Discussant Comments for Measuring AI

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Commendable Efforts by All Agencies at Measuring AI

Emin Dinlersoz, Census Bureau
Measuring AI Use by U.S. Businesses

Identified changes in existing surveys and use of new surveys to track AI use and diffusion

Michael Wolf, Bureau of Labor Statistics
Identifying Structural Change in BLS Data

Identified potential for (and potential limits to) measuring impact of AI/Technology in Occupational data for structural changes over time

Tina Highfill, Bureau of Economic Analysis Concepts and Challenges of Measuring Production of Artificial Intelligence in the U.S. Economy

Identified fundamental challenges in definitions and measures of AI production, and need for triangulation across government and private sector sources

Overarching Feedback

Need for clear and consistent definitions for AI

- AI is a broad general-purpose technology and the distinct sub-categories within it are very different in terms of creation, use, diffusion, and impact on workforce

Limits to what changes in existing surveys may be able accomplish in measuring AI

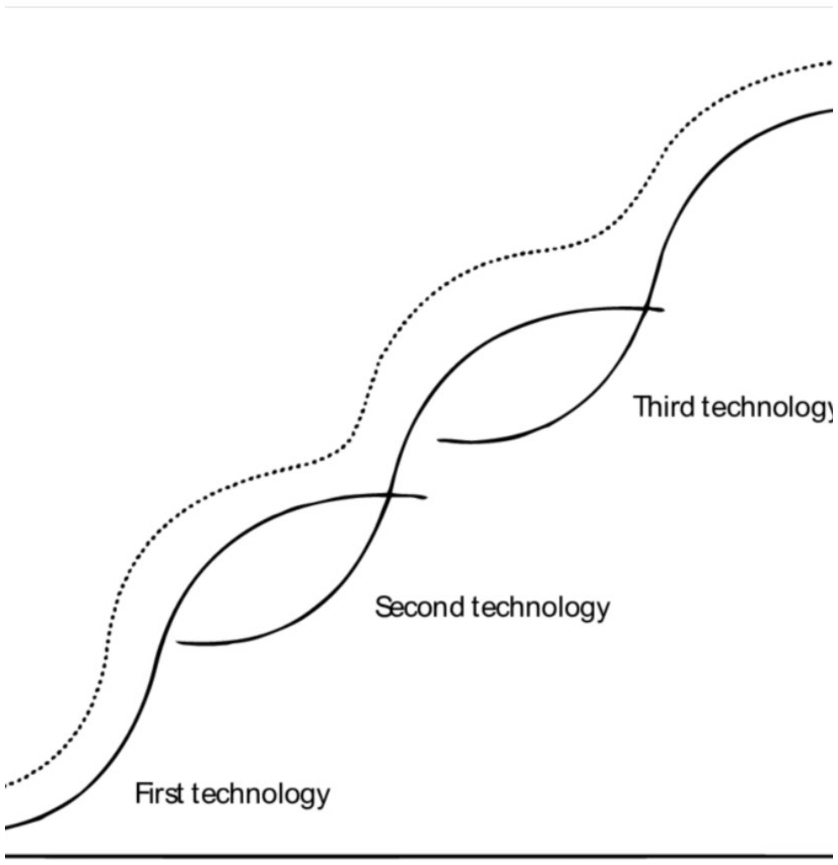
- Data instruments need to discern how AI as a technology is changing industry and occupation structure (for creation and use)

Potential for a cross-agency effort in assimilating relevant data across multiple sources

- Above issues indicate the need for integration for synergies between singular initiatives

