

Acknowledgements

Transitions Research is a social science research collective working on the intersection of technology, society and sustainability. We generate anticipatory knowledge, co-create solutions and strengthen capacity to drive transition trajectories towards a just and sustainable future for India. We centre people, engage with plural perspectives, shape human choice and democratise technological change.

This study is the outcome of a pilot project conducted by Transitions Research between July and October 2023, on the emergence of generative AI and its implications for the future of work. A big thank you to all the participants of this research for sharing their experiences and views with us.

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Abbreviations

3D	Three Dimensional
AI	Artificial Intelligence
AMT	Amazon Mechanical Turk
API	Application Programming Interface
DL	Deep Learning
GenAI	Generative Artificial intelligence
GPAI	General Purpose Artificial Intelligence
GDP	Gross Domestic Product
GPT	Generative Pre-Trained Transformer
GPU	Graphics Processing Unit
IBM	International Business Machines Corporation
IMF	International Monetary Fund
LIM	Large Image Models
LLM	Large Language Models
MIT	Massachusetts Institute of Technology
ML	Machine Learning
NGO	Non-governmental Organisation
UBI	Universal Basic Income
UI/UX	User Interface/User Experience

01 Why this study?

Rapid advances in generative AI, i.e. a type of artificial intelligence that can be used to synthesise new text, images, music, and even code, has sparked widespread debates and speculations about its potential implications for the world of work.¹ While on one hand, proponents believe that generative AI (genAI) will enhance worker productivity and fuel economic expansion, others argue that it could lead to job displacements and task automation, raising ethical questions surrounding its use.

In particular, the public release of OpenAI's large language models (LLM) such as ChatGPT, as well as text-to-image generators such as DALL-E and Midjourney, have captured people's imagination, leading to a new phase of mainstreaming AI in our everyday lives. For instance, in the case of ChatGPT, within the first five days of its release, the tool reached a million users, becoming one of the fastest growing consumer AI applications in history.² ChatGPT is the first of several LLMs currently in the pipeline of the Big Tech companies, marking a new era of AI-based text generators focussed on producing human-like outputs and interactions with users.

Besides LLMs, a number of other genAI tools have begun dotting the landscape of digital technologies that are now available for people to work 'faster', 'better' and more 'creatively'. Examples include tools that can turn text to 3D images (Dream Fusion), images to text (Flamingo); texts to video (Phenaki); texts to audio, (AudioLM); texts to code (Codex), and even create algorithms (AlphaTensor).³ With billions of dollars of investments into diverse use-cases, companies are also customising genAI tools

to cater to worker's productivity, and workflows. For instance, Adept, a newly formed AI company that has raised \$350 million of venture capital, aims to create a "universal collaborator" for all office workers, while Inflection, another Silicon Valley start-up, aims to create a "personal AI" for everyone.⁴

According to industry reports, we are now in a genAI boom, where it is expected to contribute anywhere between \$2.6 trillion to \$4.4 trillion annually to the global economy.⁵ In the context of India, genAI is expected to contribute an estimated \$1.2-1.5 trillion to the GDP over the next seven years.⁶ And, more than half of today's work activities are expected to be automated between 2030 and 2060.⁷

The ability of genAI to not only synthesise text, images, and other mediums, but to also produce compelling literature, art, music, 3D models, and realistic videos marks a new era of machines producing content previously thought to lie within the exclusive domain of human beings. In this context, discussions in the public domain are rife with speculations and concerns regarding the implications of the technology not only on

What will work look like in the future, now that machines are capable of similar, if not better, outputs?

existing jobs (particularly in the domain of knowledge and creative work), but also, on the changing nature of work itself.⁸ What will work look like in the future, now that machines are capable of similar, if not better, outputs?

Polarised predictions about genAI's impact ranges from dystopian visions of

widespread automation and job displacement to utopian scenarios where AI empowers humans to transcend the mundane, and reach new heights of productivity and creativity.

The hype surrounding these technologies has also kept pace with the rapid expansion of genAI's capabilities, and development. For instance, Eric Schmidt, former CEO of Google, and others have suggested that genAI holds the potential to “alter the fabric of reality itself”,⁹ and researchers at Microsoft have also suggested amidst contestations, that the latest iteration of ChatGPT (i.e. GPT-4) has already exhibited “sparks of general artificial intelligence”.¹⁰ Others have likened the emergence of genAI to the invention of the Gutenberg press.¹¹ Counter-narratives to hype on the other hand, suggest that genAI is to be treated as nothing more than a mere ‘toy’ – generating “facsimiles of a coherent copy”.¹²

Much of the potency of genAI emerges not merely from its technical capabilities, but from the interactions and productive friction between users and the technology.

Amid these polarising debates, there lies a clear gap in our understanding of genAI from a user-centric perspective. Most conversations about generative AI have largely been directed by experts – technologists, business leaders, and academicians– and have often overlooked the nuanced experiences of the everyday, where users interface with these technologies.

However, users do matter. And, they have come to matter more within the evolving socio-

technological assemblages and lifeworlds of AI. Much of the potency of genAI emerges not merely from its technical capabilities, but from the interactions and productive friction between users and the technology. While genAI creates seemingly “human-like” texts and images, it still takes a human to interpret its outputs, make meaning out of them, and use these technologies.¹³ Not only are emerging technologies like AI structurally dependent on human participation and use, users can no longer be seen merely as passive consumers of technology.¹⁴ Instead, users constitute an important political subject, and a stakeholder in determining the future of emerging technological trajectories.

Behind the growing hype of genAI, is a set of limited, but extremely large language, and image models known as “foundational models” or “general purpose AI” (GPAI).¹⁵ Named as such due to their ability to perform a wide range of tasks, these models are currently owned, and operated by a small, but powerful group of technology companies (mostly Big Tech). With big tech at the top, and users at the end of the pyramid, the evolving political economy, and value-chain of genAI implicates users in ways that are inherently political. From using user interactions to further train genAI systems to genAI influencing our information systems, decisions made by designers and developers of genAI have the potential to constrain and shape how users engage with technology, and with each other.

At the same time, users also “domesticate, consume and modify technologies, often in unanticipated and unforeseen ways”.¹⁶ Despite broad claims about genAI's impact on labour markets, and economies, the nuances of how genAI's impact will play out in the everyday life of workers, and it's

impact on worker well-being is yet to be explored. By examining users' perspectives on working with genAI, this study seeks to provide grounded insights into how users adapt genAI tools and applications, while actively negotiating with a new genAI-driven paradigm of work and its societal implications.

In doing so, this study aims to amplify the voices of users, and enable the co-creation of a shared language to talk about the impact of genAI on everyday life and at work.

1.2 What we did

Over the course of 4 months, between July and October 2023, we spoke to a group of 22 individuals from diverse professional backgrounds – including UI/UX developers, product managers, teachers, designers, freelancers, artists, journalists, and researchers – about the impact of genAI on their work. How do users perceive and understand genAI? What were their experiences of “working with AI”? In what ways were users experimenting with, and adopting genAI tools and applications for their work? What were the future implications of genAI, according to users, on the world of work? Through a round of semi-structured interviews, we asked participants about their hopes and aspirations, as well as their anxieties and worries about the future of work in relation to genAI.

1.3 What we hope to achieve

By focusing on users' narratives and experiences with genAI, the study aims to (1) open up the public conversation on genAI from the perspective of users; (2) spotlight users as a core stakeholder and emerging political subject in the digital age; and (3) foster societal conversations about how best

to co-shape and guide the emerging technological trajectories of AI.

We hope that the user journeys and experiences shared within this report serve as a critical compass for the development of wider societal frameworks in navigating the complex technological trajectories of genAI.

1.4 What follows next

The rest of this report examines the emerging and evolving relationship between generative AI and the world of work. Chapter 2, titled ‘Flight’, examines the situated history of genAI and its emerging political economy to arrive at a conceptual framework for understanding genAI. Chapter 3, titled ‘Frictions’, delves into the users' journeys and experiences of using generative AI as part of their everyday workflows. Chapter 4, titled ‘Futures’, explores the emerging visions and imaginaries of the diverse possible genAI and work futures, both in popular discourse as well as through user accounts. Chapter 5, titled ‘User Perspectives Towards an Ethics of GenAI’ concludes the report with by providing a set of pathways and provocations towards developing an ethics of genAI, that seek to open up a societal dialogue on the responsible use of genAI and its impact on the future work and society from users' perspectives.

02 Flight

“It is not my aim to surprise or shock you—but the simplest way I can summarise is to say that there are now in the world machines that can think, that can learn and that can create. Moreover, their ability to do these things is going to increase rapidly until – in a visible future – the range of problems they can handle will be coextensive with the range to which the human mind has been applied.”

Herbert A. Simon, Operations Research, 1957¹⁷

Between 2021 and 2023, a number of genAI applications took flight – moving out of the lab into the world. From being used to make movies to aiding in drug discovery and providing agricultural, financial, and editorial advice, genAI applications are rapidly becoming a ubiquitous presence in our work and lives. The rapid pace of its development, and spread, has led to claims that the “future of work is the future of AI.”¹⁸ However, before we enter into a conversation about the implications of genAI on the world of work, it is important to understand: what is genAI, and how did we get here?

This chapter presents a foray into a brief history of genAI, and its emerging political economy, in order to provide a critical entry-point and conceptual framework for understanding our current genAI moment.

2.1. GenAI Takes Flight

The emerging landscape of GenAI

In 1966, Joseph Wizenbaum, a computer scientist at MIT, introduced ELIZA.¹⁹ Named after the character of Eliza Doolittle in George Bernard Shaw's play *Pygmalion*, ELIZA was one of the first conversational AI programs, designed to simulate a conversation between a therapist, and a client.²⁰ For instance, if a user typed in "I am sad", Eliza would give a non-directive response, and ask "What makes you sad?" or "Why do you feel sad?"

Modelled along the lines of a Rogerian psychotherapist, who are trained to reflect clients' feelings back to them, ELIZA worked by analysing a user's input for specific keywords and phrases (e.g. I am sad). This analysis triggered a pre-programmed response in the form of a probing question, providing an illusion of understanding and empathy by the program.²¹ A few such interactions later, it would often become clear to the user that there was no real understanding or conversational exchange taking place.

Despite its limitations, ELIZA often elicited strong emotional responses from users, who "read far more understanding than is warranted into strings of symbols—especially words—strung together by computers".²² Rather than showcase the superficiality of human-computer interactions, as Wizenbaum had intended, his programme had the opposite effect. Users poured out their thoughts to ELIZA, feeling their voices heard and their lives witnessed. ELIZA thus provided a space for people to explore their thoughts, essentially operating as an abstract 'digital mirror' – reflecting pieces of their own humanity back to them.²³

Cut to the present, we now live in a world of

rapidly proliferating 'digital mirrors', in the form of genAI. Trained on vast amounts of human-generated internet content, be it books, blogs, art, images, or opinions, genAI applications work by distilling an immense corpus of human-produced 'data', and 'learning' to manufacture seemingly human-like outputs.²⁴

While the outputs produced by genAI may resemble human outputs in form, and structure, the underlying processes involve probabilistic

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reasoning rather than genuine thought.²⁵ GenAI models 'learn' to find patterns, and correlations between words, pixels and code within its training data, to probabilistically predict the next word or pixel. Further, unlike ELIZA, which was a simple academic program, the current generation of genAI applications operate on a much larger, and commercial scale – ensconced within for-profit business models, and heavily reliant on vast

amounts of data, human labour, compute power, energy and ecological resources.

Thus, between 2021-2023, several Silicon Valley companies, like OpenAI, Google, Amazon, Anthropic, and Meta have released multiple genAI tools and applications – such as ChatGPT, Bard, Midjourney, Stable Diffusion, Titan, Perplexity, and DALL-E to name just a few. Since then, the number of genAI applications has rapidly expanded with new models and upgrades being announced in rapid succession.²⁶

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At present, genAI applications extend to a diverse range of tasks and use-cases. For instance, Waymark studios in Hollywood, LA, recently created the world’s first genAI-made short-film ‘The Frost’, in which every frame was generated using DALL-E.²⁷ Grimes, a well-known American singer, used voiceAI to copywrite her voice, enabling other artists to use it to play their songs.²⁸ Less sensational use-cases include: the use of genAI to provide personalised product recommendations²⁹; financial advice, and wealth management³⁰; drug discovery in medicine³¹; generating realistic malware samples to train systems to detect and defend against threats in cyber-security³² to name just a few.

In this context, genAI has emerged as a general purpose technology, with widespread applicability that has not only fuelled growing levels of hype, but also billions in investments.³³

Alongside rising investments, the enthusiastic adoption of genAI by millions of users has spurred a new phase of mainstreaming AI, triggering an ‘AI arms race’ amongst big tech companies.³⁴

For instance, Baidu, the Chinese tech giant, is preparing to introduce a chatbot similar to

ChatGPT.³⁵ Anthropic, an AI company started by former OpenAI employees, is reportedly in talks to raise \$300 million in new funding.³⁶ And, Google is racing ahead with more than a dozen A.I. tools – its most recent release being Gemini, launched in 2023.³⁷ During May 2023, Google debuted PaLM 2, a sophisticated LLM set to enhance various Google offerings, including the Bard chatbot.³⁸

Despite its sudden explosion into public consciousness, genAI however, is not a new phenomenon. Large-scale language and image models have been in development since the 1980s, while neural networks, the key learning technique behind these applications, were researched as early as the 1940s.³⁹ Similarly, generative models have been used for years in statistics to analyse numerical data.⁴⁰ Even OpenAI’s ChatGPT application is based on ‘foundational models’ developed in the 2010s.⁴¹ What has changed, therefore, is the addition of an easy-to-use consumer interface that relies on natural language prompts, and the rapid commercialisation of genAI.

