self-driving cars, autonomous weapons, care)
- Individuals may have reservations on the introduction of particular technologies:
  - Do particular events shape the social ethical concerns (Cambridge Analytica, Uber/Tesla crash)
- Country culture may have different attitudes to AI

→ Look at social medias, parliamentary debates, newspapers using sentiment analysis.

Sentimentality around the word automation within Scientific American



Source: own research - Deep Transitions project

Future of work

- Need to consolidate evidence from different waves of automation/estimations of future trends (→ meta analysis)
- Labour markets at different levels of aggregation: use trajectories to understand future changes in AI technologies in relation to
  - **Skills requirements** – vacancies in relation to technologies (adoption) (Bakhshi et al. 2017; Lima and Bakhshi 2018; Mezzanzanica and Mercorio 2018); patents in relation to tasks (Webb, 2020)
  - Predictable **changes in skills** and adaptation (Vona and Consoli 2015)
  - **Workplace** and the organisation of production work
  - Initial structure of **industries** and skills, and likelihood of replacing existing industries (Ciarli et al 2018) – industries exposure to AI technologies
  - Changes in the **international division of labour** (Timmer et al. 2019)

Better understanding of who are AI firms/industries

Snapshot analysis:

- A profile of the AI-producing/adopting firm: average size? De novo entrant or spinoff? Unique constraints faced (in terms of product scale-up, demand structure, cost structure, strength of competition)
- Definition of the AI industry boundaries: is there an AI industry at all, or in the making?
- A taxonomy of AI firms; distribution across size, economic activities, networks of interdependencies (VC)

Dynamic analysis:

- AI Industry Life Cycle (ILC): tracking entry, exit, survival, M&A; does it replicate patterns seen in the software industry?

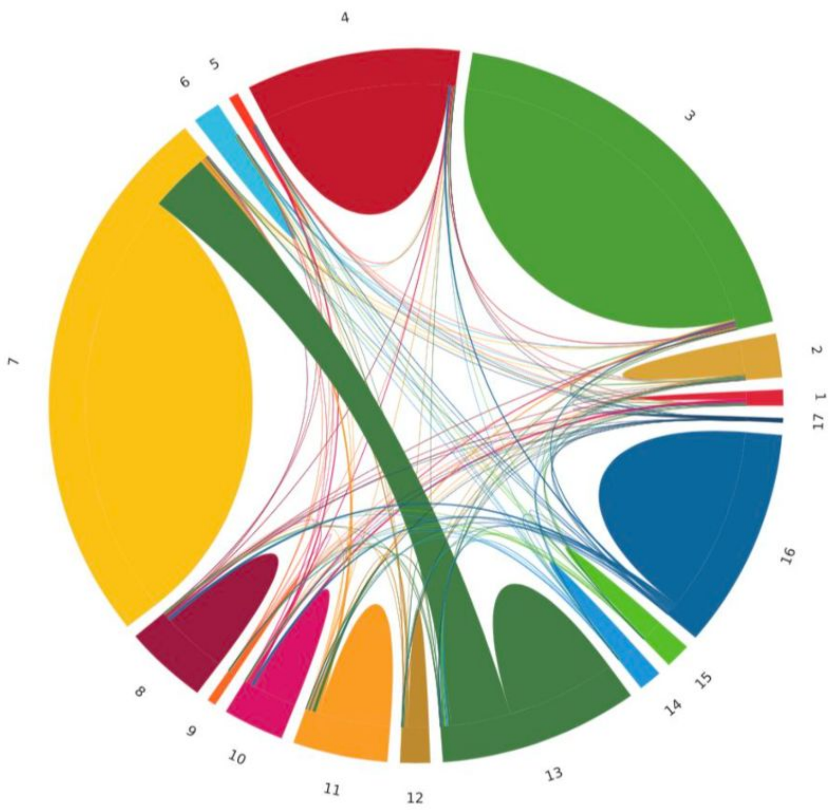
Possible way forward:

- Web-scraping of companies' descriptions to create taxonomies of AI firms/industries
  - -> Map of AI companies/industries, distinguishing production and use

Implications for the SDGs?