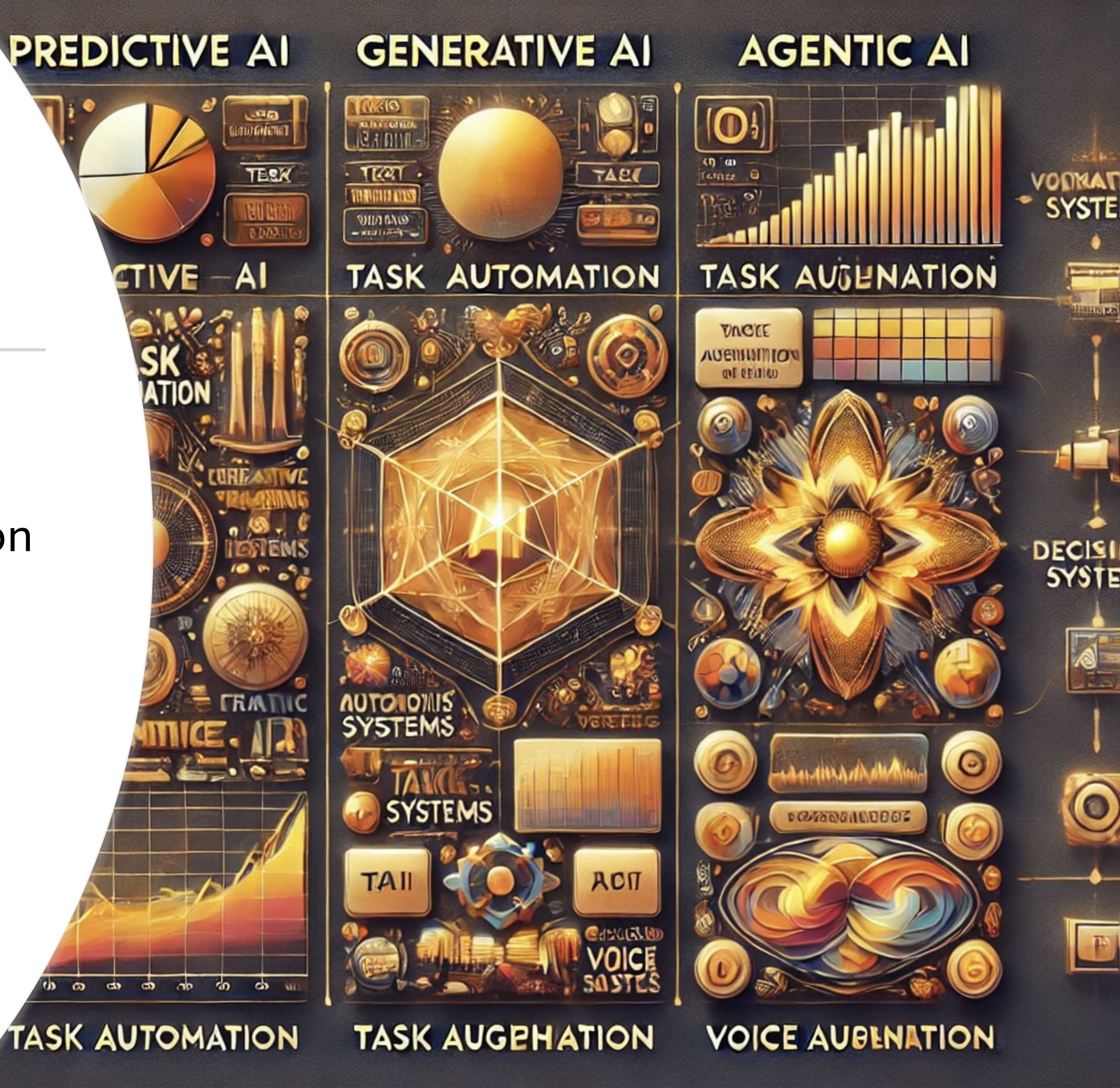
Grounding Thoughts on General purpose technologies (such as AI)

