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# AI's effect on labour: What does economic literature say?

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**Abstract**

*This literature survey examines the economic impacts of artificial intelligence (AI) on labor markets, focus-ing on job displacement, wage inequality, and the creation of new employment opportunities. By employing a systematic methodology, including Latent Dirichlet Allocation (LDA) and citation graph analysis, the study identifies key themes and influential papers within the field. The findings highlight a nuanced consensus: while AI and automation pose significant risks of job displacement and polarization, they also offer potential for job creation and complementarity, particularly in tasks requiring human intuition and empathy. The research underscores the importance of task characteristics, skill requirements, and contextual factors in understanding AI's labor market effects. Future research should address the evolving nature of AI technologies, refine quantitative methodologies, and consider broader policy responses to ensure inclusive economic growth.*

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## I. Background and motivation

Over and beyond the prevalence of recent discussion about potential existential risks of AI technology, from an economist's perspective, the broad set of technological capabilities that are collectively referenced by the term "Artificial Intelligence" (further on: AI) represents a new kind of force in the economic life of society, that bears huge promises, as well as hold significant risks for the prosperity and wellbeing of society at large. Since there is a significant amount of work dedicated already to the topic of "economic effects of AI", especially it's aspects pertaining to the labour markets, a synthesis and overview of the broader literature can be useful to provide some orientation about the current state of discussion, as well as to shed light on areas of further potential research, thus, with a broad scope analysis we endeavor to provide such an overview.

## II. Methodology

This study aimed to conduct a thorough analysis of the existing literature on the impact of artificial intelligence (AI) on the labor market. Given the extensive research activity in this area, our methodological framework was designed to systematically evaluate a broad array of academic publications to gain comprehensive insights into the topic.

### 2.1 Literature Search and Collection

Our literature search began with a targeted strategy using Google Scholar to ensure access to a wide range of academic journals and conference proceedings. We complemented this online search with a manual examination of the citation networks from key papers, which allowed us to capture additional relevant studies that might not have been indexed or immediately apparent in digital search results.

### 2.2 Screening and Selection

The search strategy resulted in an initial pool of over 2000 publications. To determine relevance, we applied a two-stage screening process. First, an automated filtering system was used to perform an initial screening based on keywords and abstract content. This reduced the pool to approximately 725 potentially relevant articles. Second, we engaged in a manual curation step narrowing down the number of immediately relevant papers for the topic of AI in the labor market. This process led to a curated set of 250 articles for in-depth analysis.

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2.3 Thematic Analysis
To uncover the thematic structure within the curated set, we utilized Latent Dirichlet Allocation (LDA) [5], a technique utilized in Natural Language Processing which allowed us to identify meaningful topics, assess their contribution to the given documents, thus to track the prevalence of these topics over time, which informed us about the focus areas within the field and their evolution.

2.4 Citation Analysis
With the aim of identifying the most influential studies, we conducted a citation graph analysis which helped us isolate a shortlist of 13 papers that were not only frequently cited but also held significant sway in shaping the discourse in the field. These papers received a detailed examination, wherein we scrutinized their hypotheses, methodologies, datasets, and findings for getting a more in depth view on the consensus in the field.

2.5 Quantitative and Content Analysis
Each paper on the shortlist underwent a rigorous quantitative and content analysis. We examined the papers' predictions and conclusions about the impact of AI on the labor market. We also identified a strand of research specifically focusing on the quantitative estimation of AI's effects on different occupations based on their associ-ated skill sets.

2.6 Identification of Research limitations
Throughout our analysis, we remained cognizant of the limitations inherent in the existing body of work. We documented these limitations and proposed directions for future research to address these gaps and to advance the understanding of AI's role in the labor market.

In the following sections of this paper, we will provide detailed descriptions of the methods used at each stage of our analysis.

## III. General trends

As a first level of analysis, we looked at the broadest set of 725 "generally relevant" articles identified by filtering the results (>2000 entries) of automated Google Scholar searches carried out for such expressions as "effects of Artificial Intelligence on the labour market".

We analyzed the temporal distribution of the broad set of 725 to get a grasp on the general trend of interest in the field.

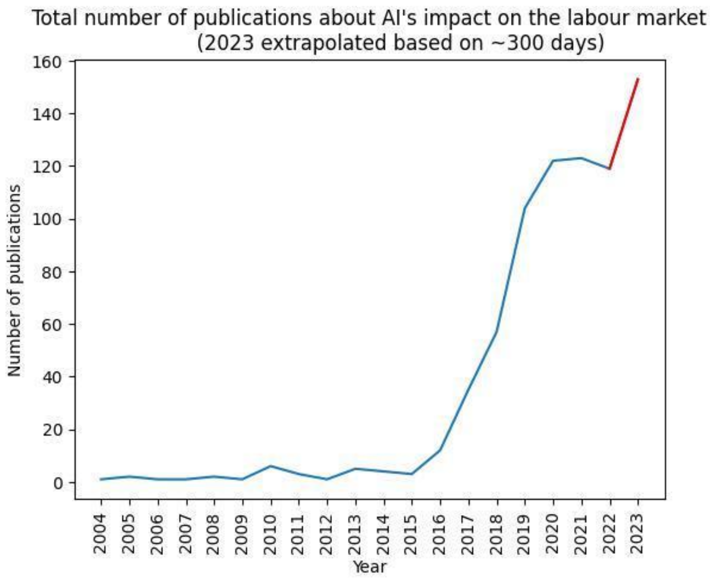


Figure 1: Broadly relevant articles

As we can see, there is a strong increasing trend visible in the number publications, with an inflection point at 2015. (For better illustration, we extrapolated - based on the proportion of days remaining in the year at the time of writing - the number of publications in 2023.)

This begs the question, why did this trend appear just in this time period, what are the prime events moving it?

