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GENERATIVE AI: RIDING THE NEW GENERAL PURPOSE TECHNOLOGY STORM

Generativni modeli veštačke inteligencije – zauzdati još jednu tehnološku revoluciju

Abstract

Generative AI promises to revolutionize many industries (entertainment, marketing, healthcare, finance, and research) by empowering machines to create new data content inspired by existing data. It experienced exponential growth in recent years. In 2023 breakout year Gen AI impact reached 2.6-4.4 trillion USD (2.5-4.2% of global GDP). The development of modern LLM-based models has been facilitated by improvements in computing power, data availability, and algorithms. These models have diverse applications in text, visual, audio, and code generation across various domains. Leading companies are rapidly deploying Gen AI for strategic decision-making at corporate executive levels. While AI-related risks have been identified, mitigation measures are still in early stages. Leaders in Gen AI adoption anticipate workforce changes and re-skilling needs. Gen AI is primarily used for text functions, big data analysis, and customer services, with the strongest impact in knowledge-based sectors. High-performing AI companies prioritize revenue generation over cost reduction, rapidly expand the use of Gen AI across various business functions, and link business value to organizational performance and structure. There is a notable lack of attention to addressing broader societal risks and the impact on the labor force. Gen AI creates new job opportunities and improves productivity in key areas. Future investment in AI is expected to rise. Concerns about the potential AI singularity, where machines surpass human intelligence, are subject to debate. Some view singularity as a risk, others are more optimistic based on human control and societal constraints. Leading experts in Gen AI predict that the coming decade can be the most prosperous in history if we manage to harness the benefits of Gen AI and control its downside.

Keywords: *AI – artificial intelligence, AI singularity, GPT – generative pre-trained transformers, LLM – large language models, generative AI models, ChatGPT, ML – machine learning*

Sažetak

Generativna VI će revolucionisati mnoge delatnosti (zabavu, marketing, zdravstvo, finansije i istraživanje), omogućavajući mašinama da kreiraju novi sadržaj inspirisan postojećim podacima. Ona je doživela eksponencijalni rast u proteklim godinama. U 2023. prelomnoj godini modeli generativne VI doprineli su 2,6-4,4 triliona USD (2,5-4,2% globalnog BDP-a). Razvoj modernih modela zasnovanih na velikim jezičkim modelima (LLM) omogućen je poboljšanjima u domenu računarske tehnike, dostupnosti podataka i boljih algoritama. Ovi modeli imaju različite primene u generisanju teksta, vizuelnog sadržaja, zvuka i programskog koda u različitim oblastima. Vodeće kompanije brzo uvode generativnu VI za strateško odlučivanje na korporativnom nivou. Iako su već identifikovani rizici povezani sa veštačkom inteligencijom, razvoj mera za njihovo ublažavanje još je u ranoj fazi. Lideri u usvajanju generativne VI očekuju promene u kvalitetu radne snage i potrebe za prekvalifikacijom. Generativna VI se pretežno koristi za generisanje teksta, analizu velikih baza podataka i pružanje korisničkih usluga, sa najjačim uticajem u sektorima zasnovanim na znanju. Kompanije koje uspešno koriste modele VI u svom poslovanju prioritet daju generisanju prihoda u odnosu na smanjenje troškova, brzo šire upotrebu generativne VI na različite poslovne funkcije i povezuju poslovne performanse sa organizacijom i strukturom kompanije. Nedovoljno pažnje posvećuje se uticaju VI na radnu snagu i širim društvenim rizicima. Generativna VI stvara nove mogućnosti za zapošljavanje i poboljšava produktivnost u ključnim oblastima. Očekuje se da će investicije u veštačku inteligenciju rasti u budućnosti. Brige oko potencijalne singularnosti VI, gde mašine prevazilaze ljudsku inteligenciju, predmet su rasprave. Neki vide singularnost kao rizik, dok optimisti veruju u efikasnost ljudske kontrole i društvenih ograničenja. Vodeći stručnjaci predviđaju da za generativnu VI naredna decenija može biti najprosperitetnija u istoriji, ukoliko uspemo da iskoristimo prednosti generativne VI i kontrolišemo njene negativne strane.