- Transform industries and occupations in a discontinuous manner
  - Technology-specific (vintage) human capital (Chari & Hopenhayn, 1991)
  - Changes in task composition and complementarities between humans and technology (for an application for AI, see Choudhury, Starr & Agarwal, 2020)
- Embody sub-categories of technological systems that diffuse at different rates
  - Direction of technological change depends on nexus of new scientific-principles-use needs (Rosenberg, 1963; Arthur, 2009)
  - Technological systems embody use of existing and novel base principles (for an application for AI in bionic prosthetics, see Kim, Agarwal & Goldfarb, 2024)



Need to create sub-categories for AI

- Building on Tina Highfill’s presentation, it would be helpful if the agencies would build and rely on AI related taxonomies in data gathering efforts
  - Predictive vs. Generative vs. Agentic AI
  - Use in visualization, text, voice, or numerical data
  - Task automation (replaces humans) vs task augmentation (complements humans)



(In)ability of existing surveys to capture changing industry and occupation structure

Based on current efforts:

Trends in from Michael Wolf's presentation showcase small and slow structural changes in occupations

Summary findings in Emin Dinlersoz's presentation note 87% of AI using businesses replace worker tasks, yet only 5% experience a change in employment (with increases more common than decreases)

Given how GPTs transform industries and occupations,

Both sets of statistics likely mask underlying changes in tasks within occupations, and complementarities between humans and technologies

In both production and use, data creation efforts need to differentiate between "volume" and "newness" within and across technological systems

Specific to BLS, occupational data similarly needs to track "new" occupations as well as changes in existing occupations

Specific to Census, are the technology modules creating artificial distinctions between digital, automaton, AI use in innovation, given blurred boundaries across them?

Examples of concerns of existing instruments and data

- Move from establishment level to firm level (*e.g.*, moving MOPS questions to ABS) may mask within-firm variation and spillovers across establishments
- Caution on taking firms at their word on what they plan/are doing regarding employment, use of AI, etc.
  - Shadow IT in firms where workers are using cloud/generative AI that senior managers may not know or is being tracked by financial controllers
- Caution on use of data
  - Despite BLS advising against time series analysis, people do so anyway
  - Lack of attention to changes in tasks within occupations can overestimate automation effects
    - See study by Arntz, Gregory & Zierahn, 2017 using German data that refutes findings in Frey & Osborne, 2017 using O-Net data by BLS)

Potential for cross-agency collaboration for creation/assimilation of data across sources

- A joint task-force that carefully addresses the conceptual and measurement issues identified in the various presentations (and discussions)
- Leverage of
    - AI itself in creating new data sources
    - external sources beyond what has been identified
- Examples:
    - For creation/production of AI: Tracking innovations and novel scientific principles through patent-publication pairs, given that most AI firms are also publishing papers, often in conjunction with academic researchers (see https://arxiv.org/
    - For jobs/occupational data in AI: https://www.aimaps.ai/ [Collaboration between academic researchers and firms which uses AI to map AI jobs using job postings across the country]

aimaps.ai

UMD-LinkUp AIMaps

In collaboration with Outrigger Group

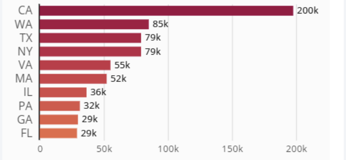
Tracking where AI jobs are being created

UNIVERSITY OF MARYLAND ROBERT H. SMITH SCHOOL OF BUSINESS

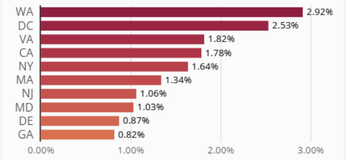
LinkUp

From West to the Rest (White Paper) Latest Month: November 2024 New AI Jobs, US Total: 16,591

