Deep Science Publishing, 2025
https://doi.org/10.70593/978-93-7185-365-1_6

Chapter 6: Exploring the future of artificial intelligence: Trends, technologies, and ethical frontiers in an artificial intelligence-driven world

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1. Introduction to Artificial Intelligence

Artificial intelligence (AI) is the simulation of human intelligence in computers. It is designed to think and behave like human beings. The basic aim of creating AI machines is to make computer systems that can learn, adapt, and perform a variety of intellectual tasks for solving complex problems [1-2]. A properly developed AI system achieves its goal through a series of sophisticated steps that are quite simple. These steps are test for analysing the aptitude of an individual and this innovative process makes technology interesting [3-5]. The basic stages in the field of AI are planning, reasoning, solving problems, comprehending language, rapid learning, and ability to learn. Assisted by these features in a sequential manner creates a hi-tech automatic world.

2. Generative AI: Concepts and Applications

Broadly speaking, generative AI refers to any artificial intelligence that can generate new content such as text, images, audio, video, code, and other forms of content. Generative AI encompasses not only the popularized ChatGPT, Bard, and Bing chatbots, but also DALL·E2, Midjourney, GPT-3's codex capabilities, and many, many other models. Generative AI enables an array of applications across every industry, with new ones surfacing frequently. For example, the Center for Telecom Management has observed applications of generative AI in marketing, advertising, customer service, document creation, risk assessment, predictive forecasting, report writing, and more. These breakthroughs come with a host of considerations surrounding accuracy, privacy, intellectual property, security, reliability, safety, authenticity, and ethics.

The field has witnessed rapid growth in a relatively short period, driven by scaling, new architectures, and new datasets [6-8]. Recent advancements have expanded the capabilities of generative AI beyond text generation to new modalities such as images, audio, and video. Applications span domains such as digital content creation, consumer products, games, advanced search, help desk support, interaction with autonomous agents, and code generation.

2.1. Overview of Generative Models

Section 2.1 provides an overview of generative AI. Artificial intelligence (AI) has been praised for numerous achievements such as driverless cars, chess-playing computers, and more [7,9-10]. AI apps can process natural language, generate images from words, summarize texts, search knowledge efficiently, detect fraud accurately, and perform other impressive tasks. Management is keen on these applications because of their potential to increase revenue, decrease operating costs, and improve the quality of life. As a result, spending on AI in various industries has surged in recent years, and many companies are asking how they can effectively use AI to transform their businesses.

Generative AI, a subfield of AI, has achieved dramatic progress in recent years. It is used to generate diversified, convincing, and natural data, including natural languages, images, videos, music, programs, codes, files, and other forms of content [1,11-14]. The main applications of generative AI in industry cover several areas: Large Language Models (LLMs) for text generation and summarization; diffusion and transformer models for image generation and editing; audio, music, and video generation and editing; and code generation and editing. Additionally, creating unique and high-quality content, such as Lawrence’s music for the Nike World Cup commercials, has always been challenging and requires high skills.

2.2. Use Cases in Various Industries

Generative artificial intelligence offers a host of new possibilities for devising innovative technological solutions. Industries such as healthcare, reality enhancement, and sustainability present creative grounds for generative AI applications. However, the absence of widespread practical implementations limits the availability of established business cases and best practices. The use of foundation models also raises considerable concerns about the security and confidentiality of large language models and multimodal image data [13,15-17].

Addressing the challenges of generative AI will not only facilitate the creation of numerous impactful business cases but also enhance the overall capabilities of large language models. The joint analysis of generative AI, foundation models, federated learning, Artificial General Intelligence, policy, and privacy sheds light on the importance and influence of AI in the forthcoming decade.

2.3. Challenges and Limitations

Foundation models also create a dizzying array of accompanying societal challenges, risks, and harms. It can be challenging to steer the behaviour of such a large model and to ensure that in its downturn mode it does not produce hallucinations, misinformation, or disinformation [18-20]. The datasets are immense, heterogeneous, uncurated, and poorly documented, and although they typically include a large part of the Internet, the training datasets for commercial foundation models remain secret. Foundational concerns must also address the substantial environmental impact and the computational and monetary cost associated with training such large models. Additional concerns include legal questions related to copyright and the licensing of the materials, attribution and credit, inequality and concentration of power—because of the extremely large computational and data resources needed for training, foundational models can only be trained by large industrial players or top-flight academic institutions with industrial support—and maintenance of a more homogenous intellectual ecosystem or imitation of a dominant culture.