Ključne reči: *VI – veštačka inteligencija, VI – singularnost, GPT – generativni unapred obučeni transformatori, LLM – veliki jezički modeli, generativni VI modeli, ChatGPT, ML – mašinsko učenje*

Introduction: The status of AI

Generative Artificial Intelligence (Generative AI or Gen AI) is defined as a subset of AI techniques, tools and models that involve/allow the creation of new data instances (text, images, sounds, music, …) that mimic or are inspired by preexisting data. Unlike traditional AI methods that focus on classification and/or prediction tasks, generative models aim to generate new data content that is indistinguishable from real data. Generative AI models have experienced exponential growth in recent years and have garnered significant attention due to their potential to revolutionize various industries, from entertainment and marketing to healthcare, finance, reasearch, and creative arts. By enabling machines to understand and create content, Generative AI opens up a plethora of opportunities for innovation and creativity.

Artificial Intelligence (AI) and Generative AI (Gen AI) models and tools have been showing unprecedented growth since 2017. A recent survey of Generative AI applications [29] has identified an exponential increase across a wide range of domains. Based on a comprehensive evaluation of more than 350 generative AI applications (as of June 2023), the survey provides a structured taxonomy of unimodal and multimodal generative AIs applicable to text, images, video, gaming, code, and brain information. By now, six months later, the number of similar applications could have doubled, and the number of users is now estimated at more than 200 million.

The explosion of generative AI models has attracted a lot of attention from businesses, governments and the general public, and triggered an enormous debate among tech scientists/specialists and academic researchers (including economists). Based on the latest Global Survey results on the state of Artificial Intelligence (AI), McKinsey [40] has labeled 2023 a breakout year for generative AI's development and application. In a separate report on economic potential of generative AI, McKinsey [41, p. 10] estimates its marginal global economic impact between 2.6 and 4.4 trillion USD for 63 new Gen AI use cases (across 16 business function). In addition, Gen AI is expected to increase labor productivity with a net value added impact of 6.1 to 7.9 trillion USD. When added to the value added contributed by existing AI-based advanced analytics, traditional machine learning, and deep learning, AI is expected to contribute a staggering total of 17.1-25.6 trillion USD (or 16.4-24.5%) to the global GDP (based on IMF forecast for 2023).

Leading world companies and organizations are rapidly deploying generative AI tools (gen AI or GAI), albeit still unevenly across business functions, industries, and locations around the globe.

Substantive improvements and explosive growth in Gen AI models, tools and programs have elevated AI issues from the level of IT and tech employees to the top layers of corporate executives. More than 25% of survey respondents confirm that AI tools are already being used in their boards to guide strategic and operational decisions, and 40% indicate an overall increase in AI investment triggered by recent advances in Gen AI.

AI-related risks are increasingly being identified but it is still too early to assess the quality of risk mitigating measures, even in areas where errors are obvious and relevant (i.e. inaccuracy of gen AI models). Organizations that are more advanced in traditional AI capabilities (high AI performers) are also leaders in adopting new GAI advances, further outpacing other companies. Most respondents anticipate workforce cuts in select areas and large-scale re-skilling/retraining efforts to respond to changing needs caused by GAI.

The expectation that Gen AI may have positive multiplier effects on the adoption of traditional AI tools has not been confirmed by the 2023 survey results: the overall use of traditional AI tools did not follow the gen AI explosion and remained stable and concentrated within a small number of business functions since 2022. The use of GAI tools by senior management levels ranged from 20% in developing and emerging markets to 24% in Europe and 28% in North America. By industry, the leaders are "technology, IT and media" companies with 33%, followed by financial services with 24%, and "business, legal and professional services" with 23% use of GAI tools.

- Most commonly used generative AI tools are modern "text functions" (27%) in producing first drafts and summaries of technical, legal and internal documents and manuals – usually edited and finalized by qualified and experienced humans.

- The second most important area is the use of GAI tools for big data analysis (16%), to establish trends in customer needs and forecast service trends. A great majority of respondents (75%) expect that generative AI will have a significant positive and disruptive impact on their industry competition in the medium run (3 years).
- The third most frequent area for using generative AI tools is in customer-related services (14%), including personalized marketing, chatbots, and similar services.

Given the very nature of generative AI tools focused on language and analytical activities, the survey predicts that the impact will be stronger in sectors relying on knowledge work, leading to increased revenues (+9% in tech industry, +5% in banking and in medical/pharma industries, and +4% in education). Expectedly, manufacturing-based industries will have the least disruptive impact.

The survey shows an amazing speed with which high AI performers have moved from initial considerations of generative AI only a year or two ago to strategic questions of how to advance the use of GAI models across business functions through investment in hardware and software. The focus is now mostly on how to customize learning of GAI models and expand their use in a broader set of core business activities and strategic questions such as:

- defining the future governance and operating models,
- optimal management of third parties including cloud and LLM providers,
- managing a wide range of risks,
- understanding the implications of technological change on people and tech stack, and
- reaching clarity about finding the balance between near-term gains and developing long-term foundations needed to scale up.

