AI and jobs: mapping forward-looking AI exposure metrics into occupational networks

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Background

Artificial Intelligence (AI) will radically transform the job market, influencing the potential elimination, complementary, substitution, and addition of different job activities and their associated skills. The debate is characterized by strong apprehension and considerable uncertainty regarding whether this upheaval will pose more risks or opportunities [1].

To quantitatively investigate the AI impact on the world of work, the first challenge to address is how to measure and quantify AI's impact on individual occupations. Previous research has used several methods to estimate the overlap between AI capabilities and the tasks that workers perform in various occupations. These methods include mapping patent descriptions to worker task descriptions [2], linking AI capabilities to occupational abilities [3], or aligning AI task benchmark evaluations with worker tasks through cognitive abilities [4], among others.

A major issue with these approaches is that they mostly depend on expert evaluations of AI capabilities in relation to occupational tasks. This reliance makes the process of gathering these evaluations less transparent, objective, and reproducible [5]. Moreover, also patent-based approaches, that use a more quantitative methodology compared to relying on subjective judgments from experts, have the significant disadvantage that patents may not cover most AI applications (AI algorithms themselves, being mathematical methods, are often not patentable).

A common issue with all these AI exposure indices, complicating the assessment of AI's real effects on labor demand, is that they inherently measure the 'potential' impact of AI on occupations rather than its actual impact [6]. For example, expert evaluations often emphasize AI's potential based on current advancements, while patents detail innovative intellectual efforts related to AI without addressing how these technologies can be practically deployed in the workplace.

Methodology

In this paper, we develop a novel occupational AI exposure index to measure the near-future actual exposure of occupations to AI, rather than their potential exposure. Using

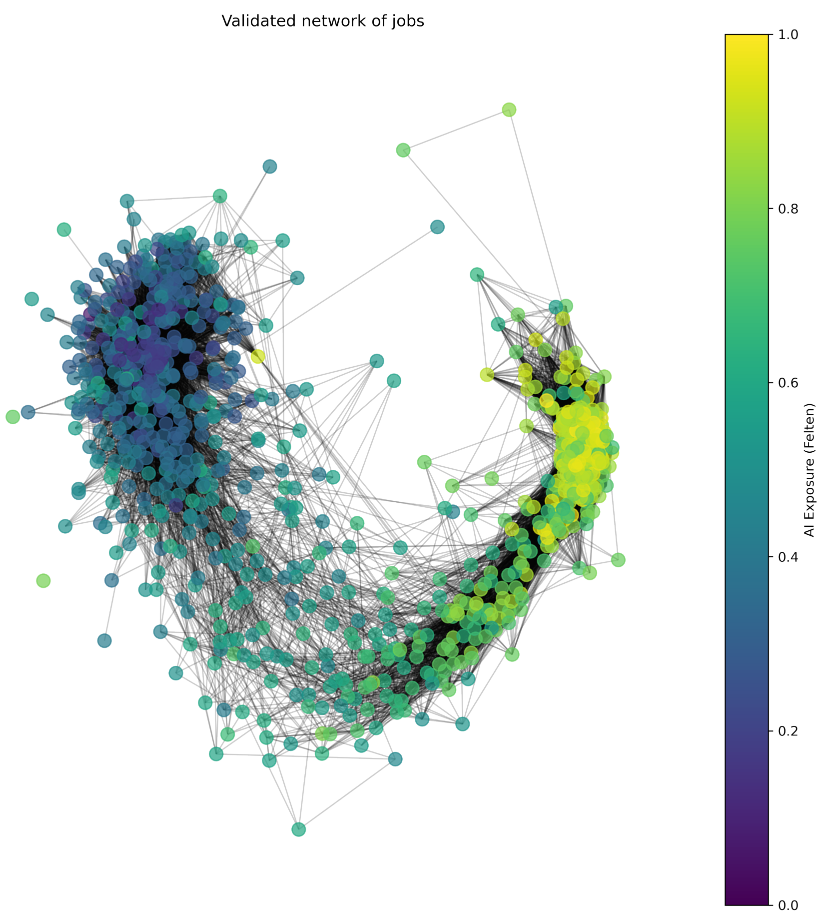

Fig. 1. Statistically validated network of jobs. The validation is made with the the Bipartite Configuration Model (BiCM) algorithm, starting from the bipartite network of jobs and abilities required. The colors represent the intensity of AI exposure computed in [3]. The network highlights that similar jobs are also similarly potentially exposed, leading to a potential ”AI trap” for workers.

data on AI applications from venture capital-funded startups, our index assigns exposure scores to occupations by leveraging a state-of-the-art open-weight large language model (LLM). With this model, we connect descriptions of AI applications developed by startups to job descriptions from the Bureau of Labor Statistics database. Unlike existing indices, our measure effectively maps concrete future market directions, as the startups considered are all backed by venture capital investments.

We compare the occupational AI exposure scores generated by our new index with those from the widely-used AI Occupational Exposure (AIOE) index introduced by Felten et al. [3]. To do this, we adopt a network perspective.

Building on recent contributions to the product space, particularly the statistically validated approach called the Product Progression Network [7], we construct a network of jobs. In this network, two jobs are connected if they require a similar set of abilities (these abilities are sourced from the US occupational network dataset). This statistically validated approach filters each link using a suitable null model (the Bipartite Configuration Model [8]), ensuring that only statistically significant links are considered. We then color the nodes (jobs) in the network according to their AI exposure, using both the AIOE index and our new index.

Results

When using the AIOE index, we observe that jobs with similar exposure levels cluster together, indicating a ”potential AI trap”. In this scenario, workers attempting to move from an AI-exposed job to a job requiring similar skills would likely end up in another job with similar potential exposure.

Conversely, when applying our new metric, we uncover a different scenario. Our index, which measures actual exposure rather than potential exposure, reveals that many occupations considered potentially exposed to AI are not actually targeted by AI startup applications. This results in the disappearance of the two big clusters evident with the AIOE index, and the emergence of more, smaller clusters. Consequently, our finding suggests that an actual AI trap is still far.

Moreover, further inspection of the different outcomes from the two exposure metrics shows that, for the same level of potential exposure, occupations requiring higher levels of education, experience, and skills are less actually exposed to near-future AI applications. This finding contradicts mainstream literature, which suggests greater exposure for high-skilled and high-education jobs. As our results are grounded in concrete investments in AI applications rather than subjective expert judgments, they pave the way for new economic models and implications regarding the AI impact on the job market.

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