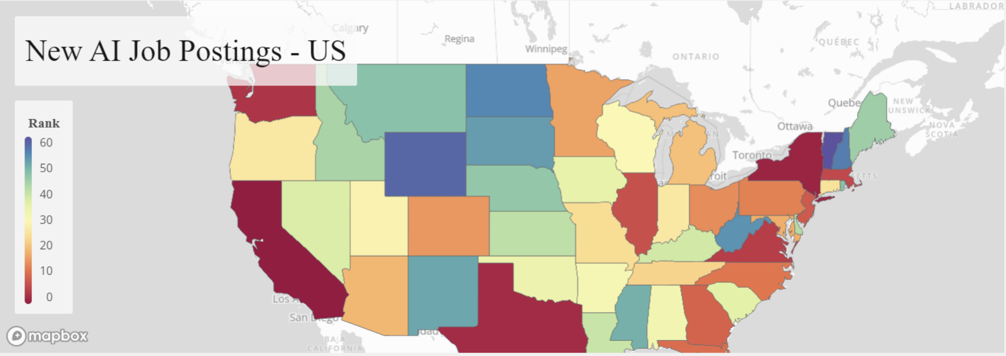
AI Jobs Growth
Since January 2018
Top 10 States (or Counties)



AI Jobs Intensity
Rolling 12 months
Top 10 States (or Counties)

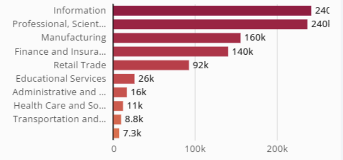


Economic Sector: Select values
Tech 10: Select values
Type of AI Data: Select value
Month: Select value



State MSA County Zip sigma

AI Jobs Growth
Since January 2018
Top 10 Sectors



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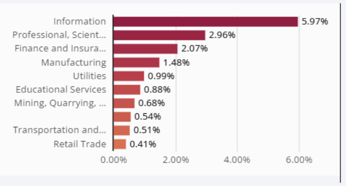
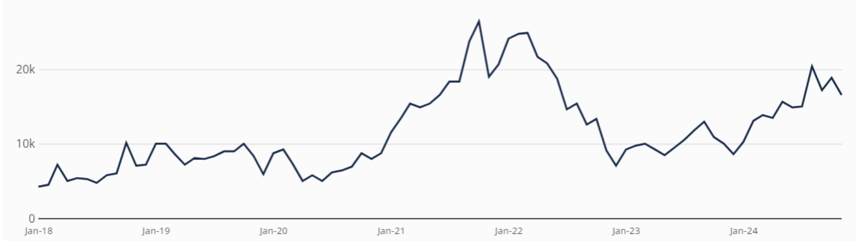
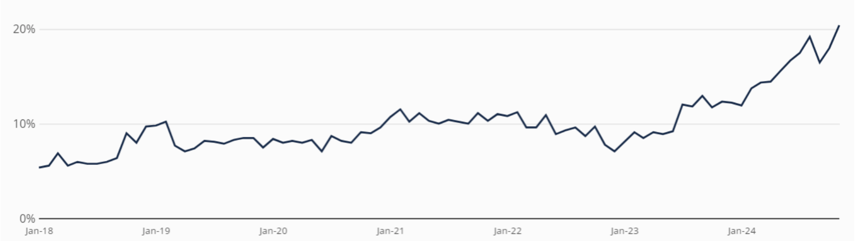


New AI Jobs – US Total (or State), Monthly Trend

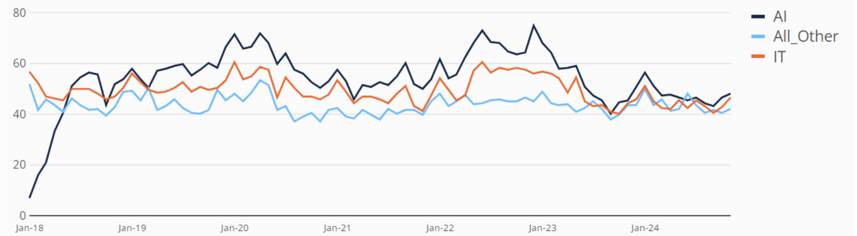


AI-to-IT Jobs Intensity – US Total (or State)



Active AI Jobs – US Total (or State), Monthly Trend

Duration of Jobs Postings – US Total (or State)



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