On the downside, most respondents indicate that almost 80% of participating organizations are not yet adequately addressing potential risks of generative AI. Very few companies have developed clear policies governing the use of gen AI, and even when they have, the policies often took a narrow focus on protecting company's proprietary information (such as data, knowledge, intellectual property rights). Broader social, humanitarian and environmental risks, as well as unintended consequences of gen AI, have either been superficially addressed or ignored.

Despite huge public interest in the employment consequences of AI, only 34% of survey participants considered the impact of AI on labor force (displacement) to be a relevant organizational risk, and mere 13% indicated that their companies are working on mitigating that socially important risk.

Survey [40] shows that AI high performers (i.e. companies that attribute more than 1/5 of their profits to AI use) are using gen and traditional AI in growing number of business functions (product and service development and cycle-management, risk and supply chain management, modernizing products and enhancing services by adding new AI features, HR and performance management, and workforce deployment optimization). Most importantly, the top objective among traditional AI users is "core business cost reduction" (often through automation which leads to labor displacement), while the top objective among high gen AI performers is to create new lines of business and sources of revenue within which the existing product/service mix will get a higher valuation (i.e. profitability).

Gen AI has become an endogenous part of the AI high performing companies, and their main challenges lie in the further development of their own "AI models and tools" (24% of answers) and "the adoption and scaling" of AI models (19%). By contrast, traditional companies still debate how to use gen AI models (AI strategy received 24% of the answers) and pay much less attention to developing own "models and tools" (only 6%) and somewhat less to "adoption and scaling" (15%) of third party AI models. It should be noted, though, that even high AI performers use gen AI components (blocks and whole programs) developed by specialized companies whenever possible (35% of answers compared to 19% for traditional companies).

Comparison of McKinsey survey results over the past six years shows that high AI performers also tend to be more strategic in identifying key factors of success that allow them to stay focused on value and rewiring (restructuring) their organizations to capture that value.

The reason seems straightforward: The search for high-value opportunities for (both generative and traditional) AI models across all business domains acts as a diagnostic tool and reveals where the “value” is and will be in the future, as well as the structural organizational rigidities that stand in the way of optimally capturing the identified value. In other words, survey results confirm that high AI performers are also leaders in linking business “value” (profit in the broadest sense) to performance and to business organization and structure.

With Generative AI models and tools, company structure (organization) becomes endogenous in its technological and HR part. High AI performers do not necessarily focus on reduction in labor as part of cost minimization, but on matching skills to needs driven by value. Few years ago AI growth led to a predictable increase in the demand for and shortage of data, machine learning and AI engineers and scientists. Last year, survey respondents indicate a 25% drop in the difficulty of finding the right AI-related software engineers, but increased demand for sector specialists who could enhance the learning process of large language models (LLM) and other gen AI models.

The purpose of the paper is to provide an overview of the most revelavant aspects of explosive Generative AI development in recent years and highlight its multifaceted impact on jobs and employment, productivity, global economy, education, prevailing economic paradigm and economic research. The paper will also outline the likely general impact on economic growth and best policy responses to the challenges posed by the exponential expansion of Gen models and technologies.

Following the overwiew of recent survey results regarding the use of Gen AI models at corporate level, and the global economic effects, the remainder of the paper is structured as follows: the second section will provide a brief review of the history of present generative AI models and tools. The third section deals with a range of issues related to changes in jobs, productivity, and employment and income inequality. The fourth section briefly reviews the impact on economic research and applied economic analysis for policymaking. The fifth section concludes and highlights issues for further research regarding impact of Gen AI on economic growth and GDP measurement.

This paper also serves as a conceptual framework for detailed empirical investigation based on microeconomic (enterprise data) and survey-based analysis in Serbia. This analysis is already underway and will appear in the next paper, focused entirely on Serbia-specific challenges and responses to the explosion of generative AI. In addition, the next paper will build on previous work on the resilience of Serbian labor market [7], the modified workings of the of the O’Kun’s law [39], and the nuanced impact of innovations on productivity and economic growth in the Serbian economy [56]. The central part of the forthcoming paper will be devoted to estimating job and occupanional exposure at the firm and sector (industry) level to automation and labor augmentation consequences of generative AI models. Last but not least, the next paper will utilize lessons learned from specific efucation, upskilling and re-skilling programs implemented in the past [34].