### 3.1 Why the trend?

Though the long term progress of some classical areas in AI research, like automated speech recognition or image classification showed steady progress through the decades, the gains in performance (or decrease in error rate, which can be considered the same) were achieved at a cost of investing considerable amounts of engineering manpower. As for example the case of "AlexNet" [28], the first really successful Deep Learning model to beat "conventional" (non-neural network based statistical models mainly relying on manual, expert driven feature engi-neering) illustrates, a paradigm shift appeared in the for of the new "end-to-end learning" paradigm. This paradigm enabled the application of single models without extensive manual feature design on large scale datasets (eg. Im-ageNet [10] in case of image classification), letting the learning procedure "figure out" the necessary features, essentially trading human expert engineering hours for computation.

The increased "compute" utilization in what Sevilla et al. [36] call the "Deep Learning era" is quite visible in the chart below.

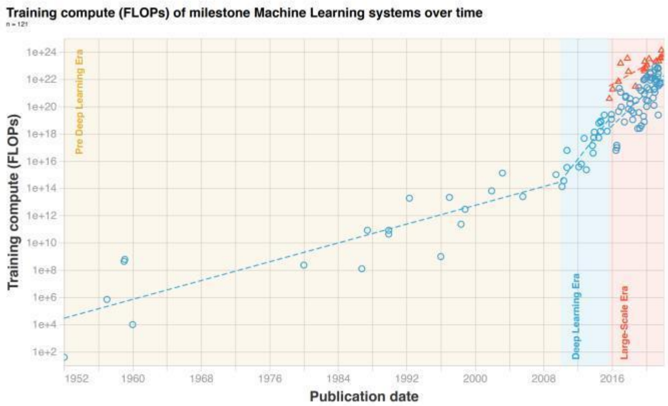


Figure 1: Trends in $n = 121$ milestone ML models between 1952 and 2022. We distinguish three eras. Notice the change of slope circa 2010, matching the advent of Deep Learning; and the emergence of a new large-scale trend in late 2015.

Figure 2: Compute usage of SOTA AI models in time [36]

This - combined with the wide availability of computation resources and larger datasets lead to a breakthrough in performance on common AI benchmarks.

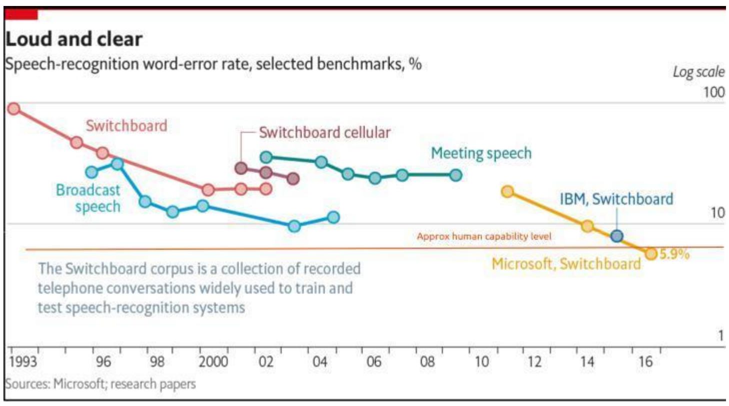


Figure 3: Automated speech recognition history[21] (modified to show approximate human level performance)

As one of the "founding fathers" of Deep Learning, the Turing Award winning computer scientist Geoffrey Hinton pointed out in his public lecture [22]: The theoretical advancements of the late 90s did not bear fruit until enough data and computing power became available (to a suitable model structure, that is Deep Learning, since other previous modeling architectures did not directly benefit from such a boost in data / computing power)

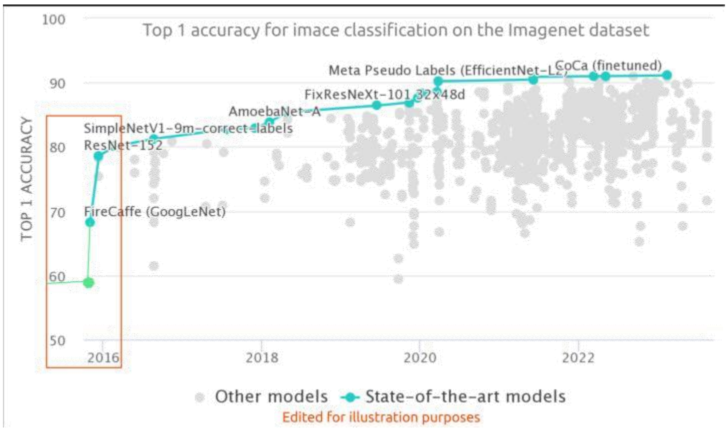

Figure 4: Image classification on Image Net

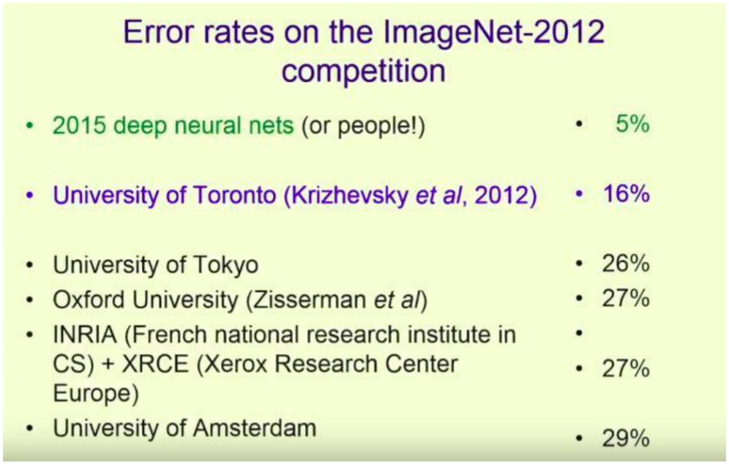

Figure 5: Geoffrey Hinton's lecture on the history of Deep Learning [22]

As the notes of Hinton illustrate, from a decades long held substantially lower performance ( 26% error rate) in image classification, in 2012 the first well trained Deep Learning model cut the error in nearly half, then in the span of approximately 3 years, on this task human level performance was achieved.

As the knowledge about this breakthrough - and the rapid increase in performance - became more common-place (as evidenced by e.g. the Google Search Trends for the term "Deep Learning") this coincides with the increase in interest by the economic sciences in the effect of AI.

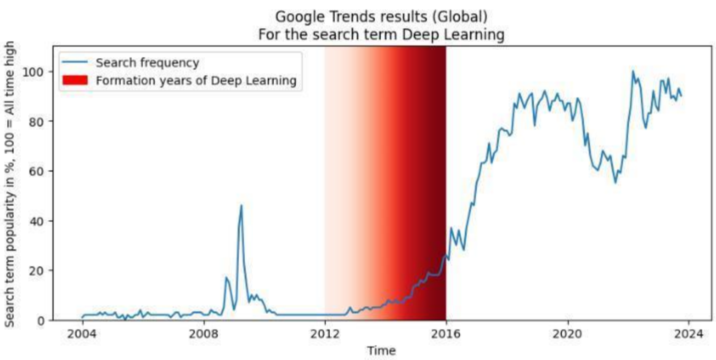

Figure 6: Google Trends Search: Deep Learning [19]

Looking closer to the number of AI related economic publications in time, there is also a small "saturation" effect visible in 2020-21, until the concept of generative AI burst into consciousness with the release of ChatGPT, and gave a new push to the discussion.

It is worth noting, that technology again rapidly and qualitatively changed with the advent of "generative AI" (which itself is somewhat of a misnomer, covering the combined advancements in Deep Learning based Large Language Models - what Stanford researchers, Bommasani et al. [6] in their paper "On the Opportunities and Risks of Foundation Models" call "foundational models", with (mainly) diffusion based image generation models [23], and their potential combination under the umbrella of "multi-modality").

The sudden gain in capabilities for "foundational models" re-sparked the interest of economic research in the effects of AI.

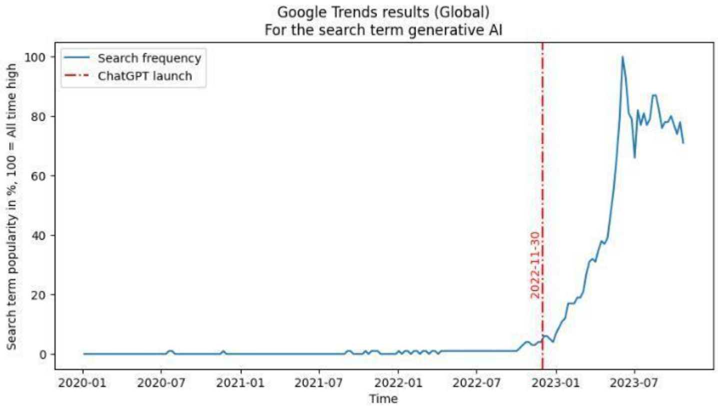


Figure 7: Google Trends Search: generative AI [20]

With this interest in mind, it is essential to point out, that the change in capabilities in this case was not just "quantitative", the set of capabilities for the foundational models expanded rapidly, thus, their practical applications changed in at least three meaningful ways:

- The accuracy of ML models on some tasks increased
- The scope of their applicability exploded
- The technological threshold for their application dropped

Based on this, we can conclude, that the discussion about AI currently must aim at a more broad set of capabilities. Essentially: talking about AI's impact before November 2022 is different than after it.

## IV. Detailed analysis: The "Curated list"

For detailed analysis, a manually curated list of 250 articles were selected, that focused more on the direct labor market influences, and at least touched upon the pertinent question of technology-induced unemployment. The main selection criterion for this manual curation was that the stated focus of the article had to have direct relevance for the theme of AI's effect on the labor market and had to at least partially concern the question of technology-induced unemployment.

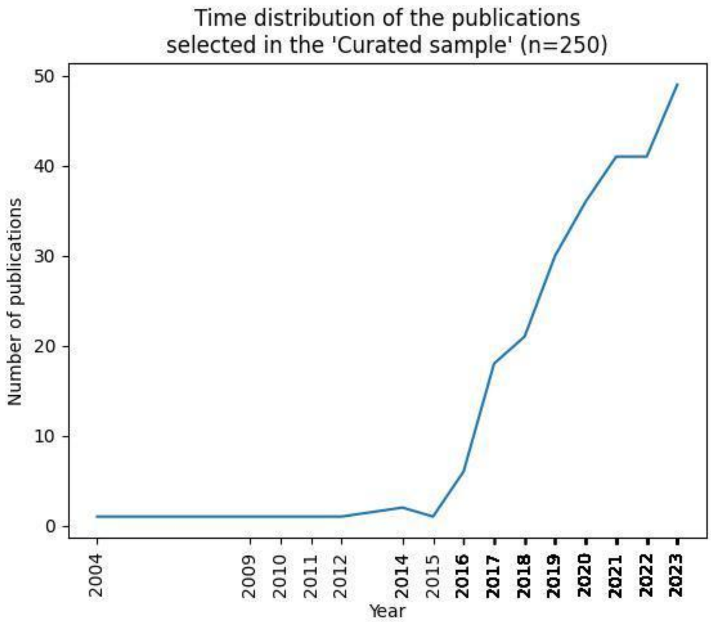


Figure 8: Time distribution of the curated set

During the curation process, we took care to ensure that the temporal distribution of articles reflects that of the broader set, thus ensuring that the general dynamics of topics remain discernable.

## 4.1 General topics present in the "Curated set"

For a more quantitatively driven - thus hopefully more objective - analysis of the topics prevalent in the "Curated set," we decided to utilize Natural Language Processing-based techniques, especially Latent Dirichlet allocation [5], which is a technique for document topic analysis. At its core, the approach assumes that the documents present in a corpus of text (in our case the 250 hand-selected articles) came to existence as a probabilistic mixture of latent topics as a generative distribution, thus every document can be interpreted as a kind of mixture of these not directly observed thematic causes.

For the training procedure of the model, we utilized the OpenSource "Gensim" library [34], and after experimentation, we settled to utilize 5 topics for modeling. With this technique, we created a topic model of this subliterature, and we identified the following topics (by interpreting the low-level LDA results). The topic labels themselves were created by the interpretation of the keyphrase probabilities of the LDA model and confirmed by manual inspection of the broader set of 750 articles.

1. Topic 1: "Job dynamics and wage variations" ("gigification", wage change and modes of changes in the work)
2. Topic 2: "Technological innovation and labor productivity (the effects on productivity gain)
3. Topic 3: "Occupational skills and digital transformation" (the "unemployment question")
4. Topic 4: "Human interaction with emerging technologies" (including AI hiring, bias, the effects of algorith-mic management)
5. Topic 5: "Robotics and labor share in industries" (Physical robotization of manufacturing as a separate topic)

### 4.1.1 Some takeaways

The presence of this topic distribution as it stands can hit to some interesting associations and structure inside the literature.

1. Job Dynamics and Wage Variations: The presence of this more distinguishable topic suggests that the litera-ture is not just concerned with the employment question in the frames of "traditional" employment relations, but the differentiation between gig work and traditional employment is getting emphasized, hinting at po-tential variance in job stability and wage trajectories. This is seems to be a noteworthy concern for the literature, raising questions about how these trends may diverge from established labor market behaviors and

whether these differences could lead to alternative employment models becoming more normative in certain sectors.

2. Technological Innovation and Labor Productivity: The presence of technology as a driver of productivity is well-documented, but its intersection with AI introduces new considerations. There appears to be a possibility that AI and automation are altering the established dynamics between capital and labor, with open questions on whether these changes lead to complementarities or new forms of substitution.

3. Occupational Skills and Digital Transformation: The observed association between the demand for new skills and unemployment rates seems to be the main area of concern, which suggests a shifting landscape. Though the causal pathways are not completely clear, this seems to be one of the main areas of interest for research, so quantifying and analyzing the changes in the skill sets demanded by employers driven by AI adoption remains one of the main areas of concern.

4. Human Interaction with Emerging Technologies: The inclusion of AI in HR processes points to an emergent field of inquiry within labor economics, where technology is not just a backdrop but a participant. The considerations around bias and algorithmic decision-making indicate a nascent concern with profound implications, which invite further examination into how these technologies reshape labor market practices.

5. Robotics and Labor Share in Industries: Robotics' specific mention reflects its visible impact on manufacturing, but also its slight distinctiveness in the area of study, since arguably it impacts a very specific subset of job areas, mainly in manufacturing and the agriculture sector, so its effects, though maybe more easily measurable, are focused on a very specific area.

In general, we can argue (giving additional legitimacy to the choice of LDA as a model specifically) that there is a deeply interwoven set of relations between the different areas. Hence, when analyzing the effects of AI on the labor economy, the picture is more like overlaying effects on top of each other, rather than some nicely separable set of distinct mechanisms.

#### 4.1.2 Topics in time

To further examine the dynamics of the topic distribution over time, getting a sense of its stability, as well as ratio of relative frequency, we analyzed the topics' prevalence by averaging their presence through the years with respect to the articles in the "curated set". For this, we utilized the property of LDA models to represent documents as a weighted mixture of topics. Thus, we could easily take the mean of the topic presences for a subset of articles published in a given year.

The resulting chart can lead us to the conclusion that the topic distribution over time is generally stable. The interest in AI's effect on hiring and the fairness question increases around 2016, presumably with the more widespread adoption of AI/ML solutions in HR processes, thus increased scrutiny from the scientific community. Beyond this, the skills and employment question is pretty important.

### 4.2 What is the consensus about the effects on unemployment specifically?

#### 4.2.1 Quantitative Analysis

Our aim was to establish an estimate of the consensus in the selected literature (250 papers) about the beneficial or harmful effects of AI on employment. For this, we endeavored to assess each paper's overall sentiment concern-ing AI's impact on unemployment by counting the number of mentions of "positive" or "negative" phenomena related to employment within the text. The count was strictly numerical, irrespective of the length or depth of the discussion surrounding each mention.

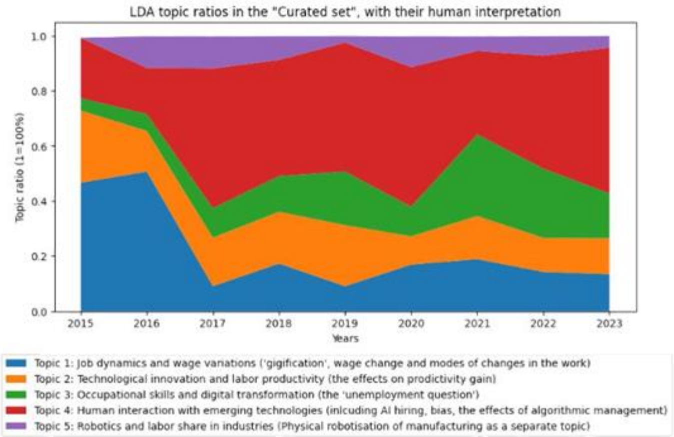


Figure 9: LDA topics, temporal distribution

#### 4.2.2 Classification Criteria

The classification of papers was contingent on a direct comparison between the counts of positive and negative mentions. We operationalized our assessment using the following criteria:

1. Class A - Positive Outlook: A paper was categorized as having a positive outlook if the count of positive mentions outnumbered the negative mentions.

2. Class B - Ambiguous Outlook: A paper was deemed to have an ambiguous outlook if the difference between positive and negative mentions was within a 2.5% margin, reflecting an almost equal consideration of both types of phenomena.

3. Class C - Negative Outlook: Conversely, a paper was classified as having a negative outlook if negative mentions surpassed positive mentions in number.

#### 4.2.3 Positive and Negative Phenomena

Positive phenomena were defined as any mention of trends or effects where AI resulted in:

- The creation of new job types.
- The simplification of job tasks, potentially requiring less skill.
- A shift towards more fulfilling tasks within existing jobs. Negative phenomena included mentions where AI was associated with:
- A decreased need for human workers, potentially resulting in layoffs.
- The competitive displacement of human labor across various sectors.

#### 4.2.4 Threshold for Classification

To classify the outlook of each paper, a threshold was set. If a paper had more than a 2.5% greater count in either direction (positive or negative mentions), it was classified accordingly. For instance, if positive phenomena were mentioned with a frequency greater than 2.5% compared to negative mentions, the paper was categorized under Class A.

#### 4.2.5 Results

If we utilize the classification framework, and then count the articles accordingly, the ratio of positively and negatively dominated articles overall is as follows:

If we would like to paint a more nuanced picture and calculate the ratio of individual positive or negative mentions, the consensus is maybe less bleak, but nonetheless remains negatively biased.

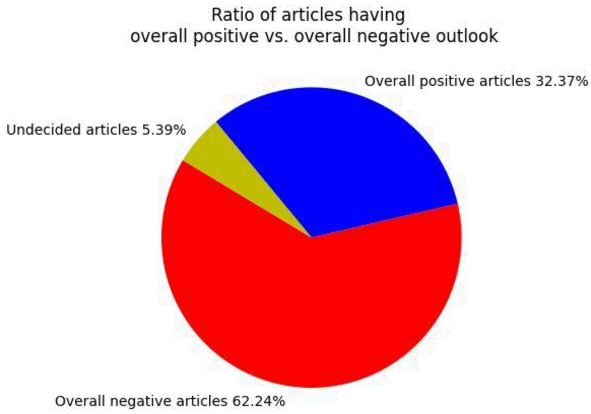


Figure 10: Positive-negative articles ratio

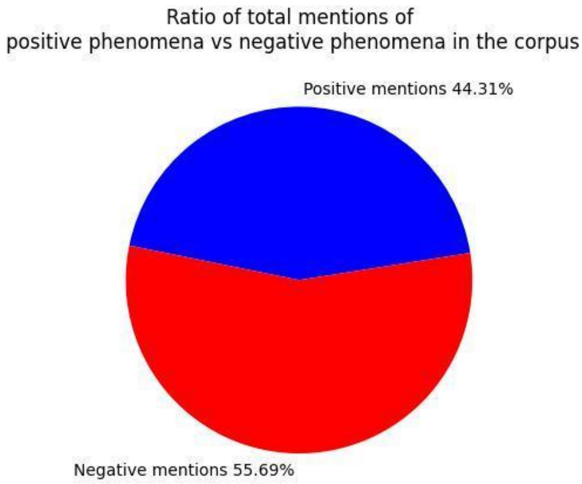


Figure 11: Positive-negative mentions ratio

As an added exercise, we analysed the temporal distribution of the "overall positive", "overall negative" and "undecided" articles in time (as in: year of publication), as well as the ratio of total individual mentions, and we found, that the not dominating, but none the less very perceptable negative dominance is generally stable.

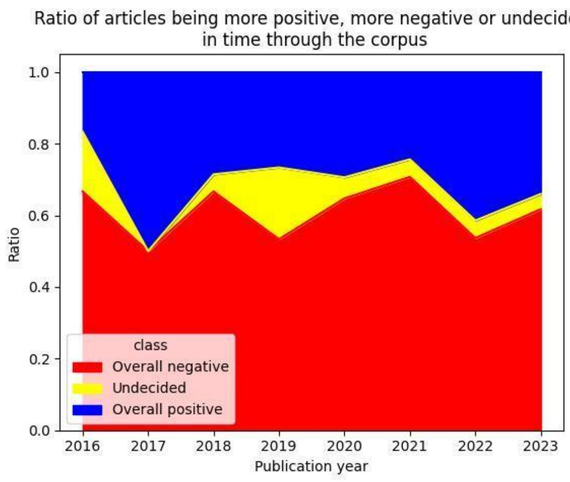


Figure 12: Positive-negative articles ratio

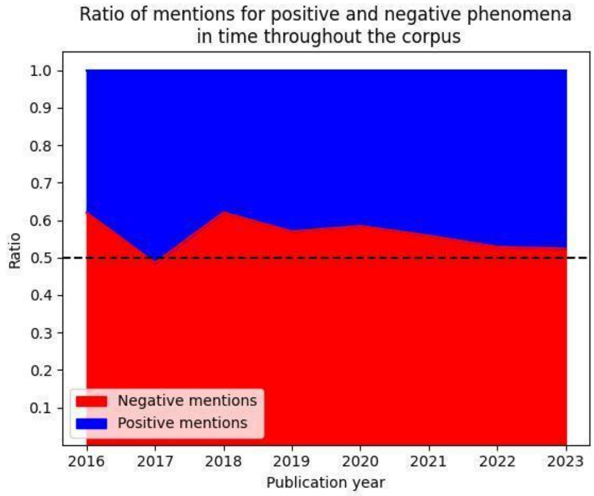


Figure 13: Positive-negative mentions ratio in time

Overall, we can conclude, that the surveyed literature can be characterized by a certain "cautious pessimism", so stopping short from being completely dominated by the outlook of negative effects of AI on the labour market, but being generally slightly pessimistic in outlook.

## V. Establishing a Foundational Subset through Citation Graph Analysis

As a methodology for identifying the core literature, to distill a foundational subset of articles having the dominant influence on the field, from the collection of 250 academic papers we implemented a citation graph analysis. This involved constructing a directed graph where the nodes represent the articles within our curated set, and the edges represent citations between these articles. For this phase of analysis, we focused exclusively on the internal citation dynamics, intentionally omitting external citations – those references pointing outwards from the curated subset. This allowed for a more concentrated examination of the discourse and intellectual lineage within the scope of our research question.

### 5.1 Assessing the Network Topology

Preliminary observations suggest that the citation graph displays characteristics reminiscent of a 'small-world network', a concept rooted in the field of network theory. Small-world networks are marked by high clustering and short path lengths between nodes. In the context of our citation graph, this could manifest in a pattern where a limited number of highly-cited papers form the backbone of the research area, with a multitude of less-cited works branching off from these central nodes. These foundational works typically serve as keystones in the construction of the field's academic edifice, setting the research agenda and framing the scientific discourse.

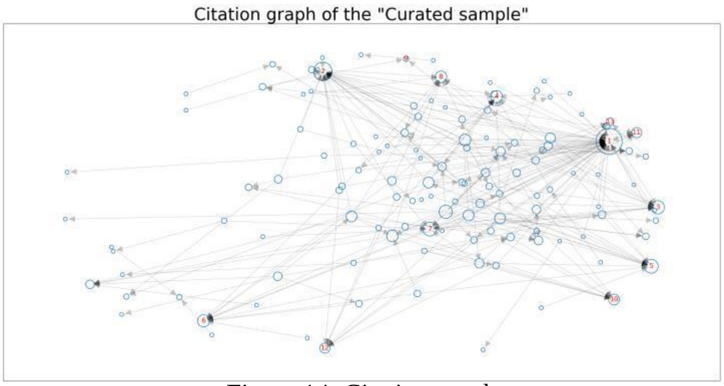


Figure 14: Citation graph

To substantiate this observation, we used numeric methods for examining the "centrality" of given articles.

5.2 Identifying Central Articles with PageRank

Utilizing the PageRank [31] algorithm, an approach famously employed by Google for ranking web pages, but also widely used as a general measure of network centrality, we utilized to identify the most ’central’ articles within our citation graph. PageRank serves as a measure of node influence in a network, based on the notion that connections to high-scoring nodes contribute more to the score of a node than equal connections to low-scoring nodes. By adapting this algorithm to our citation network, we were able to objectively quantify the influence of each paper within our subset, beyond mere citation counts, taking into account the ’quality’ of citations in terms of the influence of the citing papers.

Looking at the PageRank values, we indeed see signs of a handful of "core" papers dominating the citation graph, so we feel vindicated in creating a "shortlist" of most influential papers.

5.3 Curating a Shortlist of Influential Articles

To further refine our analysis and extract a ’shortlist’ of the most influential articles, we employed the technique outlined in "Finding a Kneedle in a Haystack: Detecting Knee Points in System Behavior" [35]. This method, designed to identify points of interest in a system’s behavior, was adeptly repurposed to determine a threshold for influence within the citation graph. By plotting the distribution of PageRank scores and identifying the ’knee point’ — the point where the curve sharply changes — we were able to delineate a natural cutoff. Papers above this threshold are considered as having a disproportionately large influence on the research field and are therefore included in our shortlist.

5.4 The shortlist

As final representatives of the "shortlist", we included:

Based on this analysis, we can conclude that by far the most "central" work of this curated set is "Why Are There Still So Many Jobs? The History and Future of Workplace Automation" by David H. Autor from 2015 [4]. This is a seminal work that "kickstarted" the study of AI’s effects on the labor market early on in the "revolution".

Also noteworthy, but somewhat misleading with two entries, is Acemoglu and Restrepo’s paper "Robots and Jobs: Evidence from US Labor Markets" [1]. It first appeared as a report from the National Bureau of Economic Research and then later got published in the Journal of Political Economy in 2020 [2]. Combining its citations makes it also a remarkable cornerstone of the topic.

Below, we endeavor to summarize the key findings of the centrality measure based "shortlist".

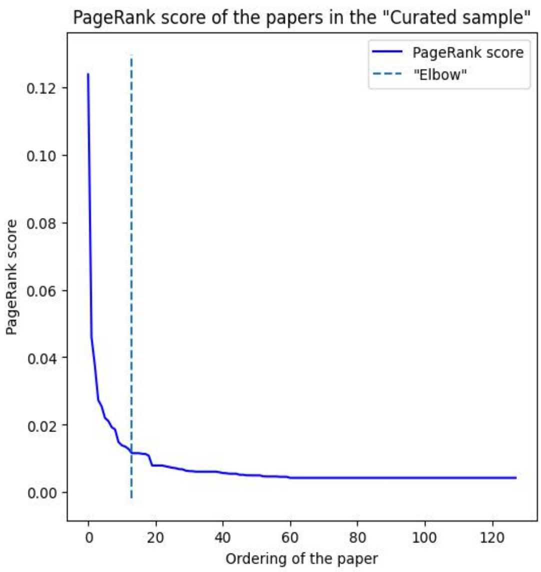


Figure 15: PageRank of the citation graph

Table 1: Shortlist of influential articles

| Author(s) | Title | Year | DOI |
|---|---|---|---|
| Autor | Why Are There Still So Many Jobs? The History and Future of Workplace Automation | 2015 | 10.1257/jep.29.3.3 |
| Acemoglu and Restrepo | Robots and Jobs: Evidence from US Labor Markets | 2020 | 10.1086/705716 |
| Acemoglu and Restrepo | Robots and Jobs: Evidence from US Labor Markets | 2017 | 10.3386/w23285 |
| Huang and Rust | Artificial Intelligence in Service | 2018 | 10.1177/1094670517752459 |
| Agrawal et al. | Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction | 2019 | 10.1257/jep.33.2.31 |
| Brynjolfsson and Mitchell | What can machine learning do? Workforce implica-tions | 2017 | 10.1126/science.aap8062 |
| Frank et al. | Toward understanding the impact of artificial intelli-gence on labor | 2019 | 10.1073/pnas.1900949116 |
| Brynjolfsson et al. | What Can Machines Learn and What Does It Mean for Occupations and the Economy? | 2018 | 10.1257/pandp.20181019 |
| Degryse | Digitalisation of the Economy and its Impact on Labour Markets | 2016 | 10.2139/ssrn.2730550 |
| Felten et al. | A Method to Link Advances in Artificial Intelligence to Occupational Abilities | 2018 | 10.1257/pandp.20181021 |
| Furman and Seamans | AI and the Economy | 2019 | 10.1086/699936 |
| DeCanio | Robots and humans – complements or substitutes? | 2016 | 10.1016/j.jmacro.2016.08.003 |
| Brougham and Haar | Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace | 2017 | 10.1017/jmo.2016.55 |

### 5.5 What are the main conclusions of the "shortlist"?

Research represented by the "shortlist" literature has focused on quantifying and illustrating the impact of automa-tion, robotics, and artificial intelligence (AI) on the labor market and the economy. Amongst the various papers exploring the implications, some common hypotheses and conclusions emerge:

One common hypothesis is that automation and technology do not necessarily lead to job loss but result in job displacement and polarization. This is supported by research papers such as Autor (2015)[4] and Acemoglu and Restrepo (2017)[1], which suggest that routine tasks are being automated, leading to growth in high-education, high-wage jobs and low-education, low-wage jobs at the expense of middle-wage, middle-education jobs such as bank tellers and brokers. It is also proposed that the main economic issue will be one of distribution, rather than scarcity.

Another common finding is that automation both eliminates and displaces jobs while also raising the value of tasks that are uniquely supplied by humans. Agrawal et al. (2019)[3] conclude that automation has ambiguous labor market impacts, as it can automate prediction tasks but may also create new opportunities. Brynjolfsson and Mitchell (2017)[7] suggest that AI can lead to job displacement in specific occupations such as legal research and gaming but create new opportunities and complement human skills in others. The key factor for workers to benefit from automation is to supply tasks that are complemented by it, such as intuitive and empathetic skills.

The impact of robotics and AI on employment and wage inequality is another recurring theme in the literature. Acemoglu and Restrepo (2020)[2] find that exposure to industrial robots in the US labor market negatively affects employment and wages, particularly in low- and medium-skill occupations such as manufacturing. This finding is supported by other studies, such as Frank et al. (2019)[16], which suggest that the rise of AI could lead to job polarization and income inequality. Furman and Seamans (2019)[17] investigate the impact of AI on occupational abilities and conclude that certain occupations such as drivers and retail workers are more susceptible to advances in AI technology.

There is also a growing consensus that the impact of technology on the labor market depends on factors such as task characteristics, contextual factors, and skill requirements. Brynjolfsson et al. (2018)[8] argue that the successful application of AI depends on a variety of task characteristics and contextual factors, and that job bundling of tasks can offer diversification with respect to machine learning exposure. Felten et al. (2018)[13] suggest that jobs that can be broken down into homogeneous tasks are more likely to be replaced by AI, even if they require higher intelligence. They also emphasize the need to acquire intuitive and empathetic skills as a strategy to counteract large-scale displacement due to AI replacing lower-skilled jobs.

In conclusion, the "shortlist" literature suggests that automation, robotics, and AI have varying impacts on the labor market and the economy. While the main concern still is job displacement and polarization, the potential for job creation and complementarity also exists. The distributional effects and implications for wage inequality represent the most important consideration.

Regarding the specific impact of technology on a given field, the consensus is that it depends on factors such as task characteristics, skill requirements, and contextual factors typical in a given area of economic activity.
On the level of broader policy, to navigate the challenges and opportunities posed by automation and technological advancements, investment in human capital and the development of skills that are complemented by technology is crucial. Additionally, policy responses and governance frameworks that address distributional chal-lenges and ensure broad-based benefits are important for inclusive economic growth.

### 5.6 What methods and data are utilized to study the unemployment question?

Looking from a more methodological angle, it is interesting to take note of the different approaches the articles in the "shortlist" take from the angle of data collection and quantitative analysis.

One group of articles, including Autor (2015)[4] and Acemoglu and Restrepo (2020)[2], uses empirical data and statistical analysis to investigate the relationship between robot adoption and employment. These articles utilize data on robot usage, employment rates, and wages to estimate the impact of robots on labor markets. They employ statistical models, such as instrumental variable (IV) estimates and regression analysis, to provide quantitative evidence on the relationship between robot adoption and employment outcomes.

Another group of articles, such as Huang and Rust (2018)[24] and Brynjolfsson et al. (2018)[8], explores the implications of AI and machine learning on workforce dynamics. These articles utilize empirical data and statistical analysis to investigate the impact of AI on various sectors, tasks, and occupations. They employ statistical methods, such as regression analysis and correlation analysis, to examine the relationship between AI adoption and employment outcomes, as well as the effect of AI on productivity and wages.

Other articles, including Frank et al. (2019)[16] and Furman and Seamans (2019)[17], focus on the impact of AI on the skill requirements of occupations. These articles utilize data on occupation-level skill requirements, automation risk, and AI advancements to analyze the changing skill demands in the labor market. They employ statistical methods, such as correlation analysis and regression analysis, to examine the relationship between AI technologies and occupational abilities.

All in all, one of the main challenges in the field seems to be the fact that hard data quantifying the phenomena of "AI adoption" in itself is hard to come by, so linking changes in general observable measurements (like wage inequality) to the effect of AI adoption is extremely challenging.

### 5.7 Quantification of AI exposure: a subliterature with great potential

While surveying the general consensus of the literature regarding AI's direct unemployment effects, as already stated, it is apparent that the question of skills from the human side is of paramount importance. It is equally important though for the task of quantifying the risk of structural unemployment to analyze the quantifiable metrics of different AI model's performance in given skills, thus bridging the gap between human job taxonomies (for example O*NET[38] or ISCO[26]) showing the necessary skills for certain occupations, and AI's specific automation risk regarding these.

In frames of our investigation, we identified a very promising direction of research, and a corresponding small set of articles trying to carry out exactly this task. If we would have to summarize their methodology, it can be roughly sketched as follows:

1. Take a taxonomy (like O*NET or ISCO) that defines a decomposition of jobs in terms of skills required for carrying them out;

2. Take a source describing AI capabilities (like Electronic Frontier Foundation's AI Progress Measurement[15]), that endeavors to quantify AI "skills" in different taxonomy domains;

3. Create a mapping (by typically manual labor) matching the AI "capabilities" to the human skills;

4. Estimate progress in AI skills by projecting progress into the future;

5. Project this progress via the skill mapping back to the jobs as an "automation risk" measure.

This strand of research is most clearly characterized by the series of papers by Edward W. Felten and colleagues in Felten et al. 2018[13], Felten et al. 2019[14], and Felten et al. 2021[11], which have the same basic pattern: utilizing O*NET for labor taxonomy, EFF's measurement for AI progress, and a mapping created by dedicated labor (acquired via Amazon's Mechanical Turk[37]). They call the resulting metric the "AI occupational exposure" (AIOE) score.

Beyond this series, though, very similar patterns appear in Colombo et al. 2019[9], though it utilizes semantic embedding methods for mapping, as well as replaces O*NET and ISCO with ESCO; Paolillo et al. 2022[32] focusing on robotics; but also in such recent works as Pizzinelli et al. 2023[33] (which explicitly references the Felten group's work) and Gmyrek et al. 2023[18], and finally an "update paper" from the Felten team [12] which even took into account the recent advancements in generative AI.

This latter work is all the more important, since it not just "corrects" for the effects of "generative AI" (so basically "large language models" or "foundational models [6] and diffusion based image generation models [23]), but they carry out a kind of "stability analysis", so analyse the correlation between the AIOE score before and after this correction.

The analysis suggests, that the AIOE score is pretty robust.

#### 5.7.1 Merits and limitations of this approach

The merits of this research methodology have to be emphasized since it "opens up" the black box of AI and does not treat it as a single set of capabilities – which, in our view, is all the more important since the term "AI" does not even represent a single set of technologies and is not static in time, meaning: newer and newer methods appear under its umbrella with their specific characteristics.

That said, since some of this research is coming from time periods representing previous iterations of technology, some empirical testing of the actual realized automation could be fruitful to reach a more precise estimate between the automation potential and its actual application.

As a general remark, it has to be pointed out that this "shifting of the goalpost," with which we "normalize" or "commoditize" technology (like the Optical Character Recognition, which once was an area at the forefront of computer vision, hence AI research, and now is treated as a solved problem that has "nothing to do with real AI"), makes it in general more difficult to systematically investigate the effects of "AI" (whatever technology it currently means) on the economy. As a more nuanced ground for observation, the different *types of technologies* (like classical expert systems, non-neural machine learning models, "classical" Deep Learning models, and now

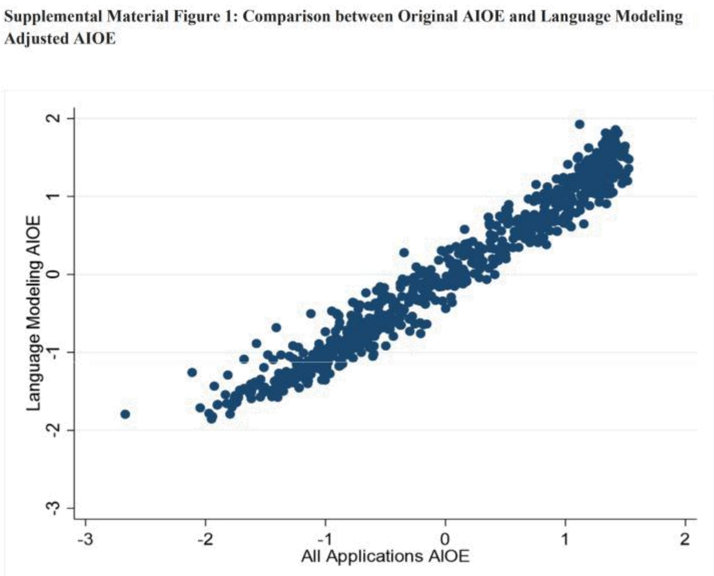


Figure 16: Correlation of original and "generative AI" adjusted AIOE scores from [12]

"foundational" models) would be more appropriate as a subject of study. In this sense, the approach to decompose AI – via possible task and skill investigations – to different aspects is all the more laudable.

## 6 Threats from an emerging paradigm

It is important to note, that recent work on foundational level language models (or simply "Large Language Mod-els", LLMs, as they are called in common parlance) shows, that these models possess - beyond their "mere" language generation skills - strong reasoning and planning abilities (see eg: [27] and [25]). Reasoning and plan-ning on large scale, in a learned manner was thought this far to be a pretty uniquely human capability, but it seems, that the the emergence of these models, and the the "Autonomous Agents" and "Agent societies"([30]) built upon them represent a whole new level of capability, that's release as available technological solutions is imminent (see eg. the "Autogen" Framework of Microsoft Research [29]), and will dramatically increase the impact of AI automation possibilities, given it is deployed at scale.

This basically means, that it is reasonable to assume, that the AIOE like scores will have to be recalculated pretty soon, or even structural changes might be necessary.

## 7 Final conclusions

After conducting a thorough literature review on the impact of artificial intelligence (AI) on the labor market and the economy, several key findings and trends have emerged.

Firstly, the overall consensus is that the effects of AI on employment are complex and nuanced. While there is concern about job displacement and polarization, there is also recognition that automation and AI can create new job opportunities and complement human skills. The distributional effects and implications for wage inequality are significant considerations in the discussion.

The literature highlights the importance of task characteristics, contextual factors, and skill requirements in understanding the impact of AI on the labor market. Different studies have explored various aspects of AI's effects, including job dynamics, labor productivity, occupational skills, human interaction with technology, and robotics in industries. These studies provide valuable insights into the specific ramifications of AI in different fields and shed light on the challenges and opportunities posed by automation and technological advancements.

Quantitative analysis plays a crucial role in studying the unemployment question. Some papers have used em-pirical data and statistical analysis to investigate the relationship between AI adoption and employment outcomes. Others have focused on the quantification of AI exposure, mapping AI capabilities to human skills and estimating the risk of automation for different occupations. These methodologies provide valuable frameworks for assessing the impact of AI on employment and should be further developed and refined in future research.

It is important to note the limitations of the existing literature. The definition of AI itself is subject to concept drift, and the rapid advancements in technology require ongoing updates and refinements in research methodologies. Additionally, the field would benefit from incorporating a broader range of AI technologies beyond machine learning and taking into account the shifting ground of AI capabilities.

In conclusion, the literature on AI's effect on the labor market and the economy presents a multifaceted picture of both challenges and opportunities. The discussion around job displacement, job creation, wage inequality, and skill requirements provides a foundation for further research and policy development. Future work should focus on refining research methodologies, incorporating a broader range of AI technologies, and addressing the evolving nature of AI capabilities. Additionally, policy responses and governance frameworks that consider the distribu-tional challenges and ensure inclusive economic growth are important to navigate the challenges and opportunities posed by AI.

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