

Making AI Count: The Next Measurement Frontier

Draft chapter for NBER volume *Economics of Transformative AI: A Research Agenda*.

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Revised August 2025

As generative Artificial Intelligence (AI) advances, it is expected to drive profound transformations in the structure of production and consumption, beyond those already brought about by digital technology. It may significantly accelerate economic growth. However, capturing AI's contributions within existing economic measurement frameworks presents significant challenges, and it would be challenging to see the early stages of transformation in current statistics.

The 2025 System of National (SNA25) recognizes the role AI as a transformative technology simply by including classification of AI as a distinct type of software. However, there are many acknowledged challenges in reflecting adequately AI activities and assets in economic statistics, beyond basic data collection, including asset valuation, the construction of price deflators, and depreciation methods. Beyond these issues, broader questions remain about how to measure AI's direct and indirect effects on output, productivity, and welfare, particularly given the platform-mediated, rapid, and potentially transformative diffusion of a general-purpose technology.

While we acknowledge the difficulties of capturing AI as an asset and the implications for wealth and capital flow accounting, this will not be the highlight of this chapter. Rather, we focus on the measurement of AI's transformation of economic structures. We will discuss measurement along the entire AI 'supply chain': inputs to AI across the stack; AI outputs; the measurement challenges transformative AI creates across the rest of the economy; transformation of business processes; transformation of work and consumption; and hence the measurement of productivity and welfare. Many of these issues are not conceptually new (although some are), but they will be exacerbated by transformative AI. Our intention is to identify what economic statistics could reveal as AI becomes transformative.

1. What is the measurement problem?

The adoption of large language models (LLMs) has become increasingly widespread, spanning a broad range of applications: from professional tasks such as drafting emails and generating presentations, to everyday activities like travel or meal planning. As generative AI technologies and applications continue to evolve, their usage is expected to expand significantly. To what extent are official macroeconomic aggregates, such as GDP and productivity statistics, capable of capturing the value provided by AI? The answer is that they will serve poorly: conventional economic statistics tell the story of transformation only with long lags, as classifications, data gathering and even concepts need updating to reflect fully the reshaped economy.

In principle, many AI-related services are recorded in official statistics through observable market transactions, such as subscription fees or usage-based payments via application programming interfaces (APIs). However, the widespread availability of "free" services offered by AI providers complicates the measurement of the value generated for users. For instance, as of May 2025, OpenAI reports approximately 15.5 million subscribers to its standard paid service.¹ This suggests that only a small

¹ See https://nerdynav.com/chatgpt-statistics/?utm_source=chatgpt.com and <https://www.theinformation.com/articles/chatgpt-subscribers-nearly-tripled-to-15-5-million-in-2024>

proportion—around 3%—of its estimated 400 million weekly active users are directly contributing to measured market output, with the remaining 97% accessing free versions. While it can be argued that the costs of providing services to free users are subsidized by paying customers, as in the case for most multisided platforms, the standard macroeconomic accounting framework would not explicitly reflect those transactions on the side of household consumption, which would limit any analysis seeking to measure the benefits of AI to consumers.

This problem is not new to economic measurement. Similar challenges have long existed in the treatment of digital services provided at zero monetary cost to consumers, such as search engines, social media platforms, and open-source software. While these services generate significant consumer benefits and enable productivity-enhancing activities, they are generally not explicitly accounted for on the consumption side of the national accounts due to the absence of market transactions with their users. The growing prevalence of generative AI will only exacerbate this gap.

Several solutions have been proposed, including recording the cost-of-service provision as part of final consumption, employing stated preference and binary choice experiments, and using market prices of paid services as proxies for the value of free versions (Coyle 2025). Most of these approaches are designed to capture the value received by households from the consumption of digital services. However, one of the most significant promises of AI lies in its potential to enhance workplace efficiency and transform production processes across a wide range of industries. In this case, AI services are consumed by firms as intermediate inputs. This will affect the construction of input-output and supply and use tables. These tables tracing outputs from one set of industries as inputs used by other industries are useful for the analysis of structural changes such as the shift from manufacturing to services (United Nations Department of Economic and Social Affairs 2018). This also poses challenges in terms of examining how the tech sector impacts other industries, or their so-called “forward linkages”. But the use of generative AI will not necessarily be captured in the input-output framework as it will change processes as much as the inputs and outputs. For example, a business might continue to purchase AI-enabled accountancy or legal services in the process of producing its own AI-assisted pharmaceutical products. The input-output relationship will not necessarily show the transformation, but rather, eventually, its consequences. By analogy, the arrival of steam engines enabled the factory system, but input output tables (had they existed at the time) would have shown increased volumes over time of both steam engines (as an input) and cotton (as an output) without rendering visible the transformation in the mode of production. For that, a count of factory construction and urban textile workers would be important complements.

However, a first step will be using administrative data or transactions data to understand what AI services are being purchased – a useful task for statistical agencies as this is not yet systematically collected – and data on categories of AI usage – likely to be provided by the major generative AI service suppliers. At present, the classifications in official statistics are insufficiently fine-grained to separate out AI; and although there are some one-off surveys on AI usage, these are not yet regular enough to monitor change. For instance, while the Management and Expectations Survey (MES) by the Office for National Statistics started including questions on AI adoption in its most recent round, this survey is only conducted every three years. The UK’s Department for Science, Innovation and Technology (DSIT) also conducted a survey adoption survey on UK firms, but there is no guarantee that this survey will be conducted on a regular basis (see Table 1). Furthermore, these surveys do not attempt to capture the value of AI services received by the firm. They merely identify whether firms report adopting AI, without providing details on

expenditure – a requirement for estimating the value of AI as intermediate inputs – or types of usage, needed to understand the transformation of production.

Table 1: Rates of AI adoption by industry, UK

	AI Not applicable		Not Using AI		Using and Testing AI	
	MES	DSIT	MES	DSIT	MES	DSIT
Agriculture, Mining, Manufacturing, & Utilities	64%	53%	21%	31%	14%	16%
Construction	74%	65%	14%	24%	12%	11%
Distribution, hotels & restaurants	65%	61%	19%	27%	16%	12%
Transport, storage, & communication	46%	35%	20%	31%	34%	34%
Finance, Real Estate, and Business Services	49%	38%	23%	35%	29%	27%
Other services	60%	53%	20%	32%	20%	15%
Total	60%	51%	20%	30%	20%	19%

Note: Table compares the rates of AI adoption by aggregate industry classifications based on the 2023 Management Expectation of the Office for National Statistics and AI adoption survey conducted by the UK's Department for Science, Innovation and Technology in 2024. Shares were calculated by the authors using unweighted counts for comparability.

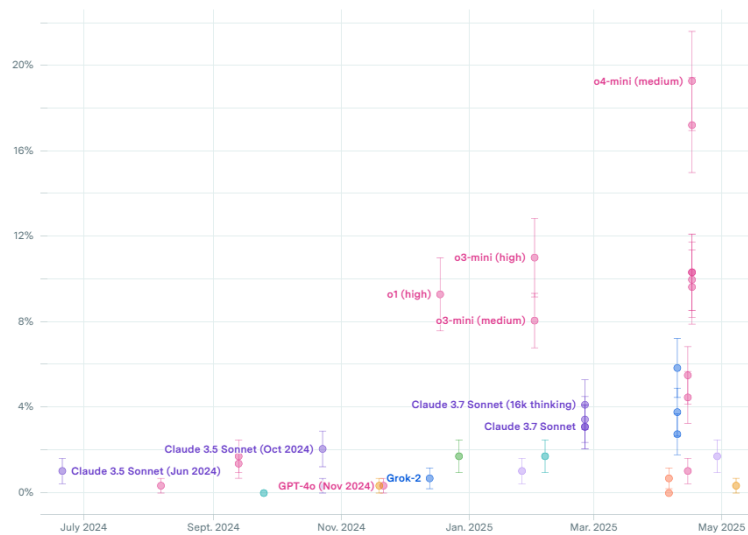
Beyond valuation challenges, the nature of AI products also complicates any efforts to account for AI services as intermediate inputs. LLMs are increasingly embedded in existing software products such as Microsoft Office and Adobe Acrobat. This integration can be viewed as a form of quality improvement, which should ideally be captured through adjustments to price deflators. However, this still fails to address the core issue: official statistics do not adequately reflect the flow of AI services across industries. The problem is compounded by the widespread embedding of AI functions in digital tools such as search engines (e.g. Google), coding platforms (e.g. GitHub), and collaborative environments (e.g. Overleaf) whose *usage* is largely not reflected as industry inputs in macroeconomic aggregates.

While it may be possible to infer AI's macroeconomic footprint from trends in software investment, software R&D, or TFP gains, from a policy perspective there is value in explicitly capturing AI services within the national statistics. Recognising AI services as intermediate inputs would provide timely indicators of sectoral diffusion and usage patterns, improve attribution in productivity analysis. Explicit accounting would involve greater data collection effort but would allow for the development of statistical framework that are more reflective of real-world industry dynamics.

These difficulties in accounting for AI services as intermediate inputs are further compounded by the growing capability of generative AI to produce creative outputs and other intellectual property that may themselves be capitalized. Examples include software, design assets, written content, and audiovisual materials—all of which can now be generated rapidly and at scale, often with minimal human intervention. This is already happening to some degree, for example with multinationals like Coca-Cola using AI Art as part of its advertising strategy (Marr 2023). One can easily imagine that this could be extended to AI-generated advertising jingles, and perhaps, full movies (or entire seasons of television series) generated by AI. It is simply unclear how to account for such phenomena in the current national accounts framework.

Traditionally, such creative outputs used in production over several periods are treated as capital formation and valued either at production cost or market price. However, AI-generated content is frequently produced at near-zero marginal cost to the user, undermining the validity of cost-based valuation methods. Market-based approaches are equally problematic, particularly given the ambiguity in defining the unit of output and the highly context-specific nature of valuation. For example, what constitutes the unit of measure for a song? Its duration? Complexity? Should AI-generated songs be valued on par with works by established artists like Taylor Swift or Oasis? What if the melody is the same as any other Oasis song?

Figure 1: AI performance on a set of expert-level mathematics problems



Source: *epoch.ai*

Lastly, even AI services that are currently captured through market transactions can pose significant measurement challenges due to rapid quality improvements. Many AI systems improve through continued use, user feedback, and fine-tuning, leading to substantial gains in performance over time without corresponding changes in price. Figure 1 shows how fast popular LLMs have improved in the past year. This dynamic complicates the application of traditional price deflators, which often assume stable product characteristics or rely on observable input costs (Coyle 2024). When AI-enhanced services deliver greater value to users—through increased accuracy, speed, or adaptability—without proportional increases in revenue, real output may be systematically underestimated. This is particularly problematic in sectors where AI is embedded within existing workflows or platforms, making it extremely difficult to isolate and adjust for quality changes. As a result, standard methods for deflating nominal output may fail to capture the true productivity gains associated with AI. Addressing this will likely require the development of new adjustment techniques or alternative indicators that better reflect the evolving nature of AI-driven services.

Given the limitations of the conventional statistical framework, this chapter goes on to consider alternative approaches to measuring the impact of transformative AI, using the concept of the AI value chain as an organizing structure. One of our messages is that no single lens on AI will make visible the whole picture of the transformation.

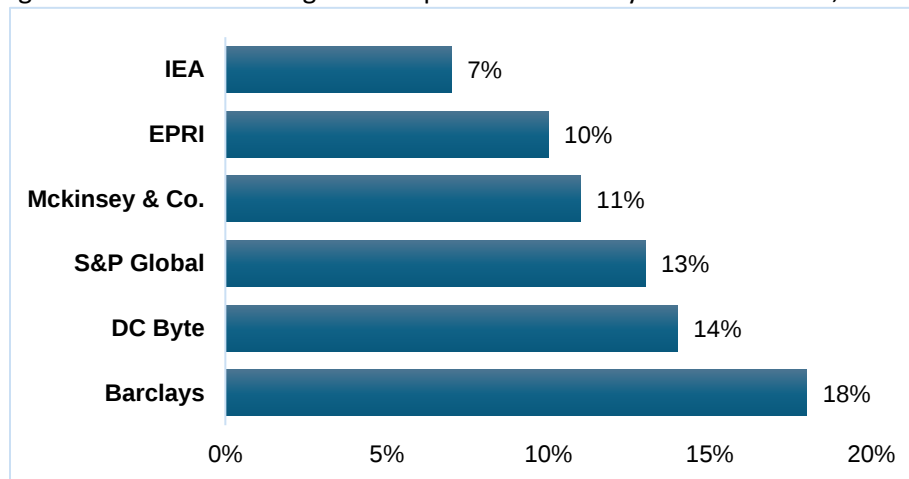
2. Accounting for AI Inputs

Much like the challenges associated with measuring AI services, accounting for the inputs to AI production itself will present significant difficulties for official statistics. AI systems differ from traditional assets in that their development and deployment rely on a complex mix of inputs. This includes large-scale computing infrastructure, specialized software, vast datasets, and ongoing human and organizational resources. These inputs have high upfront costs, are often intangible, distributed across borders, and subject to rapid technological change.

Large-scale investment in ‘hard’ infrastructure such as data centers, chips, network equipment, alongside as software and intangibles such as R&D is essential for enabling the continuing deployment of AI technologies. Accurately measuring some of these inputs, however, presents several challenges.

One key issue is the geographic dispersion of AI infrastructure. The data centers supporting training and inference may be located across multiple countries, making it difficult to attribute investment and productive capacity to specific national economies. A significant challenge for policymakers is understanding the extent to which national AI systems are exposed to foreign supply chains, especially if they consider AI systems as part of national critical infrastructure. Addressing this issue requires substantial improvements in the granularity and collection of trade statistics, as well as the development of multiregional input-output (MRIO) tables and capital flow accounts that can capture the complex, cross-border nature of AI-related investment and production.

Figure 2: Forecast annual growth in power demand by US data centres, to 2030



Source: “AI revolution: Meeting massive AI infrastructure demands” by Barclays Investment Bank (2024)

The operation of AI systems also requires a substantial amount of energy. AI models consume significantly more electricity than conventional digital services. Queries often require up to ten times more energy than a standard web search. The infrastructure underpinning AI, particularly large data centers, demands continuous and reliable power supply. Even training AI models require a substantial amount of power. Analysts estimate a 7% to 18% annual increase in energy demand due to US AI data centers (figure 2). Future innovation in both chip design and AI development will likely head in the direction of economizing

on energy (and water) use; but meanwhile the readily-measured output of electricity at national level is a useful indicator of AI usage.

Mitu and Mitu (2024) highlight that both the training and inference phases of AI entail high energy use, with training a single large-scale model producing hundreds of metric tons of CO₂ equivalent emissions. The environmental costs of AI are not all borne where AI services are consumed but where infrastructure is located and its energy generated. Yet, environmental accounting remains predominantly a national exercise. This misalignment challenges standard environmental accounting practices, and pushes us to a more cooperative effort to account for these externalities. The same issues apply to water use as well, used for cooling data centers (OECD.AI 2024). The “design of global accounts that incorporate data within and beyond national jurisdictions”, is included as part the research agenda of the SEEA Ecosystem Accounting (SEEA EA) framework (2021). As AI continues to scale globally, there is an even more pressing need to reconsider how national statistical systems track transboundary energy use and emissions, and to develop frameworks that better reflect the spatially distributed nature of digital technologies. There are already ongoing efforts. For instance, OECD’s inter-country input-output tables,² the European Commission’s Exiobase,³ the EU’s FIGARO⁴ (Full International and Global Accounts for Research in Input-Output Analysis) extends the MRIO framework for their member countries (and major trading partners in the case of FIGARO) to account for environmental flows, such as greenhouse gas emissions, energy, and water. A more global effort include those by the Global Trade Analysis Project⁵ (GTAP) MRIO by Purdue University, as well as the EORA MRIO⁶ by the University of Sydney with support from UNCTAD and World Bank. Accounting for the environmental impacts of AI will require harmonizing these approaches and updating them regularly to provide a timely indicator of AI’s environmental cost. One possible direction is the development of dedicated satellite accounts on the environmental footprint of AI,

On the labor input side, existing official data generally do not have details granular enough to distinguish engineers and other skilled talent working to produce and operate AI systems. Classifying AI-related occupations raises fundamental challenge, since AI work cuts across traditional occupational groupings. These roles often combine skills in software engineering, data science, and domain-specific knowledge. Moreover, AI development is frequently embedded in broader digital transformation roles, making it difficult to isolate in standard occupational classifications. Recent efforts, such as Calvino et al. (2024), attempt to measure industry exposure to AI human capital by analyzing job vacancy data using keyword-based classification. While innovative, these approaches are limited by the availability and representativeness of job postings (Saad et al. 2023; Vassilev, Romanko, and Evans 2021; Ao et al. 2023; Carnevale, Jayasundera, and Repnikov 2014). It also assumes that listings accurately reflect the skills required in practice. For example, in some instances vacancies listings claim a requirement for multiple programming skills for a role that primarily involves spreadsheet work.

Moving forward, addressing this measurement gap may require improvements to labor force surveys, including more detailed questions about work tasks, time devoted to tasks, and technologies used, as well as triangulation with complementary sources such as time use data, administrative records, and employer surveys. Online professional platforms like LinkedIn, which contain rich, self-reported information on skills, job titles, end employers, may also offer valuable insights into the AI-related labor force, particularly when

² See <https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html>

³ See <https://www.eea.europa.eu/data-and-maps/data/external/exiobase>

⁴ See <https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/database>

⁵ See <https://www.gtap.agecon.purdue.edu/>

⁶ See <https://worldmrio.com/>

text-based analysis of this kind can be combined with traditional survey data. There are already ongoing efforts similar this. For instance, Ramraj, Sivakumar, and others (2020) and Liu et al. (2019) developed occupational classifications using LinkedIn data. More recently, the company itself⁷ released a report examining the impact of AI on European workforce. These efforts would help build a more comprehensive picture of the human capital supporting AI production (and operation) and provide more accurate assessments of skill gaps and labor market dynamics. A future challenge as AI diffuses will be identifying the relevant workers; at present, the number of businesses involved in AI production is relatively small, certainly at the technology frontier. The AI-producing sector will grow over time, and will encompass specialist producers as well as those producing general models. One possibility is to go a step back in the human capital chain and look at the number of PhDs being granted in AI-related fields. Perhaps a more comprehensive approach would be to trace the broader set of activities and institutions involved in AI knowledge production, linking data on grants, publications, patents, and career transitions to map how talent, ideas, and capabilities accumulate and flow across sectors and over time (Lane 2023).

Lastly, AI considerably complicates standard ways of accounting for data inputs. The 2025 SNA recommends that data henceforth be recorded as an asset. Like many intangibles, there are significant measurement challenges. One key question for this exercise is how to value data. Coyle and Manley (2023) provide a review of possible approaches to valuing data. The Inter-secretariat Working Group on National Accounts (ISWGNA), however, recommended the use the sum of cost for the valuation of data assets (United Nations Statistics Division, n.d.). According to the ISWGNA, the cost of data production includes labor, intermediate inputs, capital consumption, and, for market producers, a mark-up reflecting the expected future profitability of the data. Currently, this sum-of-costs approach is regarded as the most feasible method for valuing data assets within official statistics, as noted by the ISWGNA and the OECD (Organisation for Economic Co-operation and Development 2015; 2022). This approach is consistent with how other own-account intangibles, such as R&D, are estimated.

This approach is far from perfect. First, measuring returns to capital is not straight forward. Typically, compilers of the National Accounts estimate *gross* returns to capital as a residual, derived by deducting labor cost, taxes (net of subsidies), and intermediate inputs, from the gross output. In the case of data production, however, gross output is not directly observable, especially when data is used internally rather than sold on the market.. Moreover, generative AI is itself starting to reduce data costs substantially, for example making it easier and faster to use unstructured data; sum of costs approaches involves an already-outdated assumption of no change in the data production technology.

These challenges are compounded by the fact that the value of data is highly context-dependent, shaped by its intended use, degree of exclusivity, and the algorithms that process it (Coyle and Manley 2024). As AI applications expand and model performance improves, the value of training data changes accordingly. This introduces a circularity, whereby the value of the input (data) is influenced by the value of the output (AI-driven services or products). As AI systems increasingly rely on proprietary and dynamically updated data, accurately measuring the value of data inputs will require more sophisticated methods.

These challenges just underscore the need for further methodological research to improve the valuation of data and other intangible assets in the context of national accounting. One possible avenue involves the use of experimental or quasi-experimental methods to assess how variations in training data affect model performance, thus allowing analysts to infer the relative economic value of different datasets. Another

⁷ See <https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/PDF/AI-in-the-EU-Report.pdf>

prospect is the development of data exchanges. Although in their infancy, countries from China to the UK⁸ are experimenting with establishing exchanges, which may evolve to deliver market prices for data as the units of data exchanged are standardized. It is notable that there are few existing data markets but those that exist – such as financial data markets or advertising data markets – are built on standardized units.

Any approach will demand interdisciplinary collaboration among economists, statisticians, computer scientists, and other domain experts, as well as data feeds of granular information about the nature, source, and structure of the data used in AI development. Since firms often treat training data as proprietary, it could be difficult to require sufficient information to support this type of empirical evaluation. Developing the practical and legal framework and statistical instruments capable of accounting for these complexities will be essential for improving the measurement of data as a production input and for aligning valuation practices with the realities of modern AI systems.

3. AI outputs and broader Impacts

Perhaps one of the most significant measurement challenges posed by transformative AI is capturing its wide-ranging impact across other industries – which is exactly what is needed to track transformation. For as a general-purpose technology, AI will influence not only productivity levels but also the quality and nature of outputs in a broad array of economic activities. This is particularly evident in sectors such as healthcare, finance, education, and creative industries, where AI is rapidly improving service delivery, diagnostic accuracy, content generation, and personalization. In many cases, these developments alter the structure of economic activities themselves—what constitutes “instruction,” “care,” or “creative work” may shift—posing challenges for established statistical classifications and production boundaries. Tasks will change as new ones are created, and the processes in which they are embedded will change too. Importantly, many of these challenges are not entirely new: the measurement of quality change, service innovation, and intangible outputs has long been a known difficulty in national accounts. However, the rapid and pervasive deployment of AI technologies significantly amplifies their scope and urgency.

A central difficulty lies in measuring changes in product and service quality. Traditional deflators and output measures are typically constructed to capture changes in quantity or price, not in functionality or user experience. In healthcare, for instance, AI-assisted diagnostics and predictive models can improve outcomes and reduce errors, leading to real welfare gains without proportionate changes in observable inputs or expenditures. There is already systematic evidence to how AI is making a difference in various areas in the health sector (Ullah and Ali 2025; Choudhury and Asan 2020; Koo et al. 2024; Ayorinde et al. 2024). However, output in this sector is often measured using cost or revenue data, which does not necessarily reflect improvements in quality. As a result, advances due to AI, such as greater diagnostic accuracy or more effective interventions, may go unmeasured.

Similar dynamics are evident in consumer services: AI-powered chatbots, recommendation engines, and virtual assistants enhance convenience, responsiveness, and customization. The nominal value of service output is often measured using firm revenues. In the national accounts, changes in quality should be treated as part of volume change. So, to arrive at estimates of real output, the price index needs to be adjusted for changes in quality. National statistical institutes try to account for this using matched models and hedonic approaches. While the practical implementation of these techniques is rarely straightforward, they are more often applied to goods whose product characteristics are observable and relatively stable (such as cars). AI services quality improvements will be intangible and rapidly evolving. This makes it much

⁸ See <https://www.gov.uk/government/publications/industrial-strategy>

harder to identify consistent attributes for adjustment. As discussed in the previous section, the same issue is present for software enhanced by LLMs. Quality adjustment would be necessary for the compilation of more accurate capital accounts tables, and by extension, productivity statistics.

There is virtually no work in this area within official statistics, leaving a growing gap between the lived experience of service enhancements and how they are captured in economic data (Coyle 2025). One practical way to address this is by leveraging big data sources—such as marketing analytics, platform usage metrics, and consumer sentiment—to construct indicators of perceived quality improvement. This is particularly important now, as AI increasingly drives value through enhancements of user experience will not appear in official statistics. This implies the need to experiment with novel approaches to developing quality-adjusted price indices, building on prior work, for example using web scraped prices and scanner data (Feenstra and Shapiro 2007; Ivancic, Diewert, and Fox 2011; Białek and Beręsewicz 2021; De Haan and Krsinich 2014).

Moreover, while AI can drive significant quality improvements, it also generates new externalities that are not accounted for in existing frameworks. These include negative externalities, such as algorithmic discrimination, which could trickle down to pricing. Varian (2018) explains that the wide spread use of AI provides opportunities to adjust prices based on customer characteristics. Greater personalization will prove problematic for the standard approach.

Statistical agencies already struggle to capture price changes when they vary based on individual consumer characteristics rather than broader categories like age or geographic location. For example, if an airline tailors ticket prices according to a user’s browsing history or online behavior, determining a consistent “average” price becomes difficult. This personalization complicates the construction of price indices and can introduce systematic biases into inflation measurement. As a result, official statistics may fail to reflect actual changes in the cost of living, while inadequate quality-adjusted deflators will likely understate real output in sectors using AI.

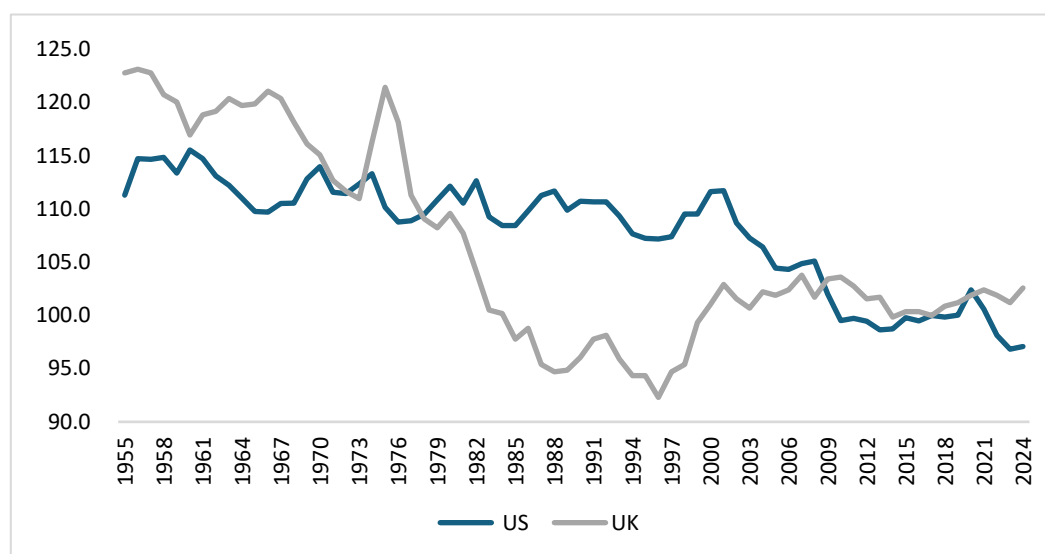
In areas of the public sector, where outputs are often in any case valued by the cost of inputs, the diffusion of AI could lead to significant underestimation of value. AI-enabled tools in services such as education, welfare administration, and policing can improve personalization, save time by reducing administrative burden, and enhance citizen engagement (Smith 2024; Local Government Association 2025). As AI continues to diffuse across the public sector, there is a growing need to strengthen efforts to adjust public service output to account for quality improvements. While there is already ongoing work in this area—particularly in sectors like education and health—the focus has often remained on quantifying outputs rather than evaluating outcomes. Yet, many of the benefits of AI in public services stem from enhanced effectiveness rather than increased volume. For example, better targeting in welfare programs or improved decision-making in policing may not immediately translate into more services delivered, but rather into more impactful services. Developing metrics that reflect these outcome-based improvements is essential to ensure that national accounts and productivity statistics adequately capture the public value created by AI-driven innovations.

4. Process changes

The rise of transformative AI is expected to significantly alter how production takes place, particularly by reshaping the complementarities between labor and capital. Traditional growth accounting frameworks rely on relatively stable distinctions between capital services, labor input, and total factor productivity, as well as a relatively stable production function. However, as AI systems increasingly substitute or augment

human tasks—particularly in knowledge-intensive and service sectors—the conventional separation between labor and capital becomes blurred. AI infrastructure, once developed and deployed, can deliver productive services across firms and sectors without a corresponding increase in measured labor input. This makes it difficult to attribute output growth accurately to specific input contributions, leading to potential distortions in productivity measurement.

Figure 5. Labor share index (2019 = 100) for the US and the UK



Source: Federal Reserve Economic Data and the UK's Office for National Statistics

From a macroeconomic perspective, this highlights the need to pay close attention to the labor share. The labor share has fallen significantly since the 1950's (see figure 4) and remained stable in recent decades. This is largely consistent with the one the stylized facts identified by Kaldor (1957) for industrialized countries. As firms increasingly adopt AI systems that perform tasks once done by workers, the value created may shift toward capital income, especially if the AI systems are owned and operated in-house. This would manifest as a further decline in labor's share. There is already early evidence showing this. Using AI patent data, in a very recent paper Minniti and co-authors (2025) shows that regional AI innovation is strongly associated with declines in regional labor shares. A review by Trammell and Korinek (2023) further supports this pattern, highlighting theoretical and mechanisms that advanced AI may lead to capital-biased technological change, where the gains from automation accrue disproportionately to the owners of capital. This shift has important implications for income distribution and macroeconomic dynamics, raising the need to keep an eye on the labor share.

This shift is already manifesting in various sectors. For example, the rollout of driverless taxis and autonomous delivery vehicles replaces human drivers with capital-intensive AI systems, transferring income from labor to firms that own the underlying technology. In media and marketing, generative AI tools are increasingly being used to create content that was once produced by freelance writers, designers, or voice actors. In each case, tasks previously performed by workers are automated, but the value they generate remains within the firm, often without corresponding increases in measured employment or wages.

It is important to note that in most of these cases, the tasks themselves remain largely unchanged; it is the factors of production that are shifting. This highlights the need to collect and analyze task-based information to better understand how work is being reorganized across sectors, even when job titles or output metrics appear stable. The descriptors of tasks will need to be updated as the AI transformation progresses.

However, the way in which tasks are organized will also change. Consider, for example, a news organization where the traditional production function involved numerous reporters and writers generating content. With the introduction of generative AI, much of the writing can now be automated (Thomson Reuters Foundation 2025), leaving a smaller number of editors to curate, refine, or fact-check the output, in an altered workflow, and with the introduction of the new factor of data. Similarly, in higher education, tasks such as exam marking—to date largely performed by humans—could soon be handled by AI tools (Gobrecht et al. 2024; Codiste Pvt. Ltd. 2024), with human oversight limited to final review. In both cases, the task is still being performed, but by a different mix of inputs combined in a different organizational ‘technology’. Job and task classifications will fail to capture such reconfigurations, when content and process of work has been fundamentally altered.

Table 2: Standard Occupational Classification (SOC) 2020 for Media professionals

249	Media professionals
2491	Newspaper, periodical and broadcast editors
249100	Newspaper, periodical and broadcast editors
2492	Newspaper and periodical broadcast journalists and reporters
249201	Broadcast journalists
249202	Newspaper journalists and reporters
249299	Newspaper and periodical broadcast journalists and reporters n.e.c.

Source: Office for National Statistics

A news organization may choose to hire fewer reporters, resulting in a recorded decline in individuals classified under occupation code 249202 (Journalists and Newspaper Editors (see Table 2). However, many of the tasks once carried out by junior writers, such as drafting routine articles, are now being performed by AI systems, with a smaller team of editors overseeing, curating, and refining the output. While the occupational title remains the same, the nature of the job and production process in which individuals work change significantly. There is a shift in skill requirements, from content generation to editorial judgement, fact-checking, and prompt engineering. To address this, improvements in time-use surveys and job task mapping are needed to track how AI is redistributing effort within occupations and across sectors. These shifts could happen fast, certainly faster than statistical agencies historically are able to adjust. New data sources will need to be sought, while time use at work seems a useful measure to try to collect.

Transformative AI could also reshape business models by shifting the source of efficiency gains away from traditional inputs like labor and physical capital toward algorithmic decision-making, predictive analytics, and autonomous systems. These innovations would enable firms to streamline operations, reduce error rates, and optimize resource allocation in ways that do not necessarily require expanding the workforce or physical infrastructure. As a result, much of the value generated through AI adoption may be realized

through internal process improvements such as faster turnaround times, better inventory management, or reduced downtime rather than through directly observable increases in output or revenue.

For example, major firms across sectors are already realizing AI-driven efficiency gains through internal process changes (De Silva 2025). UPS has deployed large language models to automate customer service interactions and is exploring robotics to streamline parcel handling. Walmart and Target use AI systems to forecast demand and optimize inventory, reducing stockouts and improving replenishment accuracy without increasing headcount. Qantas has implemented AI to optimize flight routes, achieving significant fuel savings through better scheduling and resource use (The Australian 2023). In standard macroeconomic accounting, these improvements are typically captured as changes in Multi-Factor Productivity (MFP), which is measured as a residual after accounting for labor and capital inputs. However, because MFP is a residual, it provides limited insight into the underlying drivers of productivity gains, and would also lag the changes occurring in the economy. From a policy standpoint, it is therefore important to identify and quantify the specific mechanisms through which AI enhances efficiency.

Lastly, the diffusion of transformative AI may aggravate the paradox of efficiency, wherein aggregate measured output may decline even as economic welfare increases. This arises because many of AI's most substantial benefits involve eliminating inefficiencies and compressing formerly labor-intensive or time-consuming processes. Activities such as scheduling, customer support, document verification, and various administrative services, previously intermediated by layers of personnel or procedural steps, can now be automated or streamlined by AI systems. These activities, while inefficient, contributed to measured growth through market transactions or employment. When AI renders them obsolete, their disappearance can result in a decline in measured output, despite the fact that services are being delivered more effectively and with lower resource use.

This is particularly problematic for the national accounting, which are designed to quantify production rather than welfare. To illustrate, if AI allows patients to access accurate medical triage via a chatbot instead of visiting a clinic, the recorded market output may be lower, even if the health outcome is the same or improved. Similarly, a legal firm using AI to draft contracts in minutes rather than billable hours may report lower revenues, even though clients receive faster and equally valid services. These kinds of shifts compress economic activity into more efficient forms but reduce the observable monetary flows that underpin GDP and productivity statistics. As a result, improvements in consumer surplus, time savings, and service accessibility may go unmeasured or be misclassified as economic decline. Hulten and Nakamura (2017) describes this as output-saving technical change. Given that current official statistics have failed to capture the digital transformation of the economy to date, the AI transformation will exacerbate their shortcomings. New approaches to measurement will be needed. While general equilibrium effects may eventually raise total output, the short-run impact may be a decoupling of welfare improvements and measured output, reflecting a known limitation of GDP as a welfare indicator rather than a paradox of productivity itself.

5. Time

One of these will be capturing the time savings enabled by AI. The process improvements that have historically driven dramatic productivity gains have often involved speeding up production – from sailing my steam instead of wind to the just-in-time automation revolution in manufacturing.

AI's automation capabilities have the potential to reshape not only the processes of production but also the allocation and experience of time across work, leisure, and consumption. By reducing the need for

human intervention in routine or repetitive tasks, AI systems can significantly lower the time input required for both market and non-market activities. These time savings, while often difficult to quantify, represent a core channel through which AI contributes to productivity growth and economic welfare. Likewise, the welfare benefits of AI may be most visible in how it alters people's use of time, especially in terms of reduced administrative burden, faster service delivery, and more efficient decision-making

Ha-Joon Chang (2010) argued that the washing machine changed the world more than the internet, directly altering how people, especially women, spent their time. The broader point is that technological progress should be evaluated not only by its market output, but by how it transforms everyday life and reconfigures human activity. AI may follow a similar trajectory. AI promises large time savings in cognitive, administrative, and logistical tasks—both in professional settings (e.g. automating emails, scheduling, customer queries) and personal life (e.g. travel planning, content filtering, personal finance). This creates new possibilities for reallocating time toward higher-value tasks, leisure, or care work, with substantial implications for labor markets, gender dynamics, and well-being. AI is now doing the same for white-collar and knowledge-intensive sectors.

One of the more profound implications of AI lies in its potential to free people from routine cognitive tasks, creating space for higher-order thinking, creativity, and innovation. By automating repetitive workflows such as data cleaning, literature searches, or coding routines, AI can shift the focus of knowledge workers toward more conceptual and strategic activities. For instance, an economist who previously spent considerable time writing and debugging code can now use AI tools to automate much of that work, allowing more time to refine econometric models, explore alternative specifications, or develop new theoretical insights. This reallocation of cognitive effort echoes historical shifts in manual labor, where mechanization freed workers to engage in more skilled or supervisory roles.

From a measurement standpoint, this presents a challenge in capturing the shift from routine to higher-order cognitive work. Traditional labor metrics, such as hours worked or employment counts, may remain unchanged even as the nature of tasks evolves significantly. Time use surveys offer one avenue for incorporating these effects, but they are often infrequent, coarse, and disconnected from production statistics. A richer integration of time-use data into economic measurement—particularly with respect to digital service provision, remote work, and task automation—could help to better reflect the welfare gains generated by AI.

On the household side, AI is already enhancing domestic efficiency in mundane tasks, and future advancements suggest even greater transformation. Today's AI-powered vacuum cleaners can not only clean but also intelligently identify and pick up small items, adapting to changing environments (Business Insider 2024). Within households, emerging humanoid robots are being deployed in trial homes to assist with chores and provide companionship, marking a shift toward more generalist robotic helpers (Johnson 2024; Vincent 2024). Other efforts are pushing robots toward more sophisticated, whole-body manipulation capable of tasks such as folding laundry or organizing rooms (Jiang et al. 2025). Looking ahead, these household robots promise to take on a broader variety of home production activities freeing up significant time for occupants.

To better capture the welfare gains from these advancements, it will be important to develop dedicated measures of household productivity. As AI and robotics begin to substitute for human effort in home production, traditional approaches to valuing unpaid work such as the replacement cost method, which uses equivalent market wages may no longer be sufficient. One of the key features of current household satellite accounts is their reliance on labor-based valuation, implicitly assuming that household output is

primarily driven by human input. However, as returns to capital would begin to account for a larger share of value added in this area. This mirrors the challenge discussed earlier in valuing own-account data in section 2.

Accounting for the full extent of time-related welfare gains enabled by AI, traditional statistical sources will need to be supplemented with alternative data. Conventional time-use surveys are often conducted infrequently and lack the granularity needed to track real-time changes in behavior induced by AI. However, new forms of digital trace data such as geolocation, activity logs, and interaction timestamps offer valuable potential for understanding how time is reallocated across tasks, sectors, and social groups. For instance, anonymized data from platforms like Google Maps could help measure changes in commuting time, reflecting shifts in work patterns enabled by remote work technologies and AI scheduling tools. Similarly, metadata from app usage, wearable devices, or smart assistants could offer novel indicators of task duration, intensity, and frequency.

Social media content and other user-generated data sources can also provide indirect evidence of changing time use and consumption preferences. While not without methodological challenges (including biases in representation) this type of data can shed light on how individuals experience time savings or respond to AI-enabled service enhancements. For example, scraping content related to healthcare appointments, customer service experiences, or online learning platforms could provide qualitative and quantitative insights into where AI is making processes faster or more accessible.

Many of the most relevant data are held by private technology firms whose AI products generate large-scale behavioral data across users and contexts. Carefully governed data-sharing partnerships between tech firms and national statistical agencies could provide a mutually beneficial model for expanding measurement capabilities. Such collaborations could offer insights into aggregate time patterns without compromising user privacy, especially if standardized APIs and anonymization protocols are used. These efforts would allow for the development of new indicators that track time efficiency, service responsiveness, and other dimensions of AI-enabled productivity, thus helping to bridge the gap between welfare gains and official economic statistics. As AI continues to reshape the temporal organization of the economy, incorporating these alternative data sources will be essential for a more complete and timely understanding of its impact.

6. Final remarks

This chapter has outlined some of the key challenges that transformative AI poses for economic measurement. As AI reshapes production, services, and household activities, it complicates the valuation of intangibles, the attribution of productivity gains, and the classification of labor and capital inputs. While efforts such as recognizing data as an asset and the highlighting of AI as a distinct type of software in the 2025 SNA revision are small steps in the right direction, official statistical frameworks will struggle to capture the full scope of AI's impact. Moving forward, more granular, task-based, and outcome-oriented measures will be essential to ensure that statistics remain relevant and informative in an AI-driven economy. This chapter has highlighted key areas where AI is likely to outpace current statistical frameworks.

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