History and overview of Generative AI

The history of Generative AI models reflects a continued progression towards more powerful and versatile techniques for generating new data. From early probabilistic models to modern deep learning architectures, Generative AI has undergone rapid evolution and is poised to continue driving innovation in artificial intelligence. The history of Generative AI models is a fascinating journey marked by significant advancements and milestones.

Early decades of models preceding modern Gen AI

The origins of Generative AI can be traced back to the 1950s and 1960s when researchers began exploring early techniques for generating data. Early methods, such as random number generators and simple probabilistic models, laid the foundation for future developments in Generative AI.

- Researchers made significant progress in the development of probabilistic models for generating sequences of data (text and speech) using Markov models in the 1970s and 1980s.
- Restricted Boltzmann Machines (RBMs) of the 2000s are an important milestone in developing a powerful framework for training generative models.

RBMs as a type of neural network that can learn to represent complex data distributions and generate new samples, paved the way for more sophisticated deep learning models in Generative AI.

- Autoregressive Models which existed from the early 1980s and were used extensively in time-series analysis, regained popularity for generating sequential data (for images, audio, and text), one element at a time, conditioned on previously generated elements, allowing them to capture complex dependencies in the data distribution.
- Variational Autoencoders (VAEs) introduced in 2013 represent a more recent breakthrough in Generative AI development. Based on neural network architectures VAE can learn to encode and decode data while maximizing the likelihood of generating realistic samples with applications in text and image generation.
- Generative Adversarial Networks (GANs) introduced only a year later revolutionized the field of Generative AI. GANs consist of two neural networks, a generator and a discriminator, that compete against each other in a game-theoretic framework to generate highly realistic samples with a wide range of applications.
- GPTs (Generative Pre-trained Transformers) emerged in 2017 as state-of-the-art models for text generation and other natural language processing tasks. GPT models use self-attention mechanisms to capture long-range dependencies in the data to perform a wide range of tasks with impressive performance.
- Most recent (2019-2023) additions to the growing Transformer-based Models, such as OpenAI's family of Generative AI models, include large-scale pre-trained models, such as OpenAI's GPT-3, 3.5 and 4 which can generate highly realistic text across a wide range of domains. Future improvements will be based on increasing sample size and quality, ensuring scalability, and enhancing intuitive interpretability of model results, as well as expanding use cases to areas such as healthcare, education, finance, and scientific research.

Luk [38, p. 10] empasizes that it is imperative to define what we mean by "Generative AI" and how this is distinct from the broader concepts of Artificial Intelligence (AI) and Machine Learning (ML). He explains the difference between Generative models and discriminative models: generative models generate/create new data instances that are similar to the data they were trained on, whereas discriminative models discriminate/distinguish between different data classes/categories.

For example, generative models are like artists that have been trained in certain painting styles (e.g., Impressionism), and discriminative models are like art critics. Trained Gen AI models (like artists) would be able to create a new painting in the Impressionist style, whereas discriminative models (like art critics) would be able to tell whether a painting is Impressionist or not, but unable to create new paintings on their own.

Development of modern Generative AI models: ChatGPT

Artificial Intelligence (AI) and Machine Learning (ML) have been around since the mid-1950s. Despite continuous development of AI and ML models referenced above, there were very few tangible results until 2010. After that we have seen breakthroughs in the development of AI models in tandem with deep learning neural networks, greatly improved computing power, a huge expansion in learning databases facilitated by growing digital economy, and significantly better programs/algorithms. This enabled improved modeling of probability distributions based on ample training data, and better results: Gen AI models were trained on/learned enough data patterns to generate convincing "output samples" (i.e. responses to human questions).

The first GPT – Generative Pre-Trained Transformer was produced in 2017 [38, pp.13-16] based on the concept of "attention". It was less complex than previous models and included an "ability to be trained from past data." It paved the way for the creation of the first Large Language Model (LLM). LLM models are autoregressive causal models which treat text as vectors of numbers and try to predict the next word or token based on pre-trained sequences.

The next-generation GPT-2 model (released in 2019) was trained on a much larger data base and was able to learn natural language tasks without direct supervision.

GPT-3 model was released in 2020 followed by an improved version GPT-3.5 in 2022. The latest most powerful GPT-4 model was released in March 2023.

As indicated above, until June 2023 some 340 versions of GPT models and related tools have been produced and released, covering a wide range of uses in the area of text generation and processing, visual, audio, code and other digital content, with hundreds of use cases, business and personal functions, and specialized fields (law, fiction, non-fiction writing, visual arts, music, programming code, etc.).

Generative AI awakened concern: Are we sliding to Singularity?

Explosion of ever-improving Gen AI models based on equivalent improvements in computing power, digital data availability and powerful algorithms, awoke old real and fictional fears that the level of singularity may be looming upon us if these trends continue.

Experts predict that once we create generative AI tools and models matching human level of machine intelligence (HLMI), AI systems would be able to create a higher level of machine intelligence on their own, and yet another one, and so on until humans are left behind and possibly lose control. This may generate an accelerating rate of growth beyond human ability to manage and control and give rise to AI explosion. After that point, theory suggests that AI-based systems could move to superintelligence level quite fast, but with a considerable probability of 'bad' or 'extremely bad' outcomes for humanity, developed in excruciating detail in doomsday theoretical literature often seamlessly crossing from futuristic technological predictions (still science) to mass culture Sci-Fi hyper-production.

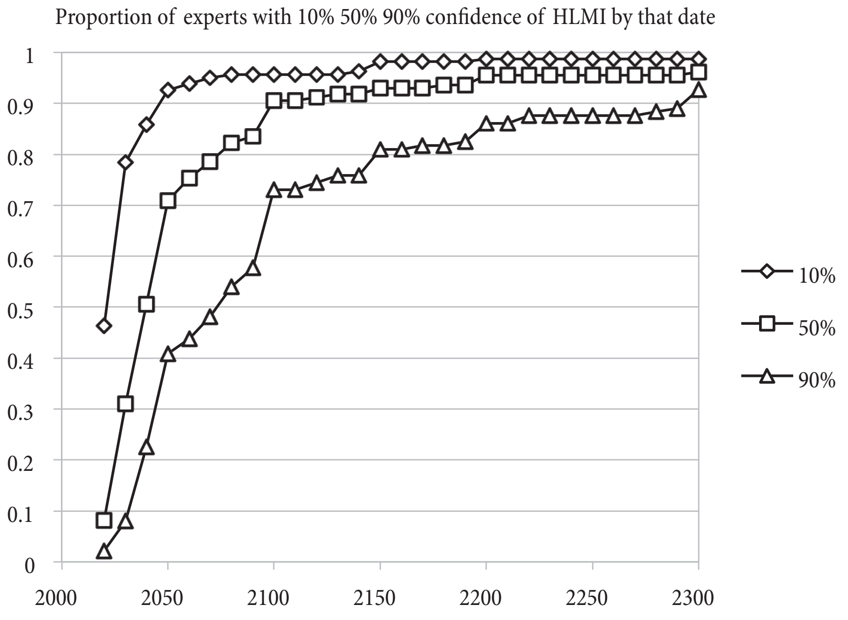
To avoid that trap and arrive at some rational answers regarding superintelligence and possible singularity, Muller and Bostrom approached more than 550 globally known scientists who did research, wrote on the subject of AI, and participated in leading conferences with an online survey seeking answers on two basic questions (see Figure 1):

- When will superintelligence be reached?
- How will things develop after that? What would be the impact and main (possibly existential) risks for humanity?

HLMI = 'high-level machine intelligence' that can carry out the professions most humans do at least as well as a typical human." The survey established three levels of human like interaction: Ability to pass a classic Turing test (language communication), pass a third grade school exam for 9 year olds, and do Nobel Prize level research.

Assuming the Turing test, the survey results show that half of the respondents (i.e. median value or line 0.5)

Figure 1: Reaching HLMI level machine intelligence by 2040



Source: Muller and Bostrom [42, pp. 11-19] think that there is a 50% probability that HLMI level of machine intelligence will be reached by year 2040. And there is a 90% probability that HLMI will be reached around year 2075.

Based on a less demanding "third school grade test," the targeted HLMI level of machine intelligence would be reached ten years earlier (2030) and, under the most demanding Nobel Prize research test, five years later (2045).

After that point, although an immediate takeoff does not appear very likely, 75% of survey respondents expect, in line with theory, that AI-based systems could move HLMI to superintelligence in less than 30 years. And they also confirm a relatively high 30% probability of 'bad' or 'extremely bad' outcomes for humanity unless effective mitigation measures are put in place.

Regarding the overall long-run impact on humanity, respondents were fairly optimistic (see Table 1). Almost 54% expect extremely good or good impact, and another 18.5% expect neutral impact. Relatively large number (27.8%) expect bad outcomes, and within that, 14% expect catastrophic impact. It is interesting to note that respondents from tech AI groups are more optimistic than the respondents approaching AI issues from the theoretical point of view, most notably in expecting good long-term outcomes after achieving superintelligence (60.5% vs. 47.0%) and fearing much less catastrophic outcomes (7% vs. 14%).

Table 1: Attitudes towards the impact of Generative AI on humanity (survey results)

	AI groups		
	Theory	Tech	Total
Good outcomes	47.0	60.5	53.8
Neutral	17.5	19.5	18.5
Bad outcomes	35.5	20.0	27.8
in which catastrophic	*21.0*	*7.0*	*14.0*
Total	100.0	100.0	100.0

Source: Muller and Bostrom [42] and own calculations

Nordhaus [45] was intrigued by the same question and conducted elaborate tests with inconclusive results.

AI singularity is a hypothetical idea where artificial intelligence becomes smarter than people (reaches a level of superintelligence which humans cannot achieve) and continues to improve and develop technology exponentially. This leads to rapid technological advances impossible for humans to understand or control and causes significant changes in society, the economy, and technology.

Views on AI singularity are divided. Some experts consider singularity a genuine and present danger, while others dismiss it as pure science fiction, be it a rosy utopia or doomsday. As already summarized in the introduction and this section of the paper, recent surveys of qualified experts (from the theoretical and technical side) and leading business leaders are fairly optimistic regarding the future of Gen AI and AI in general. Formally meeting the old, quite dated Turing criteria, does not necessarily lead to a projected "rise of the machines" depicted in Sci-Fi literature and movies, as many other social constraints and control mechanisms in the hands of humans may prevent the undesirable developments before they get out of hand.

Impact of Gen AI on jobs, productivity, employment and income inequality

Impact on jobs and productivity

Academic papers/research focused on firm-level or micro-data measurement of AI occupational exposure (AIOE) depending on the tasks that could be performed using new Gen AI text or image creating models.

Felten et al. [26] developed AIOE method and first applied it to text oriented ChatGPT, and then to a combination of text and image enabled models [25]. The most exposed occupations are telemarketers and higher level teachers (of languages, history, law), while the most exposed industries include legal and professional advisory services which rely heavily on language- and communication-related abilities. The least exposed occupations are labor-intensive building and maintenance services.

Eloundou et al. [25] look at 1000 occupations in the US to measure the exposure to LLM-based Gen AI software (number of work activities that require at least 50% less time to complete with the use of Gen AI software). They find 15% direct exposure to GenAI and a 50% combined exposure after including other software using LLM-powered technology.

In both studies occupational exposure to AI does not distinguish between the labor substitution effect (i.e. workforce displacement, bad for workers) and labor augmentation (improved productivity, good for workers).

On the experimental side, we select one illustration of ChatGPT productivity impact based on an experiment documented in Brynjofsson et al. [14]. Gen AI based conversational assistant was given to a sample of 5,000 customer support agents providing technical support to small business owners on behalf of a "Fortune 500 US company". Using OpenAI's GPT with additional ML algorithms fine-tuned on customer service interactions increased productivity (measured as number of technical issues resolved within an hour) by 14%.

McKinsey Survey results [40], [41] provide additional insights into the nature of workforce impact of AI. Traditional AI affects a small albeit important part of workforce with special skills (in machine learning, data science, and robotics) to build and enable the use of traditional AI models. These skills are often in short supply in the labor market. Generative AI also requires highly skilled specialists to build and train large models, but large number of users do not have to be IT, data science, or machine learning experts. Gen AI models promote decentralized and massive increase in the number of active users of key tools (such as ChatBot, ChatGPT etc.) just like personal computers overcame the constraints of centralized mainframe computing by providing everybody with a powerful productivity tool in a decentralized networked PCs as well as a base for increased organizational productivity.

Survey respondents predict that wide adoption of AI will reshape the roles and demand for the workforce. Regarding the number of employees, 30% expect the number to remain unchanged (i.e. +- 2%). Outside of that range, pessimistic expectations prevail as 25% percent expect a moderate decline in employment (between 3 and 10%) while only 8% expect an equivalent increase. Similarly, 18% of responses foresee a steeper decline (greater than 11%) and only 6% expect an increase greater than 11%.

Almost all respondents (93%) expect that re-skilling will be necessary: 55% expect that it will affect up to 20% of the workforce, and 38% expect that more than 20% of the resulting workforce will require re-skilling to match the demands of new AI models. A 73% majority of respondents from high AI performers expect re-skilling needs for more than 30% of the workforce in the next 3 years, compared to 21% of respondents from other companies.

Impact on employment and income inequality

Respondents expect the impact of AI on the number of employed across business functions to be uneven, from a net decrease (in "service operations") to a large expansion (in "risk", "product/service development", and "strategy and corporate finance"). Generative AI has opened new work opportunities, introduced new types of jobs (such as prompt engineering), and transformed the work process (how tasks get done). It confirms the perception of generative AI as a "labor augmenting tool" which complements rather than replaces labor. Companies leading the Gen AI explosion are focusing on pragmatic areas of improved processes and key corporate functions leading to increased productivity in production of goods and services, and faster research and innovation results. These trends are expected to continue in the future as more than 3/4 of survey respondents expect their organizations to increase investment in AI over the next 3 years. Traditional AI adoption and impact remain focused on one or few business areas, and, hence, remain important, albeit limited. The highest impact on operational cost reductions is observed in "Service operations", "Risk management" and "HR". Revenue increases attributable to AI are the highest in "HR" and "R&D for product and service development" (see Figure 2).

Historically, there was a lot of concern over potential adverse impact of technological progress on unemployment. That concern and common sentiment are best illustrated by Queen Elizabeth I of England refusal to grant a patent to an inventor of a mechanical knitting machine in 1589 out of fear that it may lead to unemployment among manual knitters. Today, leading managers seem to be less concerned about potential employment consequences. The course of the industrial revolution and developments in post-WWII period seem to indicate that significant technological improvements did not lead to permanent increase in unemployment as other positive factors (continued GDP growth, fast-growing services) prevail over the labor-saving impact of technological progress.

More importantly, global direct and indirect effects of AI on productivity referenced in the introduction approach 25% of global GDP.

We still have to address considerable disruptions likely to be caused by Gen AI and technological improvements in general. One is the massive re-skilling, upskilling, retraining and relocation of workforce to match the emerging labor demand patterns.

The second issue is the likely pressures towards growing income inequality at the company, industry, national and international level. Jobs/occupations/industries exposed more to Gen AI competition may experience declining wages relative to other occupations (with similar level of education) in the company and/or industry. Many authors have confirmed that the impact of Gen AI will be different from previous tech improvements as it will put most pressure on jobs performed by educated professionals in legal, administrative, programing, and a range of so called mid-level white collar jobs.

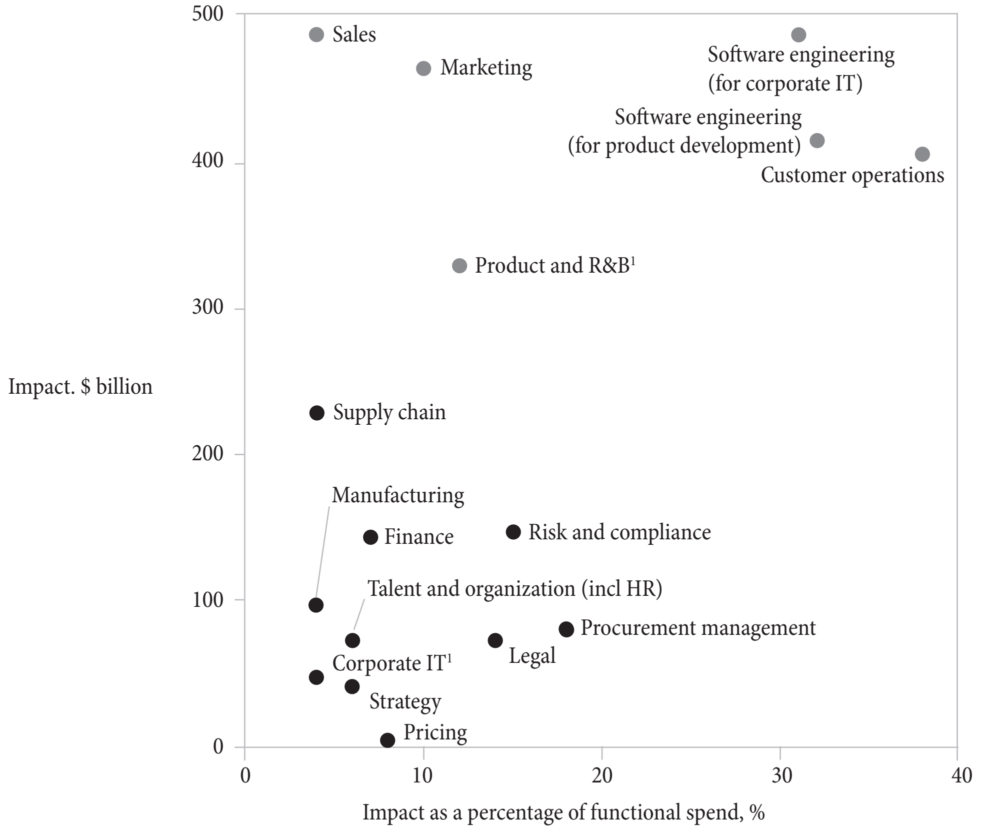
Lower and mid-level managers who have already been affected by massive relocation of jobs and incomes caused by globalization, may be further exposed to strong pressure. But this time it will be different. Managers are not likely to be replaced by Gen AI models and robots, but managers who do not use Gen AI models and tools are likely to be replaced with managers who do [15].

Impact of Gen AI on economic research and applied analysis for policymaking

Korinek [36] provides a comprehensive overview of a wide range of issues where Gen AI will likely impact economic research. He identifies six types of use cases relevant for economic research where generative AI models, tools, and related applications can have a profound impact:

- Generation/creation of research ideas and providing/receiving feedback on these ideas before research,
- Background research using various data, text, and image sources,
- Data collection, manipulation and analysis,
- Writing various stages of research documents, from initial notes to final papers and books,

Figure 2: Gen AI global impact on productivity (in bn USD, and % of spending per function)



Source: McKinsey Corporate and business function database and various other databases

- Writing computer code, and
- Mathematical modeling and derivations.

He provides a very useful summary of key features of LLM models, the single most important tool to be used by all research economists and offers a very useful illustrations on how to productively and professionally engage LLM GPT transformers through Chat to obtain meaningful answers related to the chosen research topic. He gives a range of useful suggestions on how to engage Gen AI in improving research productivity (in conducting background searches, data collection, review of literature, etc.) and in novel areas (generating research ideas). Most importantly, he also demystifies the technical side of preparing algorithms, writing computer code, formulating mathematical models and performing formula derivations, and conducting big data analysis.

Gen AI models will unleash productivity in conducting timely and accurate applied economic analysis on a range of relevant issues, informing public debate and decision-making in the area of macroeconomic policy making, budgeting, and public investment. These models will also help overcome some of the long-standing paradigm gaps between various economic schools and align them in accordance with their relevance for the public and economic issues in question.

Conclusion – and policy recommendations

Generative AI models have great potential to change job content, revolutionize the mode of operation in many industries, fundamentally change the concepts of research and creativity in writing (prose and poetry, fiction and non-fiction,…), music, visual arts, movies, TV, etc. Most of all they have the potential to deeply reshape all our interactions, directly or indirectly, based on digital content or formats. As Gen AI models expand and grow at hyper-speeds, driven both by deliberate improvements in hardware and software and indirectly by human interactions from millions of uses/sessions, they offer unprecedented capabilities to businesses, public institutions, non-profit organizations, IFIs and individuals in content creation, problem-solving, and decision-making. Their capacity to generate text, realistic images, audio, video and other data modalities unlocks novel opportunities for innovation and growth, while also enabling more personalized and efficient experiences. It is crucial to address the ethical implications and potential pitfalls associated with the use of Gen AI technology and models.

Brynjolfsson, one of the most influential researchers and prolific writers in the field on Generative AI and AI in general, concluded [14], [15] that large language models (LLM) at the heart of modern Gen AI models, are affecting almost every part of the economy and can contribute to more widely shared prosperity. If we play our cards right, the next decade could be some of the best 10 years ever in human history. We must free ourselves from a failure of imagination, narrowly expecting that AI will help us produce the same things but with fewer workers and, hence, create unemployment. Throughout history, most technologies ultimately complement humans rather than displace them.

Gen AI technology can both imitate and complement humans in its creative ability. When it imitates humans it tends to drive wages down, and when it complements humans, it tends to drive wages up. So we should not be making machines that are close images of ourselves, but as different as possible and capable of doing new things. This change in attitude may have a profound impact on the labor-displacing and labor-augmenting consequences of Gen AI technology, as emphasized by Acemoglu and Restrepo [2], [3], [4].

Preparing labor re-skilling, upskilling and retraining programs is crucial to meet the relocation needs triggered by the expected changes in the structure and skill mix of the future workforce, especially in sectors under a direct impact of Gen AI tools and models.

As Acemoglu and Johnson [1] concluded based on a thorough review of technology from Neolithic times to the ascent of artificial intelligence, technology is not our destiny. Even at this age of relentless expansion of generative AI systems, concentration of power and wealth, and seemingly unstoppable descend into technological singularity, their new book "Power and Progress" is an essential reminder that we can, and must, take back control and secure the best future for mankind.

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