Synergies and trade-offs between AI research and the SDGs

- Map SDGs across science communities
- Map AI across science communities
- Study the synergies between the two: which communities work on STI contributing to the SDGs and on AI?
- Search for literature that discuss negative impacts of AI (not immediate) and study connections within communities



Source: Dimensions

Communities within the WoS science landscape

(publication based classification, 4000 clusters, areas)

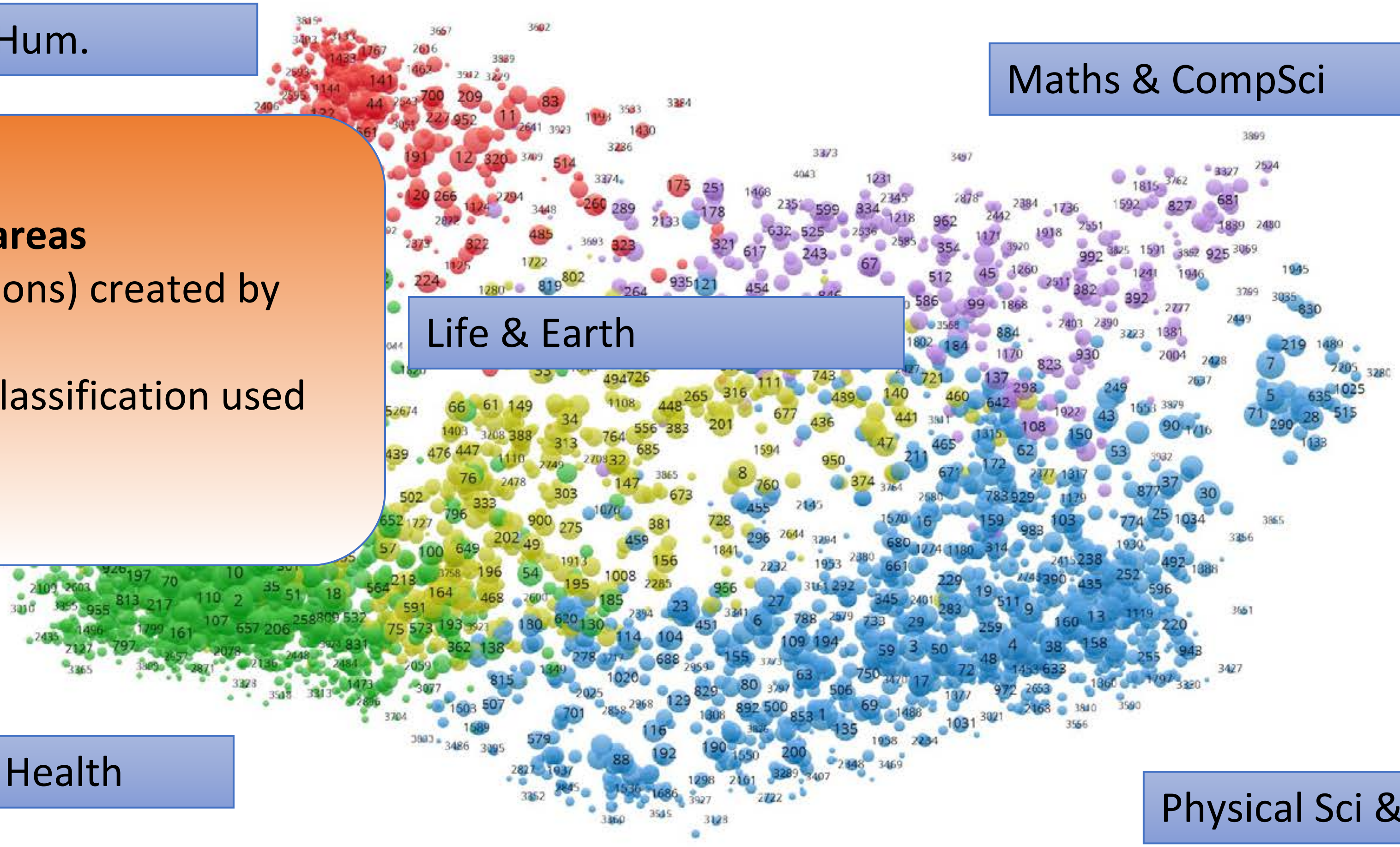
Social Sci & Hum.

Maths & CompSci

Communities or research areas

- Clusters (bags of publications) created by direct citation relations
- No journal information/ classification used

Life & Earth



Biomedical & Health

Physical Sci & Engin.

VOSviewer

Source: CWTS, University of Leiden

Better understanding of data value chains

- AI is changing the way economic value is created and should be accounted for in the National Accounts;
- Data is the main raw ingredient, within a complex data value chain
- The economic nature of data leads to massive concentration of value in a few large platforms;
- It leads to labour markets characterised by high degree of monopsony;
- It raises challenges in terms of competition policy, intellectual property rights, privacy, surveillance that add to the ethical issues mentioned above
- Any reflection on AI trajectories should include analysis of the creation and governance of data value.

Some conclusions and take home messages

- Good moment to step back and reflect on what AI is, through technologies/sector studies?
  - Including improved ways of capturing AI producers/adopters
- AI’s development relies on related technologies, should we study it in isolation from hardware development and data value chains?
- Should we reflect on barriers to diffusion to AI, both social and ethical, and whether these differ between geographies?
- Room open to design large research projects aimed at combining different disciplines & methodologies on AI (and their interaction)
- Large, interdisciplinary research projects should underpin policy priorities identified above

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