However, the emergence of genAI has not been without controversy or concern. Primary amongst them is the potential impact of genAI on the future of work. As per the International Monetary Fund, almost 40 percent of global employment is exposed to AI.⁴² While advanced economies are more at risk of AI-led disruptions, emerging markets are also not far behind.⁴³ According to a report by IBM, 40% of the global workforce, i.e. 1.4 billion of the 3.4 billion people will have to reskill in the next three years due to AI implementation.⁴⁴ Concerns have also been raised about the potential misuse of genAI for misinformation campaigns,⁴⁵ electoral interference,⁴⁶ and the further loss of data privacy,⁴⁷ and entrenchment of AI bias.⁴⁸ Law-

suits have also been filed against genAI creators, and companies for copyright infringements.⁴⁹ The impact of genAI on education has also drawn widespread concerns.⁵⁰ Other concerns surround genAI's impact on cyber-security, which has already witnessed a rise in phishing attacks.⁵¹

In the context of work, concerns not only relate to how genAI is likely to impact job displacement and automation futures, but also its impact on the “changing anatomy of work” itself.⁵² However, in order to fully grapple with this evolving landscape of genAI, and its implications, we must first situate it within its broader history and context. While a complete account of (gen)AI's history is beyond the scope of this work, the following section provides a broad overview of (gen)AI's emergence, and examines the reason for its current boom.

2.2. From Early Beginnings to Recent Developments: A Brief and Situated History of GenAI

Like all technologies, genAI too has a history. And, like all histories of techno-scientific development, it is neither a linear nor a progressive history of piecemeal advancements.⁵³ Instead, it is marked by reconsiderations, continuities and discontinuities about even the most fundamental questions of what constitutes intelligence and how to achieve it in machines

2.2.1 Early Beginnings: The pursuit of “thinking machines”

Most popular accounts of the emergence of AI as a scientific discipline trace its development to the 1956 Dartmouth Summer Conference, where computer scientist John McCarthy coined the term “artificial

intelligence”.⁵⁴ While the Dartmouth Conference holds significance for ratifying the term AI, the intellectual and material roots of the discipline go further back – to the period of the Second World War (1939–45). Rooted in wartime imperatives and the intellectual traditions of cybernetics and systems engineering, the field of AI emerged as a scientific inquiry into the creation of “thinking machines”.⁵⁵ The invention of the digital computer in the 1940s, for instance, as a direct result of the war effort, paved the way for the development of the earliest AI programmes.⁵⁶ The wartime outlook on the human-machine conjunctions, in the form of anti-aircraft gunners and artillery systems which welded humans and machines into one singular working entity; and early cybernetic theorisations of intelligent behaviour as information processing, regardless of whether it took place “in metal or in the flesh” – led to increasingly blurry views of the lines between humans and machines.⁵⁷

It was in this context, that, in 1936, British mathematician Alan Turing proposed the idea of an abstract computing machine that could function independently of any material embodiment.⁵⁸ Known as the Turing Machine, it was based on the idea that any problem can be turned into a set of clear instructions or algorithms, which can then be executed by a machine. Through this thought experiment, Turing inaugurated the idea of intelligence as an abstract, mechanical process that “can be broken down into a sequence of steps that could be mechanically emulated.”⁵⁹

Almost 20 years later, the gathering at Dartmouth reinforced this idea by premising its conference on the notion that “every aspect of learning or any other feature of intelligence can, in principle, be so precisely described that a machine can simulate it.”⁶⁰

Thus, early efforts in the quest for AI during the 1950s and 60s resulted in the creation of symbolic systems, which treated “thinking” as the manipulation of symbols (e.g., numbers, words) according to specific rules.⁶¹ These systems aimed at achieving human-like intelligence, by trying to break down human cognitive processes, and encode the rules of reasoning into computer programs.⁶² Notable examples of early symbolic AI include rule-based systems such as the Logic Theorist and Arthur Samuel’s checkers playing program.⁶³ Eventually, research into symbolic AI led to the development of expert systems that aimed to capture, and reproduce the decision-making capabilities of human experts in various fields such as medicine, and finance.⁶⁴

For much of its early history, AI relied on the human as the benchmark for intelligent behaviour. However, this idea of intelligence that emerged in the early phases of AI did not end with simulating human cognitive processes, but also depended on human perceptions.⁶⁵

In his famous paper on machine intelligence, Alan Turing proposed the imitation game, now known as the Turing Test.⁶⁶ The test involves the interaction of a human evaluator with an unseen interlocutor, which could either be a human or a machine, through a text-based medium. If the evaluator cannot reliably tell apart the machine from the human, the machine is said to have passed the test. The fundamental idea behind the test was to assess whether a machine’s behaviour could be indistinguishable from a human being’s, and not whether it could simply think like one. What was interesting about such a conception of intelligence, is that it hinges as much on the perception of the user/evaluator, as it does on

While the simulation of intelligence in machines by reproducing human heuristics, i.e. how humans think, gave way to other methodologies overtime, the idea of performative similitude or appearing “human-like” continues to be in play with today’s genAI models.

the actual competencies of the program itself.⁶⁷ Take for instance the case of language models like ChatGPT, or Gemini. These models, as researchers like Gebru et. al. point out are “haphazardly stitching together sequences of linguistic forms it has observed in its vast training data, according to probabilistic information about how they combine, but without any reference to meaning: a stochastic parrot”.⁶⁸ The same can be said for text to image models, or any other outputs of genAI. As linguistics professor Emily M. Bender notes, systems like ChatGPT are churning out “non-information”, it only becomes information or misinformation when a human interprets it.⁶⁹ Thus, from the very beginning, the idea of genAI has rested on the complex configurations of user-machine interactions within which machines appear intelligent.

2.2.2 Recent Developments: Resurgence of neural nets and industrial AI

As opposed to symbolic systems of the 1950s and 60s, current genAI models rely on a different

set of techniques, and methodologies drawing from machine and deep learning. While machine learning relies on algorithms that allow a model to learn and improve from experience, without being explicitly programmed; deep learning is a subset of machine learning that utilises artificial neural networks to analyse complex patterns and relationships in data.⁷⁰

The history of research into neural networks predates symbolic AI systems. As early as 1943, Warren McCulloch and Walter Pitts laid the theoretical foundation for artificial neural networks, by studying how neurons in the brain performed computational tasks.⁷¹ In 1957, Frank Rosenblatt built the first working computer-based neural network, the Perceptron, a single layer neural network capable of binary classification, like distinguishing between squares and circles.⁷² The perceptron was the first algorithmically described neural network, a forerunner to the complex networks we see today.

Unlike symbolic AI and expert systems, which require explicit rules for solving simple tasks like moving a chess piece, neural networks, specifically deep learning models, learn intricate patterns directly from vast quantities of data. To recognize a face, for example, a neural network does not rely on predefined instructions about facial features. Rather, it is trained on extensive collections of faces, enabling it to develop “an internal representation” of what constitutes a face.⁷³

However, as symbolic systems took over in the early phase of AI development, neural networks took a backseat. In the 1980s, a confluence of factors rebooted interest in neural networks. Key among these was discovery of backpropagation algorithm, which enabled a neural network to learn from

errors.⁷⁴ Additionally, the parallel development of reinforcement learning methods, combining principles of neural networks and behavioural psychology, expanded the scope of tasks that neural networks could tackle.⁷⁵ Eventually in the 2000s, the development of generative adversarial networks and transformer architectures led to significant advances in neural net architectures. For instance, in 2012, machine vision (i.e. where algorithms learn to detect images such as faces or objects) gained increased accuracy (see fig.1). Deep-Art, an application created by Leon Gatys and team, which allowed users to transform their photographs into the styles of popular artists like Van Gogh or Picasso, illustrated what machine vision embodied as genAI could do.⁷⁶

Even as neural networks in the brain inspired the chief architecture of modern AI, current day genAI systems rely on a system of learning mechanisms that no human can replicate, with “many powerful approaches today setting out intentionally to bypass human behaviour”.⁷⁷ The above history, however, offers only a partial account of AI’s development. As Sebastien Scheimg notes, the current advances in AI “cannot be explained by better algorithms alone”.⁷⁸

Equally, if not more, important was the exponential growth in computing power, the emergence of large-scale data infrastructures, and the ‘possibility of outsourcing clickwork via the internet on a massive scale for little or no money’.⁷⁹ Take for instance, the ImageNet Dataset, whose creation in 2012 set the benchmark for facial recognition systems. Built by scraping millions of images from the internet, and labelled by thousands of Amazon Mechanical Turk (AMT) workers, this dataset and many others like it forms the “critical information infrastructure” on which AI runs.⁸⁰ Similarly, it

was not until the arrival of microprocessors and graphics processing units (GPU) that the first landmark turn towards machine learning systems began.⁸¹ As AI Now founder Meredith Whitaker notes, “it was not the neural design itself, but rather what “large-scale data, and computational resources” enabled that architecture to do.”⁸²

Thus, what began as a small academic discipline has rapidly morphed into a growing industry, where a small number of powerful technology companies monopolise data flows, control large-scale digital infrastructures, and deploy AI systems at an industrial and planetary scale. In this context, it is important to take cognisance of the social and political dimensions of genAI, which produces new modes of digital labour, subjectivation, value creation and control.

The evolution of our social worlds into highly networked, and data-producing digital environments, as well the exploitation of material and planetary resources to build large-scale computational infrastructure are the core of what drives genAI today.

2.3. Making Sense of AI: AI as a Socio-Technological Assemblage

The problem of defining AI has been a core issue since the inception of the field. As the previous section shows, any definition of AI that relies on describing what these systems aim to do, i.e. the

pursuit of human-like intelligence in machines, neglects both the environmental, and the social configurations that AI systems depend on.

As emerging and critical literature on AI suggests, AI is neither ‘artificial’ nor ‘intelligent’.⁸³ Instead, researchers argue that we live in an era of ‘deceptive media’⁸⁴ or ‘shitty automation’⁸⁵—where “seemingly autonomous and intelligent systems such as AI are structurally dependent on human perceptions, labour, and wider social, environmental and institutional formations for it to work”.

While it may be tempting to think of AI as a cold, hard technology, however, it does not operate on purely technological logic alone. Instead, AI as we understand it, operates as a vast ‘socio-technological assemblage’ – that is, a complex and dynamic arrangement of diverse social, cultural, material, and technological elements that interact and shape each other, giving rise to new forms of power and politics.⁸⁶

Take for instance, a single AI system such as Amazon’s Alexa, an AI-based voice assistant. The production of a single Alexa, as researchers Crawford and Joler depict, connects a complex network of global value chains, production mechanisms, and human labour – connecting the lithium reserves of Salar lake in Bolivia that feed its computational hardware, to factory workers in the Philippines who label data for the system’s engineering to international Amazon warehouses, that house the product before shipping, and finally to the consumer across the world, whose interactions with the system produces more data to enhance its operations.⁸⁷

In this respect, AI is not a thing, but a constellation – not only connecting heterogeneous elements of people, planet, protocols, laws, organisations, data practices, economic incentives, but also giving rise to emergent power structures, and institutional forms that shape its evolution, and impact.

The conceptual framing of AI as socio-technological assemblage extends to genAI systems as well. A single genAI model like ChatGPT relies on huge volumes of internet data, environmental resources like water and energy, as well as scores of workers to clean datasets for the system. For instance, training GPT-3 alone is estimated to have required 700,000 litres of freshwater.⁸⁸ Outsourced data workers in Kenya, Uganda, India were used to scrub its training dataset of toxic content.⁸⁹ Furthermore, the data itself that is used to train genAI systems is scrapped from the internet, including copyrighted material. For instance, the ‘Books3’ database that has been used by companies like Meta, Bloomberg etc. to train its genAI systems, houses tens of thousands of pirated and copyrighted books.⁹⁰

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Besides the environmental, legal and labour implications of genAI’s production, there is also the politics of who can build these systems. Most of genAI applications and tools in vogue today, are either BigTech owned or heavily reliant on them.⁹¹ This is because the current generation of rapidly proliferating genAI applications are reliant on a much smaller number of so-called “foundational models” or “general purpose AI (GPAI)”.⁹² Unlike narrow applications of AI that focus on a specific or limited task, for example, text or image recognition, foundational models or GPAI are pre-trained and can be fine-tuned across a wide range of tasks and domains, such as generating text, recognize objects and scenes in images, transcribe speech, and video summarisation.⁹³

In terms of size, foundational models typically have billions to hundreds of billions of parameters. For instance, BERT, a foundational model by Google utilises 340 million parameters, and pre-trained on datasets such as BookCorpus (800M words) and Wikipedia (2,500M words).⁹⁴ GPT-3 on the other hand utilises 175 billion parameters.⁹⁵ While parameters or weights refers to the number of connections between nodes in a neural network – typically the more parameters there are in a system, the more the model can learn and the ‘better’ it performs.⁹⁶

However, training a model on billions of parameters also requires significant compute power and large-scale datasets, which only a few extremely large and powerful tech companies with immense financial, data, and computational resources can afford. For instance, OpenAI’s ChatGPT could not have been built without access to the computational infrastructure of Microsoft’s Azure platform.⁹⁷ The same goes for several other genAI applications and tools that rely on foundational

models as a platform atop which user-facing downstream applications are built.⁹⁸ While there are a few notable open-source genAI foundational models, even these, while open, continue to rely on the computational power, datasets and financial resources offered by Big Tech.⁹⁹ Thus, in the present political economy of genAI, the influence of large tech giants goes far much beyond offering ‘cutting-edge’ genAI technologies to the point that AI researchers have argued “there is no AI without Big Tech”.¹⁰⁰

2.4. Situating genAI in User’s experiences

The growing push towards increasingly large foundational models that explains and underpins much of the contemporary genAI boom also signals the creation of new and complex dependencies impacting people, power, politics, and ecological resources within the broader socio-technological assemblage of genAI.¹⁰¹ For instance, as researchers have argued, the terms of contract between Big Tech and other companies and developers racing to build specialised genAI applications will determine how much control each actor has over these systems.¹⁰² Similarly, the question of how power, agency and access are distributed within the socio-technological assemblage of genAI also raises questions about the differential impact of these systems, and the allocation of responsibility across multiple actors within the assemblage.

At the same time, users have also emerged as central figure in the development and deployment of genAI tools and applications. Widespread user adoption and experimentation with genAI for work and other purposes, not only signals a new phase of mainstreaming AI, but the evolving landscape of

genAI implicates and impacts users in ways that are likely to shape how users interact with genAI at work and in life. In such a context, understanding where and how users feature within the broader socio-technological assemblage of genAI becomes crucial, in order to develop an understanding of the politics of genAI and its emerging implications for the world of work. In this context, we turn our attention in the next chapter to the position of users within the socio-technological assemblage of genAI, and users experience genAI tools and applications, within the broader context of their work and everyday lived realities.

03 Frictions

“A wheel turns because of its encounter with the surface of the road; spinning in the air it goes nowhere. Rubbing two sticks together produces heat and light; one stick alone is just a stick.”

Anna Tsing, Friction[103]

This chapter delves into the realm of genAI and its impact on users within the context of their everyday work environment. While existing studies have predominantly focused on the broader socio-economic and labour market implications of genAI, the transformative effects of this technology will manifest on a more personal scale – where end users directly engage with genAI tools in their daily workflows. Understanding how users interact with and integrate AI into their everyday work routines provides a crucial perspective for comprehending the nuanced changes occurring at a microcosmic level.

By examining the practical, experiential aspects of how individuals utilise, adapt to, and work with AI, we gain valuable insights into the evolving landscape of work in the era of genAI.

3.1. Prelude to Pandora's Box: GenAI and the Politics of the User

In a recent interview, John Schulman, one of the cofounders of OpenAI, as well as other members of the team that built ChatGPT, expressed their enthusiasm about the unexpected success of the genAI application.¹⁰⁴ With Twitter and other social media threads filling up with users' experimental encounters with the application, Schulman and his team remarked that the reception from users had been nothing short of a surprise. In the interview, Schulman notes, he had "expected it [chatGPT] to be intuitive for people", and for it to "gain a following, but did not expect it to reach this level of mainstream popularity."¹⁰⁵

At the centre of the bemusement that the app-makers for their tool was, the staggering number of users, and the rapidity with which the subscriber base had grown. At present, ChatGPT has 100 million weekly active users, with 2 million developers using the model to build new applications including 92% of all Fortune 500 companies.¹⁰⁶ ChatGPT is only one application out of several user-facing ones that have been built recently atop large-scale foundational models.¹⁰⁷ This has resulted in a number of companies incorporating genAI applications into their pre-existing products and building new features on top of foundational models in order to respond to market demand, i.e, what users want. Examples include: Microsoft's Bing chat, which builds on top of OpenAI's GPT-4 to answer complex questions and summarise information; Duolingo Max by Duolingo, which provides AI roleplay and 'explain my answer' features for modern-language learning.¹⁰⁸

OpenAI's own business strategy, with the public

release of ChatGPT, has been to constantly improve its features in response to user feedback. In its release statement the company stated, "we are excited to introduce ChatGPT to get users' feedback and learn about its strengths and weaknesses".¹⁰⁹ Since its launch the company has iterated several new features to ChatGPT in response to user preferences – from giving it a memory, to enabling ChatGPT-4 to surf the internet.¹¹⁰ In a recent iteration, the company addressed ChatGPT-4's apparent laziness, stating: "We've heard all your feedback about GPT4 getting lazier! Model behaviour can be unpredictable, and we're looking into fixing it."¹¹¹

As much as genAI was the hero of the tech landscape in 2023, the user has emerged as an equally central figure. In some techno-imaginaries, the user appears as a testifying force to the technological prowess of genAI – whose continued use and sustained adoption of the tech is seen as a stamp of approval and a rationale for the furtherance of these technologies. In others, users are viewed as an unpredictable, and unruly force capable of co-opting the technology in unanticipated, even malicious ways: from using genAI to cheating on exams, to spreading election disinformation and creating malicious deep-fakes.

Users have always been an integral part of the broader socio-technological assemblage of AI. Users not only feature in this assemblage as end-users, i.e. "those individuals and groups who are affected downstream by products of technological innovation"¹¹², and consumers of technology, but also as suppliers of data and labour. From the digital traces that users leave on platforms, to even their facial micro-expressions, users' bodies, habits, attention, interactions and feedback provide the raw material for genAI's development in today's

digital age.¹¹³

Users' continued interaction with genAI applications and other digital platforms also contributes to both the possibility and profitability of these systems. In addition to the end-user, the AI value chain also includes the 'implicated user',

From the digital traces that users leave on platforms, to even their facial micro-expressions, users' bodies, habits, attention, interactions and feedback provide the raw material for genAI's development in today's digital age.

i.e. "those who are physically present, but who are generally silenced, ignored or made invisible by those in power."¹¹⁴ These users constitute the vast body of data labellers, annotators, and other gig workers, working at minimum wages to develop AI systems.¹¹⁵ Even amongst end-users, users also occupy different

positionalities and varying levels of agency, access, and power vis-a-vis others in the assemblage. End-users of genAI, for instance, include corporations, private businesses, and public institutions in addition to the individual worker. Thus, the question of who is a user continues to be an important one in determining the different degrees of agency and power that users have within these systems, as well as the ways in which users make use of these technologies.

The implication of the user along the value chain of genAI also means that users can no longer be

viewed as passive consumers, but active agents in the co-shaping of technological trajectories. While users adapt, experiment, and interpret emerging technologies like genAI, these technologies also configure the user in specific ways. The decisions of designers and deployers of technologies shape the ability of users to modify and domesticate technologies. For instance, OpenAI does not allow people to build applications for political campaigning and lobbying, and it does not allow engineers to create chatbots that pretend to be real people.¹¹⁶ On the other hand, users also experiment and adapt the tools and technologies to fit their purpose. For instance, user experiments with genAI have enabled people to jailbreak the system and lead it to break its own rules.¹¹⁷ Further, when it comes to the adoption of technological innovations, users also engage in invisible labour practices, such as building meaning and trust in technologies that allows for the integration of new technologies into pre-existing practices, thereby normalising and shaping technological trajectories.¹¹⁸ Thus, the relationship between users and technology is one of mutual co-constitution and shaping.

Within this context, users' perceptions of what a technology is, and what it can be used for, can be a participatory and empowering mechanism to identify and imagine the diverse trajectories that emerging technologies can take. However, the use of genAI tools does not necessarily mean that the relationship between users and the technology is one of seamless integration. Rather it is a space of friction, that is, a zone of tension and interaction where users interface with the tool and perform "work that is required to make the technology work".¹¹⁹ The rest of the chapter focuses on user journeys with genAI, and the ways in which user interactions with the tool inform new ways of

adapting and working with genAI.

3.2. Opening Up Pandora's Box: Users Journeys of GenAI

“ChatGPT is like a peeled banana...ready to eat and easy to consume”, was how one user characterised genAI. Our interviews with users typically began with a conversation about their experiences and perceptions of using generative AI. We asked participants about their understanding of genAI, its applications in their everyday work-lives, why and how they began using these applications.

**ChatGPT is
like a peeled
banana...
ready to eat
and easy to
consume”**

Drawn in by the hype and excitement surrounding genAI, most participants said they began to use genAI as a ‘matter of curiosity’, ‘to see what these tools were capable of’ and ‘because genAI has become the talk of the town’. Many began using these tools after having heard about them in the media, and from friends, family, and colleagues at work. One participant, a visual artist, said,

“I started using image generators, you know like DALL-E and Midjourney, out of curiosity... for me it was like opening up Pandora’s box, because it was visually fun to see a new world open up. These tools were putting together images and visual elements in a way that I had never thought of.”

Another participant, working for an NGO, said,

“Actually it was my supervisor at work who

turned me towards these tools [specifically, ChatGPT]; he suggested I try it out... Working on a writing assignment for a project is when first used it, and I was pleasantly surprised.”

Surprise, shock, and awe were common reactions that users noted about their first-time experience of these applications.

Most participants had broad takes on what genAI was – they told us that it was ‘basically a software’, that learned from data or information, using it to ‘respond’ to ‘prompts’ and ‘queries’ about diverse topics. There was a back-end built on ‘data’, acquired from the internet and ‘possibly other sources’. For instance, when asked how these tools worked, the NGO worker said,

“How shall I put it?... “you basically type stuff in, and it gives you an answer..”

Another user, an AI artist, noted:

“GenAI is basically operating like these delivery companies we see today...taking information and data from all sorts of sources and delivering it to you as one compiled package...”

As we continued to speak to users about their characterisations of genAI applications and how they understood the functionality of these tools, several compared tools like ChatGPT, Perplexity, and Consensus to Google or other search engines. Several noted that they used these tools as ‘information finders’, and ‘learning aids’. They noted that some tools, such as Perplexity and Consensus, which specialise in delivering sourced information, and condensing scientific insights from peer-reviewed sources, enabled them to collate information across different research areas, and find ideas they didn’t know to look for

or think about.

For instance, one user, working in the health sector, noted,

“It [ChatGPT] is basically one step ahead of Google... like earlier, if I had to research some concept like say Beta thalassemia, I had to type it into Google, read a bunch of articles in order to understand it... ChatGPT cuts out that part of the process.”

Another user, a psychology researcher and teacher, noted,

“When I used Consensus (an AI tool that collates diverse research papers), I came across topics and other research papers related to mine that I was not even aware of...It helped me narrow my search, and also made me feel like all my bases were covered.”

Users also characterised these tools as ‘time-saving devices’ that helped them cut down the time it took to complete tasks, while others noted how they used these applications to take their writing to the ‘next level’, and overcome language and communication barriers.

For instance, one user, a freelance researcher and analyst, noted,

“My mother tongue is Malayalam, ...[I am] not a native English speaker and often the inflections of Malayalam seep into my English... There are some sectors where I worked where there is a huge emphasis on how you talk and present yourself... not so much in the engineering field, but more in the social sector... In the past, you know, someone I was working with mistook my

written tone for arrogance, so sometimes, I also use AI to adjust my tone and stuff in writing...”

For many users, there was also an element of fun and play associated with the use of these tools. They noted that it was ‘fun to learn things using AI.’ Some used it as a ‘conversational partner’ and ‘curiosity engine’. Others said they used the tool to ‘kickstart their brains’, as a ‘second brain’ and to do ‘brain-dumping’ or “brain-storming”. The interactivity associated with genAI applications, due to their natural language interface, was what made it fun for many. The fact that ‘something’ talked back to them while they talked to ‘it’ was engaging for most people.

One participant, a UI/UX developer noted:

“Some of the AI tools like DALL-E and all, are really useful to do a brain dump of your ideas... instead of spending many days trying out different ideas, you prompt the engine to give you multiple versions.”

However, all the participants we spoke with were acutely aware of the shortcomings of these technologies. Even as they highlighted the utility of these applications, and ascribed roles such as ‘teacher’, ‘intern’, ‘assistant’, users were quick to qualify these ascriptions, and note the flaws in these applications, using words like ‘mediocre’, ‘bad’, and ‘flawed.’

For instance, one user a journalist, said,

“Think of it like a really mediocre assistant.”

Another, a biotech professional noted:

“It is like an assistant, but a really bad one, it

gets things wrong”

Echoing the above, another user, a freelancer noted,

“90% of the time, genAI got it wrong”, it makes a lot of calculation mistakes,

Another said:

“Image-generation AIs cannot get fingers right!”.

And yet another noted:

“There is no way you can blindly trust it, it cooks stuff up”

Based on user responses, it was quite clear that once people began using these technologies, the initial shock and awe response was soon displaced by a more critical and measured take on these tools. Users were aware of the limited utility of genAI tools, and the propensity of genAI to “hallucinate”, i.e. when the genAI model produces outputs that are ‘either nonsensical or outright false’ even though they are presented as facts.¹²⁰ Even within wider public discourse, genAI hallucinations have been promptly recognised as a cause for concern. This is because genAI hallucinations can quietly seep into its outputs, appearing as a combination of facts and falsehoods, in ways that make the lies appear entirely plausible, thus much harder to detect.¹²¹

However, as some users in this study, and others in the public discourse have highlighted, there can also be a flip-side to AI hallucinations. If genAI outputs can be completely “untethered from the realm of facts”, they can also be productive. By providing plausible alternate realities, genAI tools

could widen users’ imaginations. Besides genAI hallucinations, and producing incorrect outputs, some users were also skeptical of the ultimate utility of these tools, as often, experiments with genAI applications did not result in expected outputs. One user, a researcher noted,

“I tried testing out chatGPT to write a few paragraphs from my research, just to see what it can do. I typed in a paragraph from my paper, and prompted it to rewrite and edit it without changing the meaning of what I wrote..and it completely failed. It changed the emphasis of the points I wanted to make in that paragraph in subtle but misleading ways. So, I don’t use it as much to write anything...”

3.3 An AI Mode of Getting Things Done

In spite of the apparent flaws of genAI, most users we interviewed highlighted their continued usage of these tools. People distinguished between a ‘manual mode of doing things’ vis-a-vis an emergent ‘AI mode of doing things’, and in some cases, preferred the latter. In response to the question of why use genAI in spite of its limitations, one user, working in the biotech industry put it simply: it still cuts his work-time in half, making him more efficient. He said,

“It still cuts down the time I take to complete my work...yes, it gives inaccurate information, I just have to cross-check it, but it still gets the job done quicker than normal...”

When asked what he did with the time thus saved, the user pithily responded, “I quickly move on to other work!”

Another user, a journalist had a different take on

why he preferred genAI, explaining:

“Have you ever dealt with human beings?... Human beings are difficult to deal with, I use AI mostly as a personal assistant, to do editing and other microwork necessary... Unlike a human assistant, there is no melodrama and keech-peechee... It fits quite right into our solipsistic universe...”

Another user, a marketing lead at an AI company, noted:

“If efficiency steals away 10% of the jobs, then that is the price of innovation.”

Convenience, efficiency, and speed were the key drivers of why many users stuck with genAI. Recent literature on the culture of convenience points to the fact that not only has convenience become a cornerstone of our digital lifeworlds, but it has also evolved in shape and form. The new paradigm of convenience that marks our experiences with digital tools is one that has gone from convenience

Convenience, efficiency, and speed were the key drivers of why many users stuck with genAI.

“being about the ease of doing things” to “why having to do things at all”.¹²²

Some of the users echoed this sentiment when they brought up use-cases of genAI for writing emails, editing sentences, or quickly generating sample images and 3D models to show clients. Users said, “it freed up thinking time”, removing what they considered ‘grunt work’ within their workflows. One user, who worked for a car company, mentioned that at work they only

used genAI to do “repetitive tasks” or used it like a “minion to do work they didn’t like doing”. For instance, he said,

“There are parts of my work that can become very repetitive and boring, in this case, we use AI to automate these tasks.”

However, as sociologist Rogers Brubaker notes, the “seemingly trivial nature of convenience should not blind us to its power”.¹²³ Convenience reduces friction by enabling “us to do quickly and quasi-automatically what would otherwise require time, thought, and effort”.¹²⁴ By its nature, convenience resets expectations, forms habits and insinuates itself into our everyday routines, and ultimately helps sustain global genAI assemblages that thrive on the usage of digital tools and platforms.¹²⁵

In this context, users highlighted an element of addiction and development of habits of use. For instance, the biotech professional noted,

“It is hard to imagine a future where I do not use it (provided it’s for free). Me and [my] friends are already addicted to it”.

Another user, a UI/UX developer said,

“Once you use AI, it is hard to go back to a manual mode of doing things...you know, when there is an AI mode of getting things [done] available.”

Thus, the wider benefits that users often perceive from genAI at work involve much more than the mere affordances of these tools. What propels us to use genAI involves a combination of not just technological affordances, but also social, cultural, and behavioural norms associated with how we value, and view work. The valorisation of efficiency and speed as economic imperatives, and

The valorisation of efficiency and speed as economic imperatives, and a metric of performance in our work cultures, has led many users to perceive the “time-saving”, and “efficiency-enhancing” qualities of genAI as desirable.

a metric of performance in our work cultures, has led many users to perceive the “time-saving”, and “efficiency-enhancing” qualities of genAI as

desirable. However, the trade-off for efficiency can very well manifest in the ‘real risk of de-skilling’, as some users noted.

While the above analysis analyses the question of why we ‘use’ genAI, it still leaves open the question of ‘how’ we use it.

3.4 Adding the Human Touch: Self-Automation and AI

“Here, let me share my screen and show you”, said one user, a web designer, during one of our interviews. Opening up an application window on his computer for an image generator, he quickly types in a prompt “generate a supercar for 2030, differently-abled friendly, can go over land and water”. The image generator quickly churns out a super-looking supercar in seconds. “But you see”, he says, “it’s not perfect..it has no imagination of the inside”.

We do this exercise of generating images of

‘supercars for 2030’ a few more times, finding flaws in each image churned along the way. Sometimes, the angles are not right; in other images, parts of the car appear misshapen and crumpled.

“But then”, he says, “it helps you get started”.

In order to better understand the process of working with AI, we asked users to walk us through it. The user above went on to explain,

“The way it goes is, a problem comes to me, say I have to design something functional for a specific use...say something like a safety gear for industrial workers. Typically, we will go through a research process, come up with a couple of ideas, sketch those out and render them into 3D models of what the product could like (for the client). 3D modelling is something I do not enjoy. So I simply generate them [via genAI] using different prompts..”

Another user describes his workflow like this:

“With the text-to-image generation I was not applying it much [at work], it was primarily a hobby thing, I mostly now use it for image generation. But ChatGPT is the go-to, right, it is not really accurate, based on whatever data it has. ChatGPT was giving me wrong answers initially, then I went into the rabbit hole of querying it, it would apologise for the wrong answers, through this process I was able to get some answers out of it. How I use AI is to quickly get to a starting point. Earlier without AI, it took me [a] long time. Now, rather than me sitting through tedious amounts of work to just get started, I can test out multiple ideas, get a sense of what each would look like, and start generating and driving my own creativity... I can quickly generate multiple options, change

colours, isolate background ...it has reduced how labour-intensive my tasks are.”

However, regardless of whether they used genAI to write emails or essays, to produce images and 3D models, all the users we spoke with said that, at the end of day, ‘you still need to add your human touch’. Adding a human touch for users meant several things: from minor tweaks in outputs to a much longer learning curve that could involve hours and months trying to figure out the right prompts and ways of getting the right outputs.

‘Prompting matters’, says the user who works in the medical field, ‘you have to know what prompts to use and how’. Another user, a university teacher, explained,

“Typically what I will do is paste an email onto the AI [ChatGPT] and then ask [it] to generate a response, but once it does that, I will give it my human touch, change the tone or maybe the first sentence to sound more like how I sound in real life..”

Often users undertook multiple rounds of prompting to get the right outputs. In some instances, users noted that they relied on multiple genAI tools at once to get the output they desired.

For instance, one user, a visual artist, noted,

“If I do not get the output I want, I prompt ChatGPT to produce a prompt for Midjourney.... Prompting can also be a tedious task”.

Adding a human touch could also mean teaching genAI tools to work like a human (which is the entire thrust of the present genAI industry), but, to be more specific, to work like one specific individual

or user through varying levels of customisation. As the web designer continued to tell us,

“What I do is I have a coding window open next to my work window. I am not someone who is adept at coding, I don’t have a background in it. So I use AI to generate the code I want, however, I had to teach it a couple of things first. So, if you go to ChatGPT Playground, which is the platform for developers, it allows you to teach the bot to chat like you. So now I have taught chatgpt to answer as if it were me...”

Thus, “working with AI”, as several users noted, “was still a lot of work”. In his study of automation, media studies scholar Luke Munn dispels the myth of automation as a seamless and frictionless force, arguing that automation of any kind involves “an often frustrating and complex choreography of human-machine interactions”.¹²⁶ In the context of our genAI interviews, this complex choreography manifests in the way in which users need to edit and teach the systems to respond in ways they seek. As the web designer in our interview puts it, for him, “it was like microtraining the model, to respond as how he would respond”, thereby, automating the self.

This complex choreography of working with AI extends not only to end-users, but to all other forms of human labour, both visible and invisible, that goes into making genAI appear autonomous. Thus, unlike what most marketing campaigns of genAI would have us believe, genAI is no quick ‘silver bullet’ to eliminate work.

Furthermore, conversations with users about working with AI also led to discussions about the meaning and value of work, and the difference between “work” done by humans vis-a-vis

machines. Users pointed out that genAI could never truthfully replace human work, given that it requires meaning, experience, and subjectivity to ultimately produce “a work of value”. For instance, one user, an independent researcher, noted,

“The reason I am hired to do something is not simply because of my skill-set, but also because of the values and experiences I bring to my work. Can AI easily replicate that?”

Another user, a marketing manager argued,

“If you are generating watercolours and do not know water colours, their nature and how to work with them...what’s the point of that? When you don’t know how to do something... You need [the skills for] manual work to make whatever AI spits out into something with meaning, you need to know how to make it your own.”

Making ‘it’ your own meant working actively to induce meaning, interpretation, and subjectivity into the outputs produced by genAI. The rise of genAI and its adoption into everyday workflows not only gives rise to new form of human-machine interactions impacting how we work, create, and imagine, but also prompts reflections on the nature and value of human work and labour. User interactions with genAI led to the creation of new kinds of boundary work that seeks to negotiate the lines between humans and machines, alongside new paradigms of what constitutes work and labour. While ‘work’ was seen as creative, ‘labour’ has connotations of the mundane and repetitive. However, these boundaries between work and labour are not always clear, and have become increasingly permeable and open to debate.

Exploring the evolving relationship between users

and genAI also highlights the complex interplay of expectations, challenges, and opportunities that define this interaction. The relationship between users and genAI is one that is dynamic, recursive and even faulty at times, involving a continual process of learning, adaptation, and customization. While many users perceived advantages in terms of speed and convenience, they also acknowledged that meaningful work extends beyond mere efficiency. The ability to add a “human touch” to genAI’s outputs, whether through customization or correction, underscores the value of human skills such as empathy, creativity, and critical thinking at work. This critical perspective extends to broader societal implications of genAI adoption. As users navigate the complexities of human-machine interactions, they also raise questions about the impact of genAI on job roles, skills development, and what it means to be human alongside AI. These considerations highlight the need for a nuanced approach to genAI adoption and deployment at work that acknowledges both its potential and its limitations, ensuring that human values and agency remain central in the genAI-driven future.

04 Futures

“We live in a world where anything new is scary – climate change, technological development, political instability has all led us to a situation where it is hard to celebrate new technologies and innovations unlike [in] earlier centuries..”

Anonymous User

As new patterns unfold, and different modes of working evolve through user interactions with genAI, we witness the emergence of new visions and imaginaries of the future of work. These perspectives range from utopian idealism and workless futures to dystopian distress in the form of automation and intensification of the gig economy. Our conversations with users revealed a sense of uncertainty about the future, particularly regarding how genAI will affect their work, employment opportunities, and working environments in the future. At the same time, users also raised concerns about the implications of genAI on not just the future of work, but society as a whole.

However, the future is not singular but plural. A scoping of the potential futures of genAI within wider public discourse reveals diverse futures imaginaries of genAI – underpinned by plural rationalities, contested values, and assumptions about how to navigate the future of genAI and the world of work. By combining user insights with broader discussions in the media, academia, and public discourse, this chapter aims to provide a broad overview of the complex dynamics at play, highlighting the challenges and opportunities along the way.

4.1. The Work that Futures Do

In 1965, American political scientist, and creator of one of the earliest AI models, Herbert A. Simon, had famously predicted that “machines will be capable, within twenty years, of doing any work a man can do.”¹²⁷ Within a decade of this prediction, the opposite transpired when much of AI research and development had plunged into what is known as the first “AI winter”¹²⁸ – a period of inactivity, loss of funding, and interest in the AI hype cycle. Needless to say, two successive AI winters later, and in the current era of AI boom, we are still far from machines capable of doing “any work a man can do”.

From large-scale imaginaries and visions of the future to more pointed predictions, the technological development of AI has been accompanied by a layer of discourse that sought to capture and colonise the imagination of what the future of the technology looks like. To give another example – in 1970, Marvin Minsky, in an interview with Life Magazine, stated “in three to eight years we will have a machine with the general intelligence of an average human being.”¹²⁹ Closer to our own time, the rapid development of genAI has given birth to a wide range of ideas about the future, punctuated by predictions, visions, and imaginaries. Take, for instance, recent statements made by Google CEO, Sundar Pichai, who proclaimed that “genAI is likely to be the biggest technological shift in our lifetimes and might even turn out to be bigger than the internet itself”.¹³⁰ Other narratives centre around how genAI will unleash a world of productivity, “democratise creativity”, “boost” economies, and “empower workers”.¹³¹ These future visions are not limited utopian ideals alone; they also invoke dystopian fears and anxieties. For instance, in the

aftermath of the launch of ChatGPT, the Future of Life Institute released an open letter calling for the halt of AI development, due to their lack of predictability and control.¹³² Other experts such as AI scientist Geoffrey Hinton have called attention to the existential risks posed by AI.¹³³

While it may be tempting to dismiss future visions and imaginaries associated with genAI as mere hype or hyperbole, such visions and imaginaries are ‘fundamentally generative’, in so far as they propel specific social, material, and normative consequences into being.¹³⁴ Research in Sociology and Science and Technology Studies (STS) has long realised the import of ‘socio-technological imaginaries’, and the role that visions of the

Visions and imaginaries of the future, simply put, not only enable us to imagine a future, but also shape it.

future play in catalysing techno-scientific innovations and trajectories.¹³⁵ Technological visions do not simply describe future technologies, but also help to bring them into being. For instance, expectations can help innovators mobilise support, gain

funding, direct the attention of others, help enrol external actors, or ward off competitors. Future visions can also mature into harder requirements and path-dependencies that gain strength over time – becoming concrete expectations, institutional structures, and normative ideals.¹³⁶ Even though multiple visions of the future exist, and are contested – dominant narratives can over time prevent or marginalise alternative futures from taking shape.¹³⁷

Visions and imaginaries of the future, simply

While multiple actors jostle to legitimise their visions of the future, these visions are also under-pinned by multiple rationalities, values, and assumptions about the future.

multiple actors jostle to legitimise their visions of the future, these visions are also under-pinned by multiple rationalities, values, and assumptions about the future.¹³⁹ This raises questions about the power and politics involved in imagining the future. Who gets to imagine the future? In what ways do different actors imagine the future?

4.2. Four Futures of GenAI and Work

Conversations with users about the future of genAI and work yielded multiple interpretations and ideas about the future. While for some the future was unclear, others saw it as a realm of hope and opportunity— to reform existing practices and explore possibilities beyond current limitations. Irrespective of the future’s trajectory, a prevailing theme in our discussions was the shared sense of ownership over its direction and outcomes. Thus, as one user, an entrepreneur, bluntly pointed out, “I would be happy with/prefer a non-AI world,

put, not only enable us to imagine a future, but also shape it. Viewed from this perspective, the future is not merely a temporal abstraction or what comes after the present, but a “contested ground of social and material action”, in which “different actors, and voices vie for ascendancy and engage in a range of rhetorical, organisational, and material practices that seek to colonise the future or secure successfully for themselves a specific kind of future.”¹³⁸ While

however, if the future is that of AI and capitalism, I would want [to be] a part of it”.

User conversations on genAI and the future of work not only yielded diverse visions, but also depicted how popular imaginaries within the public discourse impinge and shape how we think about the future. While reflecting public imaginaries, nonetheless users’ narratives shed a more nuanced perspective and insight into these emerging trajectories. In this section, we provide an overview of the different futures of genAI and work by combining user perspectives with the emerging discourse around the future of genAI and work, highlighting the challenges and opportunities along the way.

4.2.1 On the Road to Utopia: Human Augmentation and the Boundless Horizon of Productivity

The rapid emergence and the surrounding hype around genAI applications has given rise to a wide number of utopian visions about the potential of the technology to unleash the “next frontier of human productivity”,¹⁴⁰ “augment creativity”, and reduce the drudgery of human labour. Take for instance, a recent Harvard Business Review article which notes that, by promoting divergent thinking, AI will enable the ‘democratisation of innovation’, leading to ‘hitherto unimaginable solutions’.¹⁴¹ These solutions could range anywhere from designing unique automobiles, to manufacturing drugs, to writing copy and producing art.¹⁴²

The utopian discourse on genAI often positions the technology as a ‘helpful assistant’ or a ‘creative partner’ that will enhance worker productivity,

cutting down the time it takes to complete mundane tasks. For example, venture fund ARK Invest predicts that “during the next eight years AI software could boost the productivity of the average knowledge worker by nearly 140%, adding approximately \$50,000 in value per worker, or \$56 trillion globally.”¹⁴³ Similarly, other consultancy firms and agencies predict anywhere between 40-70% rise in worker productivity.¹⁴⁴ Predictions about improvements in labour productivity, that is, the ratio of value-added output to labour-hours worked, rests on the ideal of augmentation rather than automation. That is, rather than genAI replacing human-beings, the introduction of genAI at the workplace is seen as a force multiplier for boundless productivity of the average knowledge worker.

Thus, proponents of the utopian view see genAI not as a replacement of human beings, but as an “amplifier” of human capabilities.¹⁴⁵ By freeing up human resources for more complex and creative endeavours, the future is expected to bring a collaborative model of work between humans and AI. Take, for instance, the marketing tagline of sudo-write, built on GPT 4, which positions the chat-assistant as a “non-judgemental”, “always on” writing partner, that never tires or runs out of ideas.¹⁴⁶ However, as economist Michael Spence argues, automation and augmentation can present two sides of the same coin.¹⁴⁷ In this context, while augmenting the tools and skills of its imagined writer, it makes way for the replacement of the user’s interlocutor – their editors, copywriters.¹⁴⁸

The utopian ideal of genAI rests on the promise of genAI being able to deliver boundless productivity and freedom that manifests itself in the form of infinite choices. “The future of creativity,” writes one author in a TIME article, “in a world of

generative AI is that it enables us to map choices as never before—to explore exponentially more combinations of choices, compare and contrast infinite approaches at a glance, and constantly test new ideas.”¹⁴⁹ Rather than waste time coming up with existing ideas, the author argues, people can apply their creative energy toward iterating, assembling, and combining to create new, powerful ideas they would not have been able to generate without AI.¹⁵⁰

While multiple actors jostle to legitimise their visions of the future, these visions are also under-pinned by multiple rationalities, values, and assumptions about the future.

This utopian ideal of genAI as a “powerful assistant” and a generator of “new ideas” is what attracted many users to test out the technology for themselves (as discussed in the previous chapter). The expectation that genAI will lower the amount of mental energy or time required to complete tasks was common to all the users

in our study. However, as many users eventually discovered, working with AI was indeed a lot of work, and nowhere near the frictionless force it is often presented to be. The utopian ideal of human augmentation with genAI demands the acquisition of new skills, and capacities from workers. As our conversations with users revealed, not only was learning how to prompt important to maximise the outputs received, in some instances, users also highlighted the need for a command over the English language.

“If you don’t know English, it will be difficult to work with genAI”, noted one user.

This is because most text-based genAI applications run on English as a natural language, with only a few offering language translations. Beyond the question of a user’s linguistic access to these tools, the training data for most LLMs itself draws from only 20 “high-resource” languages (i.e. where enough data is available), – of which English takes the majority share.¹⁵¹

Utopian visions also run the risk of invisibilizing the extractive logics of genAI-driven value creation and capture. For instance, prompting a genAI model for “new ideas” is not simply a matter of “mining human knowledge’s vast hidden treasure troves to find the nuggets of knowledge” but, instead, raises questions of copyright infringements and illegal use of the intellectual property of others.¹⁵² In this context, one user, a marketing manager, noted that,

“GenAI is not creating anything new or original, but simply plagiarising the works of others, without giving them credit for it, particularly in the music industry.”

This is not to say that gen-AI is without potential or cannot augment human thinking and creativity. Like the utopian visions, several users noted its usefulness for brainstorming ideas, learning new things, and overcoming distinct and personal challenges. One user, a visual artist, in particular noted how genAI had helped her overcome her physical disabilities after an accident:

“A couple of years ago, I had an accident, due to which I have difficulties using my hands very well. I can no longer draw by hand. In this

respect genAI tools have been useful in helping me overcome this disability.”

However, the utopian ideal of augmentation also raises the question: To what extent should human beings be augmented? For instance, one user, a researcher at an university, reflected on his anxiety about genAI taking over human beings’ capacity to think, and the decay of critical thinking faculties.

“I really worry about whether AI should take over the thinking part of human beings. What will happen to us politically if we give up thinking?”

Thus, while utopian narratives highlight the immense potential of genAI to harness and shape human thought and perception, and continues to fuel hype about the future, the past continues to be a central problematic in these visions. Not only does the past shed light on the extractive logics of current genAI systems, but past trends in the labour market impacts of AI also paint a different scenario for the future.

4.3 Keeping Up with AI: Dystopian distress, Automation, and Anomie

In contrast to the genAI utopia imagined by its proponents, critics argue that the automation of work, job displacement, and the disenfranchisement of workers continues to be a real possibility in the context of genAI. Critical of the augmentation and economic potential of genAI tools, dystopian scenarios point to the already present trend towards automation in late capitalism – from the creation of driverless cars and trucks, to the use of algorithmic systems to make hiring decisions.¹⁵³ Proponents of this view argue that genAI will not only continue,

but intensify, automation’s adverse effects on labour: including the polarisation of employment, stagnant wage growth for middle- and low-skill workers, and a lack of good jobs.¹⁵⁴ “Polarisation of employment” refers to a shift away from mid-level skilled employment (customer services, insurance underwriting, office support, etc.) and increases in the employment shares of both low-skill and high-skill occupations.¹⁵⁵ It is, thus, argued that rather than boosting worker productivity and economic growth, genAI will instead further fuel social and economic inequities, leading to the concentration of wealth.¹⁵⁶ Furthermore, the benefits of improved labour productivity, i.e. value produced in relation to hours of work, might translate to a rise, not in average worker incomes, but in capital income instead.¹⁵⁷

In some cases, genAI is already in the process of automating jobs. According to reports, Duolingo, a language-learning app company, has laid off 10% of its contract workers due an increased focus on AI-generated lessons.¹⁵⁸ Similarly, companies such as Google and StackOverflow have also reduced staff due to their pivot towards genAI technologies.¹⁵⁹ In many cases, rather than directly replacing workers, the hype of genAI is leading several companies to redirect resources towards AI infrastructures.¹⁶⁰

In the dystopian disintegration imaginary, the pervasive automation facilitated by generative AI emerges as a harbinger of profound societal challenges that could lead to social anomie and the widening of socio-economic disparities. In this respect, one user, a journalist, noted that,

“GenAI could very well lead to chaos and disintegration. Imagine if everyone did only creative work, societal division of labour would break down, and there would be chaos.

Meanwhile without social safety nets, people will come for blood, someone has to take care of all that [and vital infrastructure would be] would be impacted”.

Some users were also equally sceptical about automation claims and capabilities of AI. One user, a product manager, noted that,

“Having interacted with the tools, it is safe to say that AI won’t be automating us any time soon..It requires being human to communicate, understand, and work”.

Instead, conversations with users also highlighted the more micro-level changes that could begin to impact the way we work in the future. For many users, it was not so much the spectre of automation that worried them, but changes in routines, expectations, and the constant need to “keep up with AI”.

‘Keeping up with AI’ for users not only meant having to update and re-invent themselves at work, but extended to keeping up with the pace of AI work-production.

For instance, one user, an AI artist, noted

“There will come a time when we will have to constantly ‘update ourselves’ in relation to the machine, we will have to keep learning and upskilling, otherwise there is a real danger of automation and job loss.”

Another echoed this sentiment, by stating that,

“I can imagine a future where we will work more, not less. Already with the basic type of AI, we are taking on more projects because AI lets

you work that much faster”

This is consonant with what is already happening in some workplaces. For instance, the CEO of software firm Freshworks has said that tasks that previously took eight to 10 weeks are now being completed in days as a consequence of adopting AI tools into its workflows.¹⁶¹ Users were also concerned about the dangers of deskilling. Echoing what the user quoted above said about genAI and deskilling, recent research confirms the fact that excessive reliance on genAI tools can legitimately deskill people. In such a context the concern for many users remained staying abreast of AI, upskilling, and becoming AI-ready.

4.2.3. Working Alone Together: Gigification and the AI-assisted Independent Worker

Between these two broad imaginaries of genAI and work futures, other futures emerge in-between, which constitute both a fallout and a further intensification of trends highlighted within the utopian-dystopian divide.

One of the key implications of genAI on the future of work is the further expansion of the gig economy. Characterised by short-term, temporary work, the gig economy has been rapidly expanding in recent years, particularly from Covid-19 pandemic-induced labour market disruptions and the normalisation of remote work.¹⁶² Within this imaginary, the emergence of genAI is expected to further intensify this trend.¹⁶³

One of the key ways in which genAI is expected to impact the gig economy is by automating and streamlining parts of the job. According to a recent

McKinsey survey conducted in the US, the use of genAI tools at work could automate up to 30% of a worker's job.¹⁶⁴ Partial automation of jobs could lead companies to decide that workers “are no longer providing enough value to warrant a full-time salary and benefits”.¹⁶⁵ Further, the current state of genAI is such that it still requires human oversight to function effectively. As companies amp up genAI adoption in the future, necessary human oversight, and any gaps in tasks that are not easily automable, could simply be outsourced to gig and contract workers, or worse, laid-off workers could be “re-hired at lower wages to babysit these systems”.¹⁶⁶ Also, as AI companies continue to invest billions in genAI, existing AI development business models that utilise poorly-paid gig and freelance workers across the global south, for various kinds of data annotation, cleaning, and labelling services, could witness a further intensification.¹⁶⁷

Combined with an expanding gig economy, the potential for genAI tools to “augment” human labour has also given rise to visions of the future of work (work 5.0), centred around “AI-assisted independent workers”.¹⁶⁸ Within this vision, freelance platforms like Fiverr and Upwork argue that by speeding up the time it takes to complete tasks, AI-assisted freelance workers will be able to access “new jobs and new opportunities.”¹⁶⁹ AI companies are already gearing up to provide for such a future, by hyper-personalising genAI tools for every user/worker. For instance, OpenAI's most recent iteration, where ChatGPT has a memory that allows it to remember information about a user, and their previous chats with the app, allows greater personalisation.¹⁷⁰ In a similar vein, Inflection AI, a company founded by ex-DeepMind engineers, focuses on creating a personal AI for everyone: “Imagine your personal AI companion with the single mission of making

you happier, healthier, and more productive.”¹⁷¹ Further, the recent move by OpenAI to allow access to Application Programme Interfaces (APIs) for users and developers to build their own custom applications, allows for personalization on a much larger scale.¹⁷² In the context of work, it is expected that workers can leverage APIs for customising genAI tools, which will extend their capabilities without managing the complexities of model training.

Echoing some of the hopefulness of these narratives, users in our interviews highlighted the potential of the technology in enabling them to open up multiple income streams. One user, a UI/UX developer, highlighted,

“GenAI has enabled me to operate an entire business without hiring new personnel. The way I work is that I am outfitted with numerous AI applications and tools, which I then use to deliver the kind of work that would normally take me a few more people to deliver”.

However, a flipside of the growing opportunities for the gigification of labour is the already present pressure of freelancers having to lower labour rates, while delivering work on shorter turnaround times.¹⁷³ Working conditions under the platformised gig economy, organised as a non-collective process, where on a day-to-day basis, workers interact almost exclusively with technological apps, already hamper collective bargaining power and unionisation avenues for gig workers. The imaginary of the autonomous, independent, and AI-assisted worker thus also raises questions about its impact on worker solidarity, bargaining power, and growing levels of precarity of work in the future.

4.2.4 Workless Futures: AI Automation and Universal Basic Income

The heightened potential for automation in relation to genAI has also led to visions regarding the possibilities of a workless future. Within this envisioned post-work society, genAI has the potential to automate not just menial tasks but creative and complex work as well, challenging human roles in many sectors. For instance, in a recent dialogue at the Bletchley Park summit on AI, between British Prime Minister, and CEO of Tesla, Mr. Elon Musk, on the future of AI, the latter envisioned that “there will come a point where no job is needed - you can have a job if you want one for personal satisfaction but AI will do everything.”

While in the context of genAI and work, the idea of workless futures has gained some ground amidst the hype, it is not by itself a new idea. In 1930, John Maynard Keynes had predicted that surplus generation under capitalism and technological development would drastically reduce working time for people by 2030. The future promised more leisure time and the opportunity for people to achieve well-being with a reduced work commitment.¹⁷⁴ Karl Marx, as well, envisioned a future where human labour would be less alienated and “a man could go to work in the morning, fish in the evening”.¹⁷⁵ For both Marx and Keynes, the pursuit of escape from work and the pursuit of more non-work time were key to the political visions they outlined.¹⁷⁶

Contemporary visions of a workless future in the context of genAI, however, are fuelled less by ideas of social reform as Keynes held, or a socialist revolution as Marx envisioned, and more by the accelerating pace of technologies. Within these visions, narratives of genAI’s “productivity-

Within these visions, narratives of genAI’s “productivity-enhancing” potential are coupled to the ‘liberatory powers of technology’ to free people from the drudgery of work.

enhancing” potential are coupled to the ‘liberatory powers of technology’ to free people from the drudgery of work.¹⁷⁷ For instance, digital economy researcher Nick Srnicek argues that the positive side of technology-fuelled automation could lead to not only a shortening of the working week, but also enhance labour’s bargaining power if done right.¹⁷⁸ Rather than perceive technological automation as an inevitability, proponents of this viewpoint that full automation and technological unemployment should be a political project, that leads to workless futures, where employment is no longer the central axis around which adult life revolves.¹⁷⁹ Imagining such a future often ties in with discourses on Universal Basic Income (UBI), wherein all citizens receive a regular, unconditional sum of money from the government or another public institution, providing a safety net regardless of employment status.

However, as research suggests, technological advances do not necessarily lead to labour-saving or time-saving work, but instead to a reorganisation of work – adjusting normative standards of what work is.¹⁸⁰ Critics argue that not only does new technology introduce more work for people, it will also lead to additional kinds of work, imposing “new regimes of labour and management atop the labour required to carry out the supposedly labour-saving effort”.¹⁸¹ Thus, new technologies

often create new expectations and norms, raising standards and the amount of work required to attain them.¹⁸²

The socio-technological imaginaries related to a post-work society hinge upon the efficiencies driven by AI systems. The promise of AI-driven efficiency and productivity could contrast sharply with the parallel narrative of economic displacement and social restructuring. The potential redundancy of human labour in many fields invites speculation about how societies might reclassify ‘work’ and ‘value’.

4.3 Grappling with the four futures of GenAI and work

The different futures of work in the context of genAI outlined above are not mutually exclusive, nor are they entirely beyond the horizon. As noted in this chapter, multiple trends within these futures are already beginning to take shape. For instance, employers and company executives are increasingly looking towards genAI tools to enhance worker productivity, while workers are also preparing for a future of job displacement and disintegration through continuous upskilling and learning to work with genAI. Similarly, across industries, job displacement and automation trends are already underway, while policy initiatives in some countries like the UK have begun to consider the potential of UBI in easing the labour transition for work in the Fourth Industrial Revolution (4IR).¹⁸³

As society grapples with these divergent futures, it is crucial to approach the development and integration of genAI into the workforce with careful consideration and foresight. By fostering a nuanced understanding of the potential benefits

and pitfalls of genAI, we can work towards shaping a future where technology enhances human potential and fosters a more equitable and sustainable society.



05 User Perspectives Towards an Ethics of GenAI

Regardless of the future(s) in store, many users spoke of the feeling of inevitability associated with the emergence of genAI in their work and lives. One user, a researcher at an university, noted that,

“I know I will have to contend with genAI one way or another in the future, whether I like it or not”.

Another user, a HR manager, put it simply, “it is hard to imagine a future without AI now.”

The idea of inevitability that is often associated with socio-technological trajectories of AI, generative or otherwise, is part of a much wider discourse that hinges on technological determinism.¹⁸⁴ Techno-deterministic ideas of AI not only view technology as an inevitable outcome of the march towards techno-scientific progress, but also assert the view that technologies develop and progress through a purely internal and technical logic alone. For instance, within the realm of technology innovation, including among AI developers, engineers, techno-scientists, and companies, there is a prevalent tendency towards techno-deterministic viewpoints that often recruits mythical language to talk about the “superhuman” capabilities of AI, which “are simultaneously seen as beyond human understanding or explanation”.¹⁸⁵ Such accounts not only have the potential to oversell the current capabilities of genAI, but also create techno-optimistic narratives about the transformative impact of genAI, while obscuring the ways in which

genAI can reproduce or intensify existing biases and power asymmetries.¹⁸⁶ Within these accounts, genAI appears as a force from nowhere, impacting not just how we live, communicate and work, but also the quality and nature of human associations.

However, as this report suggests, AI is a socio-technological assemblage, which does not function autonomously, but is the outcome of the activities of human actors, and which encompasses the production, diffusion, and use of the technology.¹⁸⁷ Viewed as a socio-technological assemblage, genAI is neither neutral nor isolated from the social contexts in which it operates. Its development, deployment and use are influenced by various societal factors, including cultural norms, economic structures, and political systems. Inbuilt into technologies are decisions and choices that are inherently political, carrying inherently political consequences.¹⁸⁸

Within this wider socio-technological assemblage of genAI, users feature not only as end-users, towards whom genAI tools and applications are targeted for consumption, but also producers of data, labour, feedback which feeds into the production of genAI systems. As emerging technologies like genAI become increasingly mainstream and pervasive in our everyday lives and at work, the user emerges as an important political subject, as well as, a stakeholder in shaping technological trajectories of genAI.

Within this study, conversations with users about genAI and its impact on work were not limited to the world of work alone. For many users, the question of genAI and its implications for the future of work, were wrapped up with the complexities and challenges of the wider socio-technological assemblage of genAI. While users highlighted the

opportunities presented by genAI at work, faced with the question of whether to continue using genAI applications in the future, many users weighed the potential benefits of the technology against its impact on other aspects of the social. Concerns emanated from users not only about the impact of genAI on the organisation of work, but also about its impact on information systems in the form of misinformation and entrenchment of biases; on political systems, in the form of our ability to be informed of facts and think critically, as well as the environmental impact of genAI tools and applications.

Talking about the copyright issues and the concentration of power and profit, one user, an independent researcher noted that they “don’t feel good about uploading their intellectual contributions into genAI, or how profits are distributed, and the exploitation of labour”.

Another user, a visual artist and researcher noted,

“I worry about the biases that genAI will reproduce in society...I tried prompting AI generated images of different cultures and people from diverse countries, some of the results were shockingly biased”.

Several users we spoke with were keenly aware of the social and political dimensions of genAI. One user, a designer and entrepreneur noted that,

“What worries me most about genAI is not what it is, or what its future is, but also how we got here – the kind of data, and the mechanism of data surveillance that has gone into these systems, for us to arrive at this point”

Another user, a social entrepreneur, noted,

“GenAI can be used as a tool for polarisation..there are so many troubling possibilities, the way in it can capture your face, voice, etc..it is crazy”

In response to mounting concerns about the safety, security, and trustworthiness of genAI models, AI and technology companies have initiated measures to mitigate emerging genAI harms. For instance, companies such as Google and Meta, increasingly employing “red-teaming”, i.e. a structured testing effort to find flaws and vulnerabilities in a genAI system, and other strategies such as “provenance classifier”, that capture the authenticity and origin of genAI outputs.¹⁸⁹ However, as researchers have pointed out, technological fixes like red-teaming currently operate as a catch-all response to quiet regulatory concerns about model safety, rather than offer concrete solutions.¹⁹⁰ Relying solely on technological fixes will not suffice to address genAI’s imminent challenges, which extends beyond narrow concerns about ‘AI safety and security’.¹⁹¹ Thus, while these fixes primarily target ‘direct’ harms, such as when genAI produces misleading or inappropriate responses, discussions about genAI’s impact must consider both direct and systemic challenges – including the concentration of power and knowledge, reinforcement of biases, and exacerbation of social inequities, as well as its impact on very nature of the social. As American political theorist Langdon Winner argues, “the things we call “technologies are ways of building order in our world, and “the issue (therefore) does not concern how many jobs will be created, how much income generated...rather, the issue has to do with ways in which choices about technology have important consequences for the form and quality of human associations.”¹⁹²

In the context of genAI's impacts, many users pointed out the absence of wider societal frameworks and ethical mechanisms to navigate the future of work and society. While the lines and boundaries around the ethics of genAI and its use are still emerging, most users we spoke with proactively adopted a few guidelines of their own, which includes:

- **Adopting critical distance from genAI, and developing an ethics of care:** Regardless of whether users viewed genAI as an assistant, a creative partner, or even a collaborator, users highlighted the need to adopt critical distance from genAI. Adopting a critical distance from genAI for many users meant being aware of the limitations as well as challenges of the technology, such as its ability to perpetuate biases, and misinformation. For many, it also meant not buying into the hype surrounding genAI. Instead users highlighted the need to check, and reject the outputs produced by genAI, and in some cases, refusal to use genAI built on the exploitation of resources and labour. Advocating for an ethics of care, users highlighted the need to account for the outcomes of the genAI as a whole.
- **Greater transparency and responsibility about data and the environmental costs of genAI:** Users highlighted the need for greater transparency and responsibility regarding data and the environmental costs of genAI. This included companies taking responsibility and being open about the environmental costs of AI, as well, fostering responsible data practices when it comes to developing genAI models. For users, responsible data practices not only included responsible storage and collection, but also meant having control over the data they shared.
- **Promoting Openness and Collaboration:** Users advocated for promoting openness and collaboration in the development of genAI technologies. They emphasised the importance of open-source practices and collaborative approaches to ensure that genAI technologies are developed in a transparent and inclusive manner.
- **Regulatory Frameworks and Governance Mechanisms:** Users emphasised the need for robust regulatory frameworks and governance mechanisms to oversee the development and deployment of genAI technologies. They stressed the importance of ensuring that these frameworks are transparent, accountable, and inclusive, with input from a wide range of stakeholders.
- **Security and Privacy:** Users emphasised the need to protect the security and privacy of individuals in the development and deployment of genAI technologies. They called for robust measures to ensure that user data is protected and that genAI systems are not used for malicious purposes.
- **Worker Empowerment and Representation:** Users also advocated for including workers in decision-making processes related to the implementation of genAI technologies at work, ensuring that their voices are heard and that their interests are protected. As genAI and automation transform the nature of work, users called for investing in upskilling and reskilling programs to help workers adapt to new roles and technologies.

Ultimately, the emergence and development of technology is a social process, and therefore their trajectories need to be socially shaped, and their values aligned to societal needs. As genAI and other digital technologies continue to become a pervasive influence in the world of work, and society in general, there is a need to foster wider societal conversations, developing a shared language and visions for desirable genAI futures. Particularly, in the context of emerging technologies like genAI, whose trajectories are uncertain and social dimensions unclear, the multiple uncertainties surrounding their development, deployment and use, calls for developing strategic foresight and anticipatory knowledge in order to navigate towards more responsible and equitable futures.

Endnotes

1. CB, F., & Osborne, M. (2023). Generative AI and the future of work: a reappraisal. *Brown Journal of World Affairs*.
2. Porter, J. (2023, November 6). CHATGPT continues to be one of the fastest-growing services ever. *The Verge*. <https://www.theverge.com/2023/11/6/23948386/chatgpt-active-user-count-openai-developer-conference>
3. Gozalo-Brizuela, R., & Garrido-Merchan, E. C. (2023). ChatGPT is not all you need. *A State of the Art Review of large Generative AI models*.
4. Wiggers, K. (n.d.). Adept aims to build AI that can automate any software process. In *TechCrunch*. <https://techcrunch.com/2022/04/26/2304039/>
5. Lu, Y. (2023). Generative A.I. Can Add \$4.4 Trillion in Value to Global Economy, Study Says. *The New York Times*. <https://www.nytimes.com/2023/06/14/technology/generative-ai-global-economy.html>
6. Maggioncalda, J. (2024). GenAI may add \$1.2-1.5 trillion to India's GDP in next 7 years. In *The Economic Times*. <https://economictimes.indiatimes.com/news/economy/indicators/genai-may-add-1-2-1-5-trillion-to-indias-gdp-in-next-7-years/articleshow/107437711.cms?from=mdr>
7. Generative AI could add up to \$4.4 trillion annually to global economy. (2024). In *ZDNET*. <https://www.zdnet.com/article/generative-ai-could-add-up-to-4-4-trillion-annually-to-global-economy/>
8. Benbya, H., Strich, F., & Tamm, T. (2024). Navigating Generative Artificial Intelligence Promises and Perils for Knowledge and Creative Work. *Journal of the Association for Information Systems*, 25(1), 23-36.
9. Kissinger, H., Schmidt, E., & Huttenlocher, D. (2023). Opinion. In *WSJ*. *The Wall Street Journal*. [https://www.wsj.com/articles/chatgpt-heralds-an-intellectual-revolution-enlightenment-artificial-intelligence-homo-technicus-technology-cognition-](https://www.wsj.com/articles/chatgpt-heralds-an-intellectual-revolution-enlightenment-artificial-intelligence-homo-technicus-technology-cognition-morality-philosophy-774331c6)
10. Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., ... & Zhang, Y. (2023). Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*.
11. Phadnis, S., & John, S. (2023). 'Gen AI's impact will be as big as printing press.' In *The Times of India*. <https://timesofindia.indiatimes.com/business/international-business/gen-ais-impact-will-be-as-big-as-printing-press/articleshow/103114534.cms>
12. Thompson, D. (2023). AI Is a Waste of Time. In *The Atlantic*. <https://www.theatlantic.com/ideas/archive/2023/04/ai-technology-productivity-time-wasting/673880/>
13. Hanna, A., & Bender, E. (2023). "AI" Hurts Consumers and Workers -- and Isn't Intelligent. In *Tech Policy Press*. <https://techpolicy.press/ai-hurts-consumers-and-workers-and-isnt-intelligent>
14. Crawford, K. (2021). *The atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.
15. Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., ... & Liang, P. (2021). On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*.
16. Oudshoorn, N., & Pinch, T. (Eds.). (2005). *How users matter: The co-construction of users and technology*. MIT press.
17. Simon, H. A., & Newell, A. (1958). Heuristic problem solving: The next advance in operations research. *Operations research*, 6(1), 1-10.
18. Autor, D., Mindell, D., & Reynolds, E. B. (2024, February 18). Why 'the future of AI is the future of work'. *MIT Sloan Ideas Made to Matter*. <https://mitsloan.mit.edu/ideas-made-to-matter/why-future-ai-future-work>
19. Weizenbaum, J. (1966). ELIZA—a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1), 36-45.

20. Tarnoff, B. (2023, September 1). Weizenbaum's nightmares: how the inventor of the first chatbot turned against AI. *The Guardian*. <https://www.theguardian.com/technology/2023/jul/25/joseph-weizenbaum-inventor-eliza-chatbot-turned-against-artificial-intelligence-ai>
21. Jarow, O. (2023, March 5). From ELIZA to ChatGPT, our digital reflections show the dangers of AI. *Vox*. <https://www.vox.com/future-perfect/23617185/ai-chatbots-eliza-chatgpt-bing-sydney-artificial-intelligence-history>
22. Hofstadter, Douglas R. (1996). "Preface 4 The Ineradicable Eliza Effect and Its Dangers, Epilogue". *Fluid Concepts and Creative Analogies: Computer Models of the Fundamental Mechanisms of Thought*. Basic Books. p. 157. ISBN 978-0-465-02475-9.
23. Jarow, O. (2023, March 5). From ELIZA to ChatGPT, our digital reflections show the dangers of AI. *Vox*. <https://www.vox.com/future-perfect/23617185/ai-chatbots-eliza-chatgpt-bing-sydney-artificial-intelligence-history>
24. Ibid
25. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March). On the dangers of stochastic parrots: Can language models be too big?. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency* (pp. 610-623).
26. Generative AI will far surpass what ChatGPT can do. Here's everything on how the tech advances. (2024). In ZDNET. ZDNET. <https://www.zdnet.com/article/generative-ai-will-far-surpass-what-chatgpt-can-do-heres-everything-you-need-to-know-how-the-tech-advances/>
27. Heaven, W. D. (2023, December 18). Welcome to the new surreal: How AI-generated video is changing film. *MIT Technology Review*. <https://www.technologyreview.com/2023/06/01/1073858/surreal-ai-generative-video-changing-film/>
28. Pequeño, A. (2023, June 12). Grimes Helps Artists Distribute Songs Using Her AI Voice—If They Split Royalties. Here's How It Works. *Forbes*. <https://www.forbes.com/sites/antoniopequenoi/2023/06/12/grimes-helps-artists-distribute-songs-using-her-ai-voice--if-they-pay-royalties-heres-how-it-works/?sh=4468ebe049ae>
29. Afshar, V. (2023). How to achieve hyper-personalisation using generative AI platforms. ZDNET.
30. Luk, M. (2023). Generative AI: Overview, economic impact, and applications in asset management. *Economic Impact, and Applications in Asset Management* (September 18, 2023).
31. Tang, B., Ewalt, J., & Ng, H. L. (2021). Generative AI models for drug discovery. In *Biophysical and Computational Tools in Drug Discovery* (pp. 221-243). Cham: Springer International Publishing.
32. Dhoni, P., & Kumar, R. (2023). Synergizing generative ai and cybersecurity: Roles of generative ai entities, companies, agencies, and government in enhancing cybersecurity. *Authorea Preprints*.
33. Shrivastava, R. (2023). How ChatGPT And Billions In Investment Helped AI Go Mainstream In 2023. In *Forbes*. *Forbes*. <https://www.forbes.com/sites/rashishrivastava/2023/12/27/how-chatgpt-and-billions-in-investment-helped-ai-go-mainstream-in-2023/?sh=5b18ab2b7176>, Also see, Center, C. B. S. E. L. E. (2023). Generative AI: The New Frontier For VC Investment. *Forbes*. <https://www.forbes.com/sites/columbiabusinessschool/2023/01/17/generative-ai-the-new-frontier-for-vc-investment/?sh=6062c762519c>
34. Roose, K. (2023). How ChatGPT Kicked Off an AI Arms Race. *International New York Times, NA-NA*.
35. Huang, Z. "Chinese Search Giant Baidu to Launch AI Bot like CHATGPT Bot in March." *Bloomberg.Com*, Bloomberg, 30 Jan. 2023, www.bloomberg.com/news/articles/2023-01-30/chinese-search-giant-baidu-to-launch-chatgpt-style-bot-in-march.
36. Vincent, J. (2023). Google invested \$300 million in an AI firm founded by former OpenAI researchers. In *The Verge*. *The Verge*. <https://www.theverge.com/2023/2/3/23584540/google-anthropic-investment-300-million-openai-chatgpt-rival-claude>
37. Fung, B., & Thorbecke, C. (2023). Google launches Gemini, its most-advanced AI model yet, as it races

- to compete with ChatGPT. In <https://edition.cnn.com/2023/12/06/tech/google-launches-gemini-compete-with-chatgpt/index.html>
38. Roth, E. (2023). The nine biggest announcements from Google I/O 2023. *The Verge*. <https://www.theverge.com/23718158/google-io-2023-biggest-announcements-ai-pixel-fold-tablet-android-14>
 39. Johnston, J. (2008). *The allure of machinic life: Cybernetics, artificial life, and the new AI*. MIT Press.
 40. Harshvardhan, G. M., Gourisaria, M. K., Pandey, M., & Rautaray, S. S. (2020). A comprehensive survey and analysis of generative models in machine learning. *Computer Science Review*, 38, 100285.
 41. Heaven, W. D. (2023). The inside story of how ChatGPT was built from the people who made it. *MIT Tech. Rev.*
 42. Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., ... & Tavares, M. M. (2024). Gen-AI: Artificial Intelligence and the Future of Work. Staff Discussion Notes, 2024(001).
 43. Ibid
 44. Ortiz, S. (2024). 40% of workers will have to reskill in the next three years due to AI, says IBM study. In ZDNET. <https://www.zdnet.com/article/40-of-workers-will-have-to-reskill-in-the-next-three-years-due-to-ai-says-ibm-study/>
 45. Shin, D., & Kee, K. F. (2023). Editorial note for special issue on AI and fake news, mis (dis) information, and algorithmic bias. *Journal of Broadcasting & Electronic Media*, 67(3), 241-245.
 46. Lamb, K., Potkin, F., & Teresia, A. (2024). Generative AI may change elections this year. Indonesia shows how. In Reuters. <https://www.reuters.com/technology/generative-ai-faces-major-test-indonesia-holds-largest-election-since-boom-2024-02-08/>
 47. ET Online. (2023). AI and Privacy: The privacy concerns surrounding AI, its potential impact on personal data. In *The Economic Times*. <https://m.economictimes.com/news/how-to-ai-and-privacy-the-privacy-concerns-surrounding-ai-its-potential-impact-on-personal-data/articleshows/99738234.cms>
 48. ul Ain, N. (2023). Gender Biases in Generative AI: Unveiling Prejudices and Prospects in the Age of ChatGPT.
 49. Roy, A. (2024). Indian publishers seek rules for copyright protection against generative AI models. In *The Economic Times*. <https://m.economictimes.com/tech/technology/indian-publishers-seek-rules-for-copyright-protection-against-generative-ai-models/articleshows/107154425.cms>
 50. Alasadi, E. A., & Baiz, C. R. (2023). Generative AI in education and research: Opportunities, concerns, and solutions. *Journal of Chemical Education*, 100(8), 2965-2971.
 51. IANS. (2023). Phishing attacks up 50%, education sector most targeted: Report. In *The Economic Times*. <https://economictimes.indiatimes.com/tech/technology/phishing-attacks-up-50-education-sector-most-targeted->
 52. Joshi, M. P. A. (n.d.). *How Generative AI Is Changing Work*. Harvard Business School Publishing. Retrieved March 21, 2024, from <https://hbr.org/insight-center/how-generative-ai-is-changing-work>
 53. Kuhn, T. (1964). *The Structure of Scientific Revolutions*.
 54. Moor, J. (2006). The Dartmouth College artificial intelligence conference: The next fifty years. *Ai Magazine*, 27(4), 87-87.
 55. Dick, S. (2019). Artificial Intelligence. In *Harvard Data Science Review*. Stephanie Dick. <https://hdr.mitpress.mit.edu/pub/0aytgrau/release/3>,
 56. Nilsson, N. J., Hilpisch, Y., Yao, M., Zhou, A., Jia, M., Baesen, B., ... & Verbeke, W. (2010). The quest for ai: A history of ideas and achievements. Eri im adresi: <http://ai.stanford.edu/~nilsson/>(Özgün eser 2009 tarihlidir).
 57. Galison, P. (1994). The ontology of the enemy: Norbert Wiener and the cybernetic vision. *Critical inquiry*, 21(1), 228-266.
 58. Johnston, J. (2008). *The allure of machinic life: Cybernetics, artificial life, and the new AI*. MIT Press.
 59. Ibid
 60. Moor, J. (2006). *The Dartmouth College artificial*

- intelligence conference: The next fifty years. *Ai Magazine*, 27(4), 87-87.
61. Johnston, J. (2008). *The allure of machinic life: Cybernetics, artificial life, and the new AI*. MIT Press.
 62. Englemore, R. S., & Feigenbaum, E. (1993). Expert systems and artificial intelligence. *Expert Systems*, 100(2), 2007-08.
 63. Crevier, D. (1993). *AI: the tumultuous history of the search for artificial intelligence*. Basic Books, Inc..
 64. Durkin, J. (1996). Expert systems: a view of the field. *IEEE Intelligent Systems*, 11(02), 56-63.
 65. Natale, S. (2021). *Deceitful media: Artificial intelligence and social life after the Turing test*. Oxford University Press, USA.
 66. Turing, A. M. (2009). Computing machinery and intelligence (pp. 23-65). Springer Netherlands.
 67. Natale, S. (2021). *Deceitful media: Artificial intelligence and social life after the Turing test*. Oxford University Press, USA.
 68. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency* (pp. 610-623).
 69. The Great A.I. Hallucination. (n.d.). In *The New Republic*. The New Republic. Retrieved March 21, 2024, from <https://newrepublic.com/article/172454/great-ai-hallucination-chatgp>
 70. Ongsulee, P. (2017, November). Artificial intelligence, machine learning and deep learning. In *2017 15th international conference on ICT and knowledge engineering (ICT&KE)* (pp. 1-6). IEEE.
 71. Johnston, J. (2008). *The allure of machinic life: Cybernetics, artificial life, and the new AI*. mit Press.
 72. Johnston, J. (2008). *The allure of machinic life: Cybernetics, artificial life, and the new AI*. MIT Press.
 73. Campolo, A., & Crawford, K. (2020). Enchanted determinism: Power without responsibility in artificial intelligence. *Engaging Science, Technology, and Society*.
 74. Andrew, A. M., & Andrew, A. M. (2009). Backpropagation. *A Missing Link in Cybernetics: Logic and Continuity*, 85-104.
 75. Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1995). An introduction to reinforcement learning. *The Biology and Technology of Intelligent Autonomous Agents*, 90-127.
 76. Creating artwork with an algorithm: an interview with Leon Gatys. (2017). In *Neuromag*. *Neuromag*. <https://blog.neuromag.net/2017/03/13/deepart>
 77. Dick, S. (2019). Artificial Intelligence. In *Harvard Data Science Review*. Stephanie Dick. <https://hdr.mitpress.mit.edu/pub/0aytgrau/release/3>,
 78. Schmiege, S. (2018) *Humans As Software Extensions*. <http://sebastianschmiege.com/text/humans-as-software-extensions/>
 79. Ibid
 80. Denton, E., Hanna, A., Amironesei, R., Smart, A., & Nicole, H. (2021). On the genealogy of machine learning datasets: A critical history of ImageNet. *Big Data & Society*, 8(2), 20539517211035955.
 81. Hwang, T. (2018). Computational power and the social impact of artificial intelligence. *arXiv preprint arXiv:1803.08971*.
 82. Whittaker, Meredith. 2021. "The Steep Cost of Capture." *Interactions* 28, no. 6: 50–55.
 83. Crawford, K. (2021). *The atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.
 84. Natale, S. (2021). *Deceitful media: Artificial intelligence and social life after the Turing test*. Oxford University Press, USA.
 85. Paulsen, K. (2020). "Shitty automation": Art, artificial intelligence, humans in the loop. *Media-N*, 16(1), 4-23.
 86. Rather than being static systems, assemblages indicate fluid connections that also evolve over time. See, Müller, M. (2015). *Assemblages and actors-networks: Rethinking socio-material power, politics and space*. *Geography compass*, 9(1), 27-41.
 87. Crawford, K., & Joler, V. (2018). *Anatomy of an AI System*. *Anatomy of an AI System*.
 88. Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). Making ai less "thirsty": Uncovering and addressing the secret water footprint of ai models. *arXiv preprint*

- arXiv:2304.03271.
89. Perrigo, B. (2024). Exclusive: The \$2 Per Hour Workers Who Made ChatGPT Safer. In TIME. TIME USA. <https://time.com/6247678/openai-chatgpt-kenya-workers/>
 90. Reisner, A. (2023). These 183,000 Books Are Fueling the Biggest Fight in Publishing and Tech. In The Atlantic. The Atlantic. <https://www.theatlantic.com/technology/archive/2023/09/books3-database-generative-ai-training-copyright-infringement/675363/>
 91. Kak, A. et. al(2023). Make no mistake—AI is owned by Big Tech. In MIT Technology Review. MIT Technology Review. <https://www.technologyreview.com/2023/12/05/1084393/make-no-mistake-ai-is-owned-by-big-tech/>
 92. Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., ... & Liang, P. (2021). On the opportunities and risks of foundation models. arXiv preprint arXiv:2108.07258.
 93. Jones, E. 2023. Explainer: What is a Foundational Model? <https://www.adalovelaceinstitute.org/resource/foundation-models-explainer/>
 94. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
 95. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in neural information processing systems*, 33, 1877-1901.
 96. Gholami, S., & Omar, M. (2023). Do Generative Large Language Models need billions of parameters?. arXiv preprint arXiv:2309.06589.
 97. Monroe, D. (n.d.). Silicon Landlords: On the Narrowing of AI's Horizon. In The Nation. The Nation. <https://www.thenation.com/article/culture/ai-big-tech-monopoly/>
 98. Jones, E. 2023. Explainer: What is a Foundational Model? <https://www.adalovelaceinstitute.org/resource/foundation-models-explainer/>
 99. Heaven, W. D. (2023). The open-source AI boom is built on Big Tech's handouts. How long will it last?
 100. Kak, A. et. al(2023). Make no mistake— AI is owned by Big Tech. In MIT Technology Review. MIT Technology Review. <https://www.technologyreview.com/2023/12/05/1084393/make-no-mistake-ai-is-owned-by-big-tech/>
 101. Manning, C. D. (2022). Human language understanding & reasoning. *Daedalus*, 151(2), 127-138.
 102. Kspert, S. (2024). The value chain of general-purpose AI. Nuffield Foundation. <https://www.adalovelaceinstitute.org/blog/value-chain-general-purpose-ai/>
 103. Tsing, A. L. (2005). *Friction: An ethnography of global connection*. Princeton University Press.
 104. Heaven, W. D. (2023). The inside story of how ChatGPT was built from the people who made it. MIT Technology Review.
 105. Heaven, W. D. (2023). The inside story of how ChatGPT was built from the people who made it. In MIT Technology Review. MIT Technology Review.
 106. Porter, J. (2023). ChatGPT continues to be one of the fastest-growing services ever. The Verge. <https://www.theverge.com/2023/11/6/23948386/chatgpt-active-user-count-openai-developer-conference>
 107. Foundation Models Powering Generative AI: The Fundamentals. (2024). S&P Global. <https://www.spglobal.com/en/research-insights/featured/special-editorial/foundation-models-powering-generative-ai-the-fundamentals>
 108. Jones, E. 2023. Explainer: What is a Foundational Model? <https://www.adalovelaceinstitute.org/resource/foundation-models-explainer/>
 109. Pierce, D. (2023). ChatGPT started a new kind of AI race — and made text boxes cool again. In The Verge. The Verge. <https://www.theverge.com/2023/3/26/23655456/chatgpt-bard-bing-ai-race-text-boxes>
 110. Pierce, D. (2024). ChatGPT is getting 'memory' to remember who you are and what you like. In The Verge. The Verge. <https://www.theverge.com/2024/2/13/24071106/chatgpt-memory-openai-ai-chatbot-history>; Also see, Reuters. (2023).

- ChatGPT users can now browse internet, OpenAI says. In Reuters. Reuters. <https://www.reuters.com/technology/openai-says-chatgpt-can-now-browse-internet-2023-09-27/>
111. Livemint. (2023). ChatGPT responds to complaints of being 'lazy.' Livemint. <https://www.livemint.com/ai/artificial-intelligence/chatgpt-responds-to-complaints-of-being-lazy-says-model-behavior-can-be-unpredictable-11702027871730.html>
 112. Oudshoorn, N., & Pinch, T. (Eds.). (2005). *How users matter: The co-construction of users and technology*. MIT press.
 113. Emerging Technology from the arXiv. (2015). Machine Vision Algorithm Learns to Recognize Hidden Facial Expressions. MIT Technology Review. <https://www.technologyreview.com/2015/11/13/10130/machine-vision-algorithm-learns-to-recognize-hidden-facial-expressions/>
 114. Oudshoorn, N., & Pinch, T. (Eds.). (2005). *How users matter: The co-construction of users and technology*. MIT press.
 115. Newlands, G. (2021). Lifting the curtain: Strategic visibility of human labour in AI-as-a-Service. In *Big Data & Society* (Vol. 8, Issue 1, p. 205395172110160). SAGE Publications. <https://doi.org/10.1177/20539517211016026>
 116. Davis, W. (2024). How AI companies are reckoning with elections. The Verge. <https://www.theverge.com/2024/3/19/24098381/ai-chatbots-election-misinformation-chatgpt-gemini-copilot-bing-claude>
 117. Liu, Y., Deng, G., Xu, Z., Li, Y., Zheng, Y., Zhang, Y., ... & Liu, Y. (2023). Jailbreaking chatgpt via prompt engineering: An empirical study. arXiv preprint arXiv:2305.13860.
 118. Trupia, D. V., Mathieu-Fritz, A., & Duong, T. A. (2021). The sociological perspective of users' invisible work: a qualitative research framework for studying digital health innovations integration. *Journal of Medical Internet Research*, 23(11), e25159.
 119. Ibid
 120. TELUS International. (n.d.). Generative AI Hallucinations: Explanation and Prevention. TELUS International. <https://www.telusinternational.com/insights/ai-data/article/generative-ai-hallucinations>
 121. Simonite, T. (2018). AI Has a Hallucination Problem That's Proving Tough to Fix. WIRED. <https://www.wired.com/story/ai-has-a-hallucination-problem-thats-proving-tough-to-fix/>
 122. Brubaker, R. (2022). *Hyperconnectivity and Its Discontents*. John Wiley & Sons.
 123. Ibid
 124. Ibid
 125. Ibid
 126. Munn, L. (2022). *Automation is a Myth*. Stanford University Press.
 127. Simon, H. A. (1965), *The Shape of Automation for Men and Management*, New York: Harper & Row.
 128. Lloyd, J. W. (1995). *Surviving the AI winter*.
 129. Funk, J., & Smith, G. (2021, May 4). Why ambitious predictions about A.I. are always wrong. Slate Magazine. <https://slate.com/technology/2021/05/artificial-intelligence-moonshots-usually-fail.html>
 130. Gupta, A. (2023). Google CEO Sundar Pichai says AI may become bigger than the internet. In mint. [mint. https://www.livemint.com/ai/artificial-intelligence/google-ceo-sundar-pichai-claims-ai-will-be-the-biggest-technological-shift-says-bigger-than-internet-11694053190344.html](https://www.livemint.com/ai/artificial-intelligence/google-ceo-sundar-pichai-claims-ai-will-be-the-biggest-technological-shift-says-bigger-than-internet-11694053190344.html)
 131. Jordan, S. (2024). Honeywell BrandVoice: How Organizations Can Unleash The Transformative Power Of GenAI. Forbes. <https://www.forbes.com/sites/honeywell/2024/02/14/how-organizations-can-unleash-the-transformative-power-of-genai/?sh=5f1a8fb3a7d7>. Also see, Santoreneos, A. (2023). 700 million images: Aussie GenAI startup banks \$47m to 'democratise creativity.' In Forbes Australia. Success Publishing Pty Ltd luding content reproduced under license from Forbes IP (HK) LTD. <https://www.forbes.com.au/news/innovation/gen-ai-leonardo-ai-47-million-raise/> Also see, Alavi, M. (n.d.). How Generative AI Will Transform Knowledge Work. In *Harvard Business Review*. Harvard Business

- School Publishing. <https://hbr.org/2023/11/how-generative-ai-will-transform-knowledge-work>
132. Paul, K. (2024). Letter signed by Elon Musk demanding AI research pause sparks controversy. In the Guardian. Guardian News & Media Limited or its affiliated companies. <https://www.theguardian.com/technology/2023/mar/31/ai-research-pause-elon-musk-chatgpt>
133. Daniel, W. (2023). The ‘godfather of A.I.’ says his technology is a bigger threat than climate change: ‘It’s not at all clear what you should do.’ In Fortune. Fortune. <https://fortune.com/2023/05/08/godfather-artificial-intelligence-geoffrey-hinton-climate-change/>
134. Rajan, K. S. (Ed.). (2012). Lively capital: Biotechnologies, ethics, and governance in global markets. Duke University Press.
135. Bareis, J., & Katzenbach, C. (2022). Talking AI into being: The narratives and imaginaries of national AI strategies and their performative politics. *Science, Technology, & Human Values*, 47(5), 855-881.
136. Mager, A., & Katzenbach, C. (2021). Future imaginaries in the making and governing of digital technology: Multiple, contested, commodified. *New Media & Society*, 23(2), 223-236.
137. Ibid
138. Brown, N., & Rappert, B. (2017). Contested futures: A sociology of prospective techno-science. Routledge.
139. Gupta, A., Möller, I., Biermann, F., Jinnah, S., Kashwan, P., Mathur, V., ... & Nicholson, S. (2020). Anticipatory governance of solar geoengineering: conflicting visions of the future and their links to governance proposals. *Current opinion in environmental sustainability*, 45, 10-19.
140. Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K., Sukharevsky, A., ... & Zimmel, R. (2023). The economic potential of generative AI The next productivity frontier..
141. How Generative AI Can Augment Human Creativity. (n.d.). In Harvard Business Review. Harvard Business Review. <https://hbr.org/2023/07/how-generative-ai-can-augment-human-creativity>
142. Ibid
143. Renieris, E. M. (2023). Will AI Actually Mean We’ll Be Able to Work Less? In The Walrus. The Walrus. <https://thewalrus.ca/will-ai-actually-mean-well-be-able-to-work-less/>
144. Waber, B. (n.d.). Is GenAI’s Impact on Productivity Overblown? In Harvard Business Review. Harvard Business School Publishing. <https://hbr.org/2024/01/is-genais-impact-on-productivity-overblown>
145. Planning for AGI and beyond. (2024). <https://openai.com/blog/planning-for-agi-and-beyond>
146. See <https://www.sudowrite.com/>
147. Spence, M. (2022). Automation, Augmentation, Value Creation & the Distribution of Income & Wealth. *Daedalus*, 151(2), 244-255.
148. Hille, P. (2023). AI: Chatbots replace journalists – DW – 06/21/2023. In dw.com. Deutsche Welle. <https://www.dw.com/en/ai-chatbots-replace-journalists-in-news-writing/a-65988172>
149. Iyengar, S. (2024). AI Could Help Free Human Creativity. In TIME. TIME USA. <https://time.com/6289278/ai-affect-human-creativity/>
150. Ibid
151. How language gaps constrain generative AI development. (n.d.). In Brookings. Brookings. <https://www.brookings.edu/articles/how-language-gaps-constrain-generative-ai-development/>
152. Iyengar, S. (2024). AI Could Help Free Human Creativity. TIME USA. <https://time.com/6289278/ai-affect-human-creativity/>
153. Tyson, L. D., & Zysman, J. (2022). Automation, AI & Work. In *Daedalus* (Vol. 151, Issue 2, pp. 256–271). MIT Press. https://doi.org/10.1162/daed_a_01914
154. Ibid
155. Ibid
156. Gupta, R. (2023). AI and the future of employment: The possibility of AI leading to large-scale loss of jobs is no longer faraway. In The Indian Express. The Indian Express. <https://indianexpress.com/article/opinion/columns/possibility-of-ai-leading-to-large-scale-loss-of-jobs-no-longer->

- faraway-8545672/
157. Brynjolfsson, E. (2022). The turing trap: The promise & peril of human-like artificial intelligence. *Daedalus*, 151(2), 272-287.
 158. <https://www.washingtonpost.com/technology/2024/01/10/duolingo-ai-layoffs/>
 159. Davis, W. (2023). Stack Overflow lays off over 100 people as the AI coding boom continues. In *The Verge*. The Verge. <https://www.theverge.com/2023/10/16/23919004/stack-overflow-layoff-ai-profitability>
 160. Kahn, J. (2024). Stories of AI-driven layoffs are not what they seem. In *Fortune*. Fortune. <https://fortune.com/2024/02/13/ai-is-leading-to-job-losses-but-not-in-the-way-people-feared/>
 161. Automation, Efficiency, Insights: Freshworks Leverages Generative AI to Transform Customer Experiences. (2023). TechCrunch. <https://techcrunch.com/sponsor/freshworks/automation-efficiency-insights-freshworks-leverages-generative-ai-to-transform-customer-experiences/>
 162. Woodcock, J., & Graham, M. (2019). *The gig economy. A critical introduction*. Cambridge: Polity.
 163. Hanna, A., & Bender, E. (2023). "AI" Hurts Consumers and Workers -- and Isn't Intelligent. In Tech Policy Press. Tech Policy Press. <https://www.techpolicy.press/ai-hurts-consumers-and-workers-and-isnt-intelligent/>
 164. Tech Talk by Leslie D'Monte. (n.d.). In mint. HT Digital Streams. Retrieved March 29, 2024, from <https://www.livemint.com/mint-top-newsletter/techtalk08092023.html#:~:text=In%20July%2C%20McKinsey%20wrote%20about,trend%20accelerated%20by%20Generative%20AI.>
 165. Zinkula, J. (2023). The AI boom could force you to enter the gig economy. In *Business Insider*. Business Insider India. <https://www.businessinsider.in/policy/economy/news/the-ai-boom-could-force-you-to-enter-the-gig-economy/articleshow/106296323.cms>
 166. Ibid
 167. Chandran, R., Smith, A., Ramos, M., & Thomson Reuters Foundation. (2023). FEATURE-AI boom is dream and nightmare for workers in Global South. In Reuters. Reuters. <https://www.reuters.com/article/idUSL5N2XI2X8/>
 168. Kolade, O., & Owoseni, A. (2022). Employment 5.0: The work of the future and the future of work. In *Technology in Society* (Vol. 71, p. 102086). Elsevier BV. <https://doi.org/10.1016/j.techsoc.2022.102086>
 169. Patterson, D. (2024). This is how generative AI will change the gig economy for the better. In ZDNET. ZDNET. <https://www.zdnet.com/article/this-is-how-generative-ai-will-change-the-gig-economy-for-the-better/>
 170. Pierce, D. (2024). ChatGPT is getting 'memory' to remember who you are and what you like. In *The Verge*. The Verge. <https://www.theverge.com/2024/2/13/24071106/chatgpt-memory-openai-ai-chatbot-history>
 171. Inflection AI Blog why personal AI <https://inflection.ai/why-create-personal-ai>
 172. Knight, W. (2023). OpenAI Wants Everyone to Build Their Own Version of ChatGPT. In WIRED. WIRED. <https://www.wired.com/story/openai-wants-everyone-to-build-their-own-version-of-chatgpt/>
 173. The workers at the frontlines of the AI revolution. (2024). In Rest of World. Rest of World. <https://restofworld.org/2023/ai-revolution-outsourced-workers/>
 174. Spencer, D. A. (2023). Marx, Keynes and the future of working time. In *Cambridge Journal of Economics* (Vol. 48, Issue 1, pp. 25–40). Oxford University Press (OUP). <https://doi.org/10.1093/cje/bead046>
 175. Marx, K., & Engels, F. (1965). *The German Ideology (1845)*. London.
 176. Spencer, D. A. (2023). Marx, Keynes and the future of working time. In *Cambridge Journal of Economics* (Vol. 48, Issue 1, pp. 25–40). Oxford University Press (OUP). <https://doi.org/10.1093/cje/bead046>
 177. Taylor, C. (2023). Elon Musk says AI will create a future where 'no job is needed': 'The AI will be

- able to do everything.' In Fortune. Fortune. <https://fortune.com/2023/11/03/elon-musk-ai-no-job-needed-work/>
178. Dellot, B., ed, (2018). *A Field Guide to the Future of Work: Collected Essays*. RSA. <https://www.thersa.org/reports/field-guide-to-the-future-of-work-essay-collection>
179. Srnicek, N., & Williams, A. (2015). *Inventing the future: Postcapitalism and a world without work*. Verso Books.
180. Renieris, E. M. (2023). Will AI Actually Mean We'll Be Able to Work Less? In *The Walrus*. The Walrus. <https://thewalrus.ca/will-ai-actually-mean-well-be-able-to-work-less/>
181. Bogost, I. (2023). ChatGPT Is About to Dump More Work on Everyone. In *The Atlantic*. The Atlantic. <https://www.theatlantic.com/technology/archive/2023/02/chatgpt-ai-detector-machine-learning-technology-bureaucracy/672927/>
182. Ibid
183. Hussen, D. A. (2023). Universal basic income of £1,600 a month to be trialled in two places in England. In *the Guardian*. The Guardian. <https://www.theguardian.com/society/2023/jun/04/universal-basic-income-of-1600-pounds-a-month-to-be-trialled-in-england>
184. Héder, M. (2021). AI and the resurrection of Technological Determinism. *INFORMÁCIÓS TÁRSADALOM: TÁRSADALOMTUDOMÁNYI FOLYÓIRAT*, 21(2), 119-130.
185. Campolo, A., & Crawford, K. (2020). Enchanted determinism: Power without responsibility in artificial intelligence. *Engaging Science, Technology, and Society*.
186. Ibid
187. Transitions Research, *AI for All: 10 Social Conundrums for India*, Transitions Research - FES, 2018.
188. Winner, L. (2017). Do artifacts have politics?. In *Computer ethics* (pp. 177-192). Routledge.
189. Feffer, M., Sinha, A., Lipton, Z. C., & Heidari, H. (2024). Red-Teaming for Generative AI: Silver Bullet or Security Theater?. arXiv preprint [arXiv:2401.15897](https://arxiv.org/abs/2401.15897).
190. Ibid
191. P., D. AI safety: necessary, but insufficient and possibly problematic. *AI & Soc* (2024). <https://doi.org/10.1007/s00146-024-01899-y>
192. Winner, L. (2017). Do artifacts have politics?. In *Computer ethics* (pp. 177-192). Routledge.