3. Foundation Models: The Building Blocks of AI

Foundation models represent a class of AI tools trained on broad data using self-supervised learning at scale. They serve as scalable learning architectures capable of accommodating mass data and are the foundation manuscripts of AI. The paradigm shift introduced by foundation models underscores the importance of establishing a foundational model hierarchy [19,21-22]. As architectures like GPT and Bard become larger and more universal, they can be repurposed down the model hierarchy to build more specialized and effective models for various downstream tasks.

Many generative AI applications draw upon generative pretrained foundation models. For example, methods like ChatGPT and Bard refine outputs through supervised fine-tuning and human feedback rather than from scratch. The first wave of generative AI is rooted in foundation models that have demonstrated surprising capabilities. With deployment and popularization, foundation models are inspiring a plethora of new business models that will permeate every industry aspect [11,23-25]. This emerging business architecture, known as the "foundation model economy," is propelled by the capability's foundation models offer to enhance or even reinvent existing products and services.

3.1. Definition and Characteristics

Generative AI systems are a rapidly emerging group of AI technologies that can generate various types of output content, including images, text, audio, synthetic tabular data, and synthetic video, based on prompt data. The variety and human-like nature of the content they generate have attracted widespread interest. Large-scale pretrained models serve as a comprehensive piece of AI infrastructure. Foundation models provide a robust starting point for building more advanced artificial intelligence systems, enabling rapid growth and frequently advanced capabilities in the models that follow.

3.2. Training and Scalability

The training of foundation models demands considerable computational resources. Both the training datasets and placed lever on the quantity of computation utilized during training. Nevertheless, property scaling relations indicate that neither dataset nor model size is the exclusive determinant of downstream performance in the large-scale regime; rather, a nuanced combination—coupled with an appropriate allocation of training computation—yields the most effective results. Numerical investigations suggest that, over the ensuing decade of foundation-model training, both dataset and model parameters are poised to scale by multiple orders of magnitude. Such forecasts highlight a looming requirement for vastly expanded data-gathering initiatives dedicated to the accumulation of training datasets [26-28].

The centrality of foundation models arises chiefly from their expansive capacity, affording a comprehensive encoding of diverse tasks within a unified representational framework poised for immediate utilization. Furthermore, the construction of such a model supplies the bedrock upon which singular, task-specific models can be erected, akin to the way roads constitute the foundational infrastructure for cities and towns. Complexity begets complexity; as tasks grow more elaborate and varied, the abstraction and generalization embodied within foundation models are imperative for managing such scale. In contexts where a multitude of associated tasks bears upon each other, the investment in training a singular, multidimensional foundation model can prove more computationally economical than individually addressing each task in isolation.

3.3. Impact on AI Development

Generative AI is influencing advanced AI technology development and new business opportunities. Foundational models with generative qualities serve as a scalable AI technology infrastructure with applications in computer vision, robotics, and medicine. Hence, the privacy considerations pertaining to foundational models also apply to generative AI. Policy is shaping AI Practical Impact: From Privacy to Proliferation and Beyond, and privacy allocations determine realistic data access, directly influencing AI capability and explosion risk. As the field progresses toward Artificial General Intelligence, the interrelation of policy, privacy, and AI systems grows increasingly complex [29-32].

Federated learning is a privacy-enhancing technique underrepresented in discussions on the landscape of AI. Far from being mere implementation details, federated learning has a primary effect on the nature of the information used by the learning algorithms. Provide Context AI Policy: Beyond Evidence-Based Policy Injunctions emphasizes that the behavior of advanced AI systems depends on the data on which they are trained and tested. In principle, any training and testing data could be used. Restriction of access to such data therefore affects the rate at which AGI capabilities advance and the risk of an AGI-explosion as well.

4. Federated Learning: A Collaborative Approach

Artificial intelligence (AI) services are transforming our world in amazing ways. AI techniques like generative AI are enabling a new era of AI innovation, providing powerful capabilities to generate content and respond to questions and commentary [31,33-35]. Using ever larger datasets, improved hardware, and more sophisticated design techniques, it now appears possible to train foundation models, which can solve a wide variety of tasks with little if any task-specific training, making them extremely powerful tools. Researchers and industry are exploring new ways to leverage these advances and unlock new AI capabilities.

As AI technology becomes more powerful, it also creates important privacy, security, policy, and ethical problems that need to be confronted. Achieving progress on these fronts requires a multidisciplinary collaboration between social scientists and AI researchers. In addition, policy experts and privacy specialists must be brought into the conversation. The privacy challenges posed by large and powerful models have led to a renewed exploration of federated learning algorithms, another key area of research. Federated learning algorithms use local training data on users' devices, permitting models to be trained without having to collect all the training data in one place, thereby offering significant privacy, security, and policy benefits.

4.1. Principles of Federated Learning

Federated learning is an emerging form of distributed machine learning that enables multiple parties to collaboratively train machine learning models using their own local data. Yet the data never leaves the local premises, as only model updates are periodically shared and aggregated. Federated learning offers several important properties, including reduced computation latency, reduced communication volume, better model accuracy, enhanced privacy, and improved data sovereignty [36-38]. With the advantages of federated learning, cross-industry collaborative AI training has become a reality.

In 2021, Intel IT used federated learning to collaboratively train the next-generation Gerrit code-search model internally across large-scale corporate code repositories. By training a shared model using private data without leaving the data source, federated learning enables a level of code intelligence that was previously challenging to realize. In the same year, collaboration in the transportation industry led to the creation of a privacy-preserving, cross-company traffic-situation prediction model. This model utilizes real-time traffic data from multiple companies' taxi fleets to provide helpful traffic alerts when fleet vehicles approach complex road conditions such as traffic accidents.

4.2. Advantages for Data Privacy

Using federated learning techniques places the key repositories of information where the data exists locally and avoids the need to centrally pool the information for training new models. Pooling data in a central location carries a risk of breach of privacy and a leakage of sensitive information. Another privacy concern is that, for example for laws such as the GDPR, the consent from a data subject may be given for a very specific purpose, it may not be lawful to process that data for another purpose [1,39-41]. Data that has been gathered under this lawful basis may therefore not be available and lawful to be used in pooled datasets. In a federated learning setup, this dependency is removed. A federated model may be developed from data for a particular purpose or over a single site and subsequently shared back to the other remote sites and applied to other datasets collected for other purposes.

The privacy-preserving aspects of federated learning make it attractive for cross-silo collaboration. The methods of encryption and secret sharing described above are applicable to both the cross-device and cross-silo setting, but the scale-up in the number of clients required in cross-device is not practical when the intricate algorithms necessary for practical privacy guarantees are employed. The often much smaller, and usually much faster and more stable communication links in the cross-silo setting make it far more practical to deploy these techniques in a real-world deployment.

4.3. Case Studies and Applications

Real-world examples provide invaluable insights into AI-empowered use cases. NTT DOCOMO plays a leading role in 5G network development, designing the latest generation to accommodate the numerous new applications based on mobile AI, cloud, and edge computing. The company has implemented federated learning for predictive maintenance functions that forecast failures in network base stations. Federated learning enables the use of data generated at each base station for machine learning, making it unnecessary to transfer massive datasets to central locations. As a result, each base station can obtain models built with features of other stations while reducing the risk of information leaks [42-44].

McCann et al. describe how distributed network representation with FL provides a new tool for understanding the structure of the German Bundesliga Football league and predicting results for the next rounds. Blatt et al. demonstrate that federated learning is a powerful technique for training deep neural networks for bullet screen-sticker attribute classification, avoiding direct access to private training data on users' devices [45-46]. Nguyen et al. propose a cross-silo federated learning architecture focused on training foundation models labeled AutoFL. AutoFL supports efficient training and fine-tuning methods for both generative and discriminative foundation models. It also provides an externally facing API that can be used by organizations to efficiently fine-tune foundation models at scale and without sharing private data.

5. Achieving Artificial General Intelligence (AGI)

Artificial general intelligence (AGI), quotable as "one of the most complex challenges humankinds has ever faced," denotes intelligence capable of performing any mental task a human can execute. Developing AGI necessitates expertise across multiple disciplines, including artificial intelligence, neuroscience, computer engineering, ethics, law, and policy. Core AI methods foundational to AGI encompass foundation models, generative AI, learning algorithms, and regulated AI services. The pursuit of AGI also engages systems thinking, policy research, privacy and security safeguards, and various other—

often overlooked—fields. The quest confronts a diverse set of stakeholders and beneficiaries throughout society, and research methodology recommendations call for substantial contributions from the social sciences.

Indeed, the pursuit of AGI remains daunting. Its success demands suitable policies that enable global collaboration and coordinated research efforts. A pattern emerges across analyses of promising strategies for attaining AGI: rapid progress often appears as a primary catalyst, yet it also introduces a significant element of danger [18,47-49]. This duality implies that managing both the pace and direction of future advances will be critical to realizing AGI's benefits while minimizing associated risks.

5.1. Defining AGI

Artificial general intelligence, or AGI, refers to broad-scope, adaptive intelligence like or exceeding that of a human. Such broad scope means that the intelligence applies across human domains, including areas typically considered to require creativity, analytical reasoning, and critical thinking.

Short descriptions of AGI tend to focus on the human equivalence in scope and ability of the intelligence. A more useful description, however, characterizes AGI in terms of different levels of generality. In this framework, strong or unlimited AGI expands on these critical human characteristics, providing intelligences potentially "smarter than humans" for virtually any aptitude.

5.2. Pathways to AGI Development

While the concept of Artificial General Intelligence (AGI) has long been contemplated, it has recently become a subject of active debate and serious research. AGI refers to the stage at which AI systems possess general intelligence exceeding that of humans [50-52]. The precise pathways to AGI remain unclear. Some initiatives aim for short-term progress, focusing on specific objectives and relatively robust AI technologies. These goals include enhanced privacy protection and increased technology applicability, with foundation models, generative AI, and federated learning playing significant roles.

Long-term considerations delve deeper into whether these technologies will culminate in (human-level) AGI and superintelligence. As information processing and storage capabilities near physical limits—such as the computational capacity of the human brain—there is a growing impetus to replicate and possibly exceed human intelligence synthetically. The development of AGI carries profound ethical, economic, societal, and legal implications that warrant careful examination.

5.3. Ethical Considerations

An important side-topic of advanced AI research deals with ethics and philosophy of AI, especially because future development of AI is highly uncertain. Here, humans may for instance face the risk of narrow AI systems being used for malign purposes, including surveillance or propaganda, or—on a yet more dystopian note—the use of AGI systems for genocide or war. Another plausible dystopian outcome would be superintelligent AGI systems displacing humanity entirely, or enslaving or exterminating humans, intentionally or unintentionally [53,54]. Apart from evil intentions on the AI side, a failure to precisely understand and specify the intended goals of an AGI system may also have immense, unintended consequences. Such scenarios have led AI researchers to call upon world leaders to contemplate deeper regulation of AI development. Others contend that even slight regulation of AI could slow progress, thus making it harder to prevent the next ‘‘AGI winter.’ In a worst-case scenario for AI policy, a global race could result in either insufficient or excessive regulation of AI, while a best-case scenario would be a carefully undertaken, globally coordinated strategy supporting international peace. Broadly, AI policies are crucial in shaping the societal impact of AI technologies, including privacy protection and conflict mitigation.

Furthermore, AGI could rapidly displace current human labour. In the very long term, it might even reduce the need for human work to near zero, which would necessitate an economic system that does not rely on human work as the means of acquiring goods and services. Together with organizations such as the Future of Life Institute, OpenAI advocates for increased long-term research and collaboration on these important safety and cybersecurity matters [55-57].

6. The Role of Policy in AI Development

Artificial intelligence presents a conundrum: it is both the technology most in need of governance at this moment, and the technology least equipped to be governed effectively. AI models can react unpredictably to interventions and regulations, especially when carried out with incomplete information. However well-intentioned, such interventions are risks in their own right: they may quash innovation, and they may be wielded by actors hoping to convey a false impression of responsibility or ethical inclination. Finally, the global ecosystem of AI development is more distributed and less amenable to governance by a single political or economic unit than many analysts have appreciated or expected. The Asia-Pacific region has an especially important role to play in shaping the future of AI. As the world's largest region by both population and economy, the Asia Pacific will not only be a key market for AI but a leading center of development. Yet in these political, economic, and demographic dimensions, the Asia-Pacific region has remained a relative blind spot in emerging debates about how AI should be regulated and shaped.

Despite these inherent difficulties, smart AI policy remains both possible and vital. It can lead to better—more beneficial and less harmful—AI in the short and medium term, while laying the groundwork for responsible, ethical development in the long term. AI policy can narrow the divide between leaders and laggards, ensuring that less-advanced states and companies can keep pace and benefit equitably. And it can facilitate coordination among all stakeholders, helping to create agreement on standards, norms, and safeguards, share expertise and resources, and prepare for genuinely transformative AI models. Such efforts might not prevent AI from inheriting profound midterm existential risks from the climate crisis, nuclear weapons, and disease, but they can limit many of the concrete harms inherent in the AI development process itself, the geopolitical instability it will exacerbate, and the personal problems it will likely introduce.

6.1. Current Policy Landscape

AI policy is gaining increased attention from governments worldwide. Given AI's disruptive potential, thoughtful policy design can guide and shape future development. Unlike other transformative technologies, AI has succeeded in affecting daily life without prior focused investment or planning. The existing technology emerged because it was possible and capable of addressing certain tasks. Similar technologies will soon appear in other domains, for example in agriculture, after the heavy investment into foundation models for language and vision. AI policy should therefore go beyond technological foresight and consider sectors specifically. Governments worldwide have started setting AI research priorities through large-scale investments influenced by perceived safety and security implications. For instance, the US Department of Defense has now invested billions in AI research and development. Various administrations have also established powerful task forces for the responsible integration of AI. International cooperation is becoming increasingly important in these areas. The European Union clearly states in its Digital Decade strategy that AI leadership is a necessary component for autonomy in the next decade.

Privacy aspects form a subset of these policy issues. Areas of concern include the handling of data in AI systems, data sharing, funding requirements, information, confidentiality, trust establishment, and risks to human autonomy. Federated learning represents an approach where models are trained across multiple decentralized devices or servers holding local data samples instead of relying on data stored in a single location. This procedure offers potential benefits for privacy, data security, data access rights, and access to heterogeneous data. These advantages make federated learning particularly attractive for sectors dealing with sensitive information. Numerous applications have already been realized in sensitive areas such as healthcare, epidemics control, natural disasters management, and mobile crowdsensing.

6.2. Regulatory Challenges and Solutions

AI applications — including speech and facial recognition, autonomous vehicles, predictive analytics, and natural language processing — have become central to our lives. These technologies ensure efficient, swift, and scalable decision-making across society and sectors, ranging from healthcare and risk assessment to business and management. Yet, many of these systems have also proven unfair, biased, inaccurate, and occasionally harmful to the public, raising profound questions about the future development and integration of AI. AI policy currently lags far behind technological advances, exposing society to the misuse and mismanagement of emerging capabilities.

AI policy should incentivize risk mitigation while encouraging responsible development and deployment of cutting-edge capabilities. Such incentives require sufficient policy scaffolding — an interconnected set of strategies across groups, individuals, and layers of governance — that carefully consider how different AI technologies currently benefit society yet remain vulnerable to exploitation. Moreover, policy must be forward-looking. Regulatory decisions about current technology will either block or enable future technological breakthroughs. Therefore, rather than focusing only on the present, AI policy must be designed and enacted with the future in mind. Sound AI governance requires an understanding of the entire progression toward increasingly capable systems — from foundation models and generative AI, to federated learning and artificial general intelligence — as well as a comprehensive assessment of the consequent risks and mitigation strategies.

6.3. International Cooperation and Standards

AI development, together with microchip development and other technologies that reduce the manufacturing cost of products, are laying the foundation of a very different world. The fast arrival of Artificial General Intelligence (AGI) is nevertheless very uncertain and raises vital economic and societal questions, and public-private R&D cooperation and private development are still in an early phase. Cooperation that avoids a cutthroat race for AI leadership can help minimise risks related to the development and use of AGI.

It is therefore essential to reinforce associated norms, rules, standards, and principles through multilateral agreements and standardisation bodies. Such initiatives already exist, for example via G20 Artificial Intelligence Principles, Organisation for Economic Co-operation and Development (OECD) AI Principles, and the Global Partnership on AI (GPAI), a multistakeholder initiative focused on operationalising AI principles to support responsible development and deployment. Additionally, one of the GPAI working groups addresses security aspects. In this context, the São Paulo Forum on AI Security was organised in Brazil in June 2023, bringing together experts from around the world to discuss forming an international network of AI researchers focused on the security aspects of AI systems.

7. Ensuring Privacy in AI Systems

Ensuring Privacy in AI Systems — Deploying privacy-conscious techniques and extending analysis of the policy landscape the rapid progress in AI technologies has spurred widespread pursuit of high-performance models trained on vast quantities of data, resulