Institute for the Future of Work

Toolkit

# Recent Methodologies on AI and Labour - a Desk Review

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# Overview

This desk review toolkit brings together recent methodologies used to analyse AI's effects on employment, wages, and productivity.

It is structured into two tables:

Table 1 covers original works from 2003 to 2020

Table 2 focuses on academic, policy, and think tank works from 2021 to 2025. After 2023 especially, significant is the focus on LLMs.

Each table categorises methodologies, high-level findings, and method-specific critiques to provide a comprehensive overview of the field.

## Key points to note from most recent methodologies (Table 2)

### Shift from Occupation-Level to Task-Level Analysis:

Recent methodologies increasingly focus on tasks rather than entire occupations, recognising the heterogeneity within jobs. For example, Felten et al. (2023) and Eloundou et al. (2023) use AI exposure indices to measure task-specific impacts.

### Integration of Advanced Technologies:

Methods now incorporate Natural Language Processing (NLP) (e.g., BERT, LSTM) and LLMs (e.g., GPT-4) to analyse job descriptions and predict automation risks (Xu et al., 2025; Hampole et al., 2025).

### Scenario Planning and Policy Focus:

Think tanks like TBI and IPPR, and organisations like IMF emphasise scenario-based modelling to inform policy, highlighting the need for reskilling and labour market reforms (TBI, 2024; IPPR, 2024, Korinek, 2023). They assume different 'initial conditions' in adoption to estimate different conclusions in employment, wages, productivity ect.

Studies consistently find that AI's impact varies by skill level, with low-skilled workers facing higher displacement risks and high-skilled workers benefiting from augmentation (Brynjolfsson et al., 2023; Chen et al., 2024).

Many methodologies struggle with static assumptions, lack of causal evidence, and overreliance on theoretical models. For instance, Acemoglu & Restrepo (2022) assume fixed comparative advantage, while Webb (2020) ignores adaptation.

As of year 2025, conclusions of some of the pre-2020 research is already redundant in terms of what professions will remain or not. The pre-2020 conclusion that creative and intellectual occupations will remain in high demand, has already been disproven.

# Table 1 - Original Works 2003 - 2020

| Methodology | High-level findings | Critique |
|---|---|---|
| **Task-Based Approach**<br>(Autor et al., 2003)<br>• Computer capital as<br>i) substitute and<br>ii) complement to workers.<br>• Mapping of work tasks within occupations: Routine vs Non-routine.<br>• Historical data analysis. | • Computerisation reduces labour input for routine tasks and increases it for non-routine cognitive tasks.<br>• Explains 60% of the demand shift favouring college labour (1970-1998). | • Static view: Assumes tasks remain fixed over time.<br>• Ignores task reconfiguration within jobs.<br>• Binary classification (routine vs. nonroutine). |
| **Occupation-Based Approach**<br>(Frey & Osborne, 2013)<br>• Occupation level analysis: Routine vs Non-routine.<br>• Expert assessments or automation scores: "computerisable" or "non-computerisable".<br>• Gaussian Process Classifier (GPC) to estimate the probability of computerisation. | • 47% of US employment is in occupations at high risk of computerisation.<br>• Jobs in transportation, logistics, and office support are most susceptible.<br>• Occupations requiring creative intelligence, social intelligence, and fine motor skills are less susceptible to computerisation. | • Lacks granularity: Occupations contain heterogeneous tasks.<br>• Static view: Ignores worker adaptation.<br>• Technologically deterministic: automation exposure equates to automation adoption.<br>• Occupations requiring creative intelligence as of year 2025 are more exposed due to LLMs. |
| **Task- and Occupation-Based Approach with Social Dimensions (OECD)**<br>(Arntz et al., 2016)<br>• Task-Based Automation Framework within occupations.<br>• Firms and workers adaptability.<br>• Tech adoption faces economic, legal, and societal barriers, slowing displacement.<br>• Emergence of new jobs emerge from tech demand and productivity gains. | • Only 9% of jobs are at high risk of automation.<br>• Workers adapt by shifting to non-automatable tasks.<br>• Higher automation potential in countries with lower average skill levels.<br>• Higher-educated workers face lower risk due to task complexity.<br>• Countries with rigid task specialisation (e.g., Germany) show higher risk.<br>• Nations with existing robotics/IT infrastructure (e.g., South Korea) have fewer remaining automatable tasks. | • Focuses on current technology, missing future advancements.<br>• Assumes task adaptability, which may not hold for low-skilled workers.<br>• Although they consider wider socio-economic dimensions, they Ignore cost-benefit analysis of automation adoption (e.g., firms may retain workers if wages are low).<br>• No discussion of AI-augmented roles.<br>• Does not model job creation from new technologies. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **Task-Based, Ability-Centric Framework**<br>(Felten et al., 2019)<br>• Distinction between "narrow AI" (current, domain-specific) and "general AI" (future, hypothetical).<br>• Introduces the AI Occupational Impact (AIOI) measure: it captures complementarity and substitution. | • AI exposure linked to higher wages, especially in high-skill jobs.<br>• AI's benefits more among high-skill, high-income, software-intensive jobs, potentially exacerbating labour market polarisation.<br>• No significant job loss observed. | • Correlational, not causal.<br>• Static snapshot of occupational structures.<br>• Techno-deterministic: Ignores economic and regulatory factors.<br>• It does not address the potential for displacement or wage suppression in lower-skill roles. |
| **Expert Elicitation and Surveys**<br>(Grace et al., 2018)<br>• Underlying premise: expert predictions more reliable forecast than relying solely on objective measures or individual predictions.<br>• Survey to elicit predictions about AI timelines, capabilities, and societal impacts. | • 50% chance of AI achieving "High-Level Machine Intelligence" (HLMI) within 45 years.<br>• Asian respondents expect HLMI sooner than North Americans.<br>• HLMI to outperform humans in tasks like language translation by 2024, writing high-school essays by 2026, driving trucks by 2027, working in retail by 2031, writing a bestselling book by 2049, and working as a surgeon by 2053. | • Subjective expert bias, (researchers from two specific conferences were surveyed., overly optimistic or pessimistic due to their immersion in the field, not be fully aware of the limits of their knowledge).<br>• Lacks empirical grounding.<br>• Broad and ambiguous definitions.<br>• Examples like writing high-school essays fell into the predicted timeline already as of year 2025.<br>• Techno-deterministic: does not consider the economic, social & political factors. |
| **Political Economy of Task-Based Approach with Job Displacement vs. Job Creation**<br>(Acemoglu & Restrepo, 2018)<br>Theoretical, not empirical, work with 3 Countervailing Forces:<br>• Productivity Effect.<br>• Capital Accumulation.<br>• Deepening of Automation. | • Productivity Effect: increasing demand & creating jobs.<br>• Capital Accumulation: driving investment in capital & jobs.<br>• Deepening of Automation, with labour demand falling leading to job displacement. | • Theoretical, lacks empirical testing.<br>• Difficult to measure new task creation.<br>• Limited policy implications. |
| **Suitability for Machine Learning (SML) Rubric**<br>(Brynjolfsson et al., 2018)<br>• Employs algorithms (e.g., regression, random forests, neural networks) to model & predict labour market trends using historical data & AI exposure indices.<br>• Rubric-based task scoring for SML. | • Most occupations have some SML tasks; few have all.<br>• Job redesign required to leverage ML potential.<br>• SML correlation with wage percentile/wage bill is low: this wave of automation may affect a different part of the labour force than previous ones. | • Opaque "black box" models.<br>• Subjectivity of SML Rubric.<br>• Limited empirical validation.<br>• Techno-deterministic: ignores economic and organisational factors. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **Scenario Analysis**<br>(OECD, 2019)<br>• Eclectic approach including:<br>i) Skills-Biased Technological Change (SBTC)<br>ii) Task-Based Approach based on Autor et al. (2003)<br>iii) Human Capital Theory<br>iv) Institutional Economics on labour market outcomes<br>v) Welfare Economics. | • 14% of jobs could disappear due to automation in the next 15-20 years within OECD countries<br>• 32% of jobs may change radically.<br>• Non-standard workers are more vulnerable. | • Highly dependent on assumptions.<br>• Broad generalisations without country-specific nuances.<br>• Techno-optimistic about job creation.<br>• Less focus on innovation policy VS. the skills development & adaptation: employee-, firm- and market-level individualism. |
| **Historical data for Task Within Occupation Approach**<br>(Das et al., 2020)<br>• "Task-share" for each task within each occupation.<br>• Time series of task-shares to predict future task demands (ARIMA model). | • Big data & AI have risen significantly among high-wage occupations.<br>• There are 15 tasks that are mentioned in more than 300 occupations, 3,976 tasks that occur in fewer than 10 occupations, some of the tasks that appear in only 1 occupation.<br>• Healthcare and IT industries involve more tasks. | • Job postings may not reflect actual work.<br>• Limited scope (2010-2017 data).<br>• ARIMA model may not capture labour market complexities.<br>• It documents change in task demands but does not fully explore their underlying causes. |
| **Historical data for Input-Output Economic Modelling**<br>(Acemoglu & Restrepo, 2020)<br>• Model Inputs: industrial robot density, employment data, wage, demographic and economic controls.<br>• Model Outputs: employment, wage, labour market polarisation, displacement & productivity effects. | • 1 robot per 1,000 workers reduces employment by 0.39% and average wages by 0.77% between 1990 and 2007.<br>• Effects are most pronounced in manufacturing. | • Focuses on industrial robots, not service-sector AI.<br>• Short time frame (1993-2007).<br>• Does not account for long-term worker adaptation. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **Text-Based Approach on Job Task Descriptions & Patents Analysis**<br>(Webb, 2020)<br>• Task-Based within Occupation Framework adapting Acemoglu and Restrepo (2018)<br>• Patent-Text Analysis using verb-noun pairs extracted from job descriptions and patents to quantify the overlap, calculating an exposure score.<br>• Originally applied to software and robots, estimating exposure scores & employment and wages (1980-2010), then applied to AI exposure. | • AI disproportionately affects high-skilled tasks, potentially reducing 90:10 wage inequality.<br>• Higher education, lower exposure for robots (higher) & software (lower).<br>• Higher education, higher exposure for AI.<br>• Estimates sectoral impacts and job displacement. | • Assumes fixed technology adoption patterns.<br>• Ignores worker and firm adaptation.<br>• Relies on patent data, which may lag behind actual trends. A fragment of patents is adopted.<br>• Techno-deterministic: ignores economic and organisational factors. |
| **NBER Task Exposure Index**<br>(Acemoglu et al., 2020)<br>• They classify establishments as “AI-exposed” based on the compatibility of their workers’ tasks with current AI capabilities, using 3 measures (Felten et al., 2019, SML from Brynjolfsson et al., 2019 & Webb, 2020).<br>• Also correlation between AI exposure and employment / wages | • 15% rise in AI vacancies for exposed sectors.<br>• No aggregate employment or wage effects at industry/ occupation level.<br>• 3 measures agree: Information, Professional services & Manufacturing more exposed, VS. retail trade that are less.<br>• 3 measures disagree: Agriculture, Mining, Government.<br>• SML shows smooth wage changes per occupation, Felten et al. staggering effects on occupation wage, & Webb shows diminishing returns. | • Limited by online vacancy data representativeness.<br>• Measures exposure, not actual impact.<br>• Short time frame (2010-2018).<br>• It focuses on establishments using AI, rather than producing it.<br>• Possible endogeneity as firms experiencing declining hiring may be more likely to adopt AI. |

# Table 2 - Recent Academic, Policy, and Think Tank Works (2021-2025)

| Methodology | High-level findings | Critique |
| --- | --- | --- |
| **Political Economy of Dynamic Task Share Analysis & Historical data**<br>(Acemoglu & Restrepo, 2022)<br>• Task-Based Framework, where automation displaces workers from tasks where they have comparative advantage, reducing their wages.<br>• Key mechanisms: Automation,<br>• Skill-Biased Technological Change (SBTC), General Equilibrium Analysis. | • 50-70% of US wage structure changes (1980-2016) driven by automation.<br>• Robots, software, and machinery adoption explain 45% of industry labour share declines (1987–2016).<br>• Automation raised TFP by 3.4% but caused stagnant wages. | • Relies on routine tasks as a proxy, missing AI's impact on non-routine roles.<br>• Static assumptions about worker adaptation.<br>• Despite large distributional effects, modest productivity gains raise questions about automation's net benefits. |
| **Technology Adoption Model (Firm-Based)**<br>(Acemoglu et al., 2022)<br>• Task-Based Framework, where automation displaces workers from tasks where they have comparative advantage, reducing their wages.<br>• It links technology adoption with firm characteristics. | • Adoption of these technologies remains low, especially for AI (3.2% of firms) and robotics (2% of firms).<br>• Higher adoption rate for specialised software (40.2%) and cloud computing (34%).<br>• Use of advanced technologies is associated with an 11.4% higher labour productivity, and lower labour shares. | • Descriptive, not causal.<br>• Limited time frame (2016-2018).<br>• Self-reported data by firms may be biased.<br>• Skill heterogeneity among groups or demographic groups not dealt with. |
| **Firm Case Study on Productivity Analysis**<br>(Brynjolfsson et al., 2023)<br>• Quasi-Experimental Design and Difference-in-Differences (DiD) Approach touching upon the task-based framework of automation and explores AI effects of across different skill levels at a Fortune 500 firm selling business-process software. | • AI assistance increased productivity by 14-15%.<br>• Less experienced workers benefited most (34-35% gains). | • Single-firm, single-task context.<br>• Short-term effects only.<br>• No wage or aggregate employment data. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **LLM-Driven Task- and Ability-based framework Job Impact**<br>(Felten et al., 2023)<br>• It builds on a task- and ability-based framework AI Occupational Exposure (AIOE) from Felten et al. (2018, 2021).<br>• Using GPT-4 to score occupation-level AI exposure, validating with human experts.<br>• “Exposure” can be either automation or enhancement. | • Telemarketers, teachers, and psychologists are most exposed to LLMs.<br>• High-wage jobs are more exposed. | • Exposure does not distinguish augmentation vs. displacement.<br>• Static snapshot. |
| **Scenario Planning for AGI Future**<br>(Korinek & Suh, 2024, Korinek 2023)<br>• The paper models AGI’s impact on output and wages, assuming work is made of tasks with: bounded vs. unbounded task complexity.<br>• It shows wages depend on the balance between automation and capital-driven demand. | • (a) Business-as-usual scenario (b) Baseline AGI scenario (c) Aggressive AGI scenario (d) Mixed scenario<br>• Bounded task complexity could lead to wage collapse; unbounded could sustain wage growth.<br>• AGI may cause rapid growth but risks wage declines. | • Theoretical, lacks empirical validation.<br>• Assumes exogenous automation index growth.<br>• Simplifies labour and capital dynamics. |
| **Task-Based within Occupation Exposure Analysis on LLMs**<br>(Eloundou et al., 2023)<br>• Task exposure, acknowledging both potential augmentation and displacement effects.<br>• Development of a new rubric to assess occupations based on their alignment with LLM capabilities.<br>• Integration of human expertise and GPT-4 classifications to apply rubric to occupational data. | • 80% of US workers could have ≥10% of tasks affected by LLMs.<br>• 19% may see ≥50% task impact. | • Techno-deterministic: findings rely on exposure, not adaptation.<br>• Limited data (2023); too early for empirical validation.<br>• Potential bias in human/GPT-4 annotations. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **Tony Blair Institute (TBI) – Scenario-Based Modelling**<br>(TBI, 2024)<br>• AI's impact on labour markets through: Labour Demand, Labour Supply, and Task-based.<br>• Scenario analysis: Tailwind, Jet Stream, Whirlwind, Breeze.<br>• UK labour-market data to contextualise AI-induced displacements | • AI could displace 1-3 million UK jobs, peaking at 60,000-275,000 annually.<br>• Potential GDP growth up to 6% by 2035.<br>• 23% private-sector productivity gains, with admin roles most exposed to displacement. | • Reliance on historical analogies, and assumption that AI's impact will mirror past technologies (e.g., ICT).<br>• Assumes smooth transition; underestimates wage polarisation.<br>• 'Time-saving' focus might underplay job displacement.<br>• TBI regional data complements the Good Work Monitor 2025: areas excelling in Good Work are more exposed to AI, while lower-performing regions face less exposure—possibly due to firms prioritising automation of high-wage, high-autonomy roles. |
| **IPPR – Task-Based Exposure Analysis**<br>(Jung & Srinivasa Desikan, 2024)<br>• Task-based assessment of GenAI.<br>• GenAI on labour market depends on the i) design, ii) adoption, and iii) policy choices.<br>• AI can be used for "augmentation" (boosting worker productivity) or "displacement" (reducing labour demand).<br>• Scenario planning: Full Augmentation, Full Displacement, Central Scenario (augmentation and displacement) | • 11% of tasks in the UK (scaled by hours worked) are exposed to 'here and now' GenAI.<br>• Full Augmentation: Widespread integration of generative AI leads to a 13% boost to GDP with zero job displacement.<br>• Full Displacement: 8 million jobs are lost with no GDP gains.<br>• Central Scenario (Augmentation and displacement): 4.4 million jobs are lost, but there are significant economic gains of about 6.4% of GDP.<br>• Advocates for "job-centric industrial strategy" in the UK. | • Relies on three scenarios with uncertain AI adoption assumptions ('here and now GenAI' vs more integrated AI systems).<br>• Heavy use of expert surveys, lacking labour market dynamics.<br>• Qualitative metrics lack clarity and causal AI links.<br>• Empirical analysis is limited; outcomes are exploratory, not predictive. |
| **Harvard Business School (HBS) Augmentation Index**<br>(Chen et al., 2024)<br>• GenAI on the labour market through displacement or complementation.<br>• Argument: Automatable tasks will experience displacement, while those mixed occupations (automatable & non-automatable tasks) augmentation.<br>• GenAI's target: cognitive tasks VS past manual/blue-collar work.<br>• Synthetic Difference-in-Differences (DiD). | • 17% decrease in job postings for automatable roles.<br>• 22% increase for augmentation-prone roles.<br>• 24% decrease in GenAI-exposed skills among jobs in the top quartile of automation exposure.<br>• 15% increase in GenAI-exposed skills for jobs most susceptible to augmentation. | • Limited longitudinal perspective.<br>• DiD can address endogeneity better than simple correlations, but it is still difficult to establish causality.<br>• ChatGPT introduces subjectivity. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **AI Startup Exposure (AISE) Index**<br>(Fenoaltea et al., 2024)<br>• Index based on occupational descriptions & AI applications.<br>• Critiques techno-determinist models, proposing analysis on dynamics & market realities.<br>• Startups as indicative of venture capital investments, reflecting economic viability & societal desirability.<br>• Compare AISE rankings with Felten et al. (2019/2021)'s AI Occupational Exposure (AIOE) index. | • High-skilled roles are heterogeneously targeted by startups.<br>• Roles with routine tasks show significant exposure.<br>• Ethical or high-stakes jobs (e.g. judges, surgeons) see lower exposure.<br>• AI impact is concentrated in knowledge hubs and service sectors. | • Focuses on startups, missing broader industry trends.<br>• Semantic similarity ≠ actual impact.<br>• Llama3 is a black box—it adds objectivity, but its internal logic and similarity scoring remain opaque. |
| **Natural Language Processing (NLP) – Task-based Exposure Measurement**<br>(Hampole et al., 2025)<br>• Task-based framework of AI on labour demand through direct displacement and indirect productivity effects.<br>• Argument: workers shift effort to non-automatable tasks, dampening job losses.<br>• NLP-driven exposure measures to construct AI task exposure indices at the worker and firm levels (2010–2023). | • Higher task dispersion mitigates displacement effects.<br>• AI exposure slightly reduces labour demand but is offset by task reallocation & productivity gains.<br>• No evidence of large-scale job losses (2010-2023).<br>• Demand for routine skills declines, while AI-complementary skills remain stable. | • NLP models rely on quality data and may miss context around AI adoption<br>• Misses post-ChatGPT acceleration.<br>• Relies on job descriptions, which may not reflect actual skill use or adaptation.<br>• Productivity gains are modelled but not empirically validated at the macro level. |

| Methodology | High-level findings | Critique |
|---|---|---|
| **Deep Learning Models – LSTM for Labour Demand Forecasting**<br>(Kim, 2025)<br>• Applies Long Short-Term Memory (LSTM) models (a type of recurrent neural network, RNN) to forecast Job Openings and Labour Turnover Survey (JOLTS) data.<br>• Then compares performance with traditional autoregressive (including ARIMA, SARIMA, & Holt-Winters) models. | • LSTM outperforms traditional models in predicting JOLT job openings.<br>• Captures complex temporal dependencies. | • Mainly methodological research.<br>• High computational cost.<br>• Limited interpretability.<br>• Overstates LSTM advantages without acknowledging limitations. |
| **Task-Level Automatability Prediction Using BERT**<br>(Xu et al., 2025)<br>• Skill-Biased Technological Change (SBTC) & Routine-Biased Technological Change (RBTC) hypotheses.<br>• Utilises a BERT-based classifier (Bidirectional Encoder Representations from Transformers) to analyse & classify text to assess the automatability of individual tasks across occupations, offering a granular analysis. | • 25.1% of occupations at substantial automation risk.<br>• BERT outperforms traditional ML models. | • Relies on quality of training data.<br>• The expertise of the annotators is not fully detailed.<br>• GPT-4 Reliance.<br>• No real-world validation. It does not examine the economic feasibility of these tasks getting automated<br>• Limited details on baseline models |
| **Deloitte Employee Surveys**<br>(Cantrell et al., 2025)<br>• Employee Value Proposition (EVP) as a unique set of benefits that an employee receives in return for their skills, capabilities, and experience.<br>• Human-Machine Collaboration proposes a shift from task replacement to augmentation & ultimately to convergence. | • AI can automate 40–60% of routine tasks, but few complex ones.<br>• 77% say AI has increased workload & reduced productivity; 61% expect more burnout.<br>• 14% of EU workers face algorithmic management, which may lower care & accuracy.<br>• 33% report less human interaction; 28% feel a loss of personal connection.<br>• 54% worry about blurred lines between human and AI work.<br>• 60% link increased turnover to AI-driven worker data use. | • Methodology details (e.g. sampling, analysis) are missing.<br>• Potential bias between findings and company's services.<br>• Data reflects business/HR leaders more than workers.<br>• Terms like "convergence" & "human capabilities" lack clear definitions.<br>• Focuses on AI's benefits & EVP adaptation, with little attention to inequality or worker challenges.<br>• Minimal discussion of algorithmic bias, privacy, job displacement. |

Figure 1: Methods on AI's impact on labour markets

https://public.flourish.studio/visualisation/22803877/

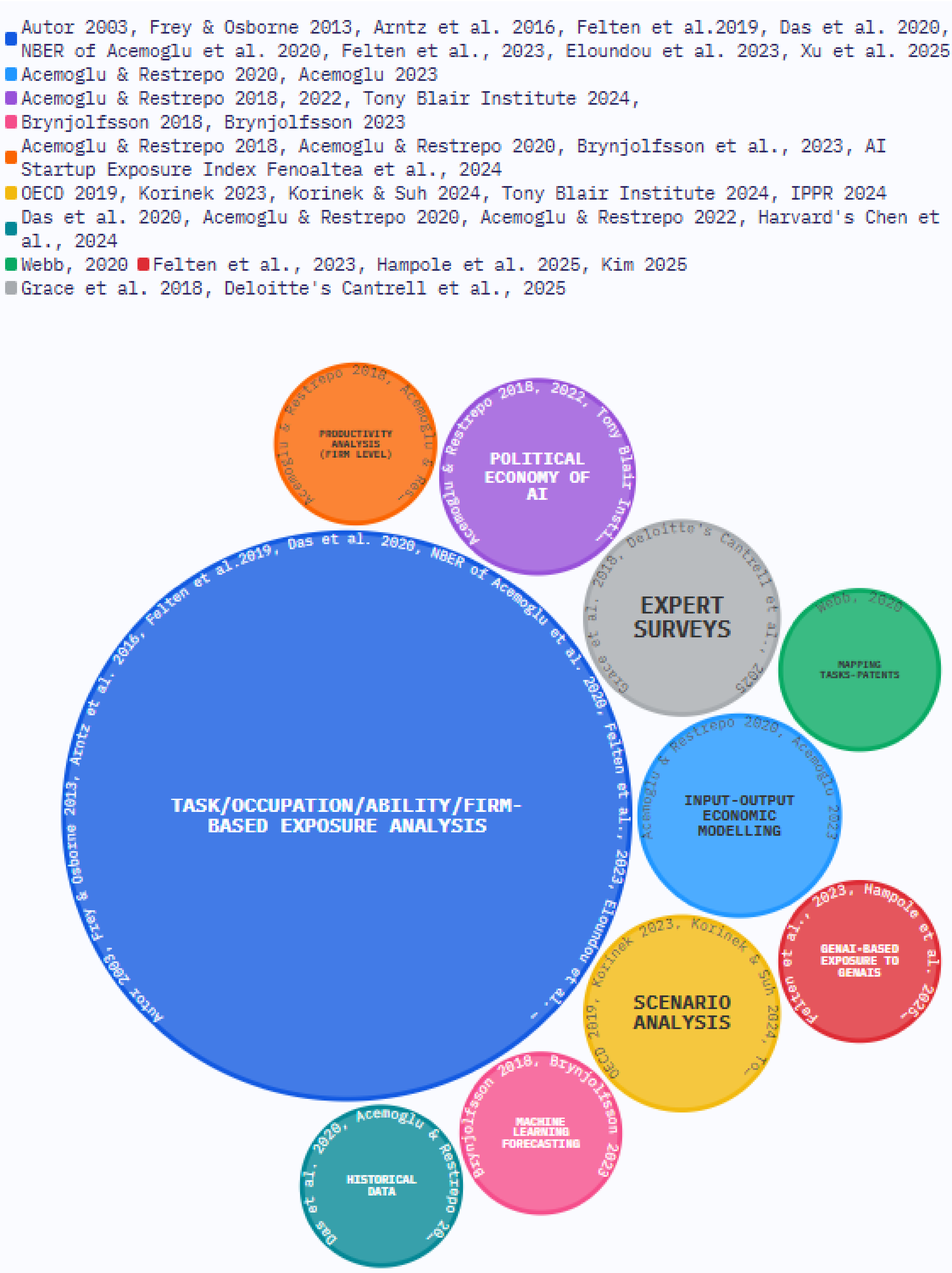
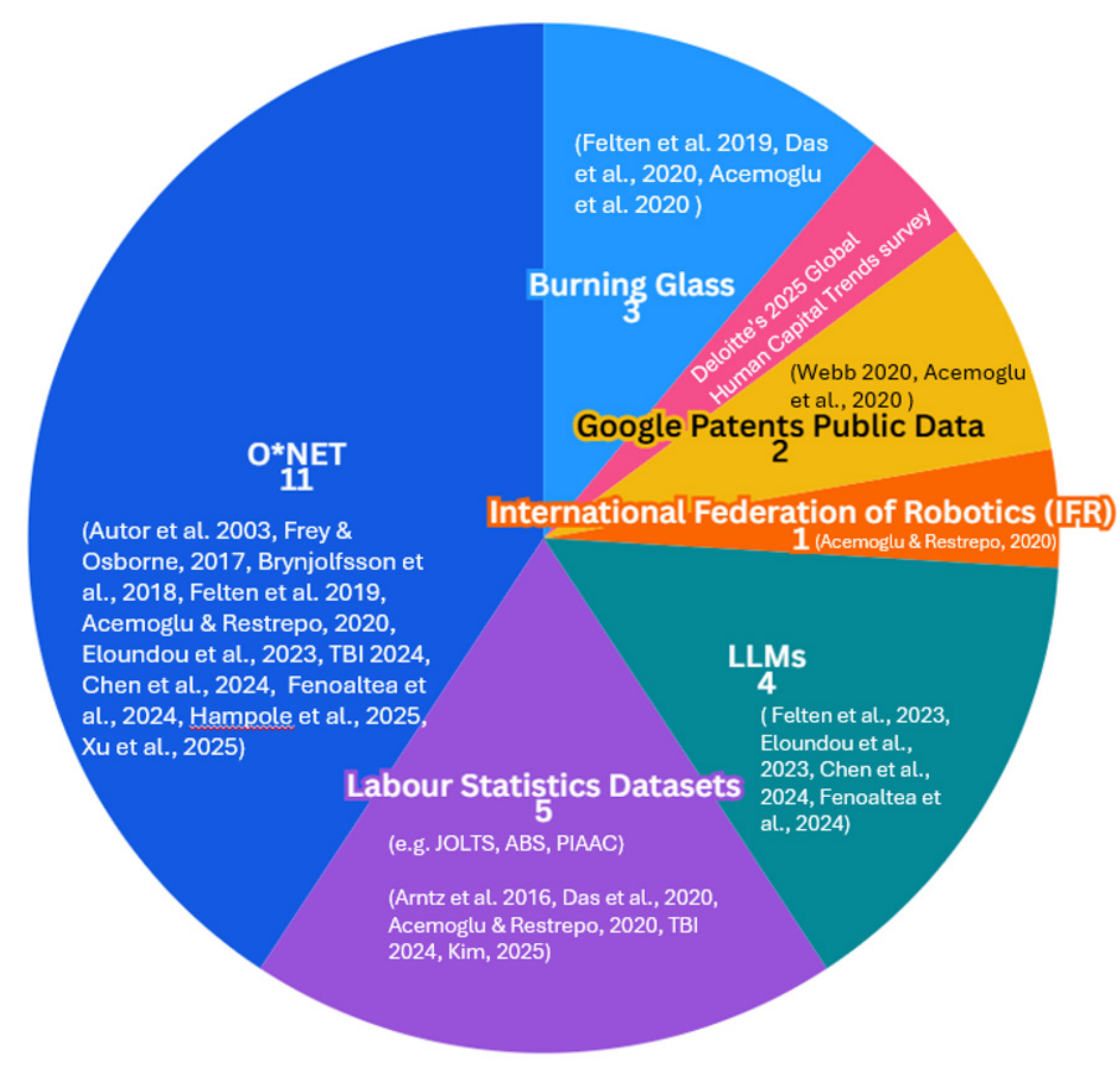


Figure 2: Datasets used

https://public.flourish.studio/visualisation/22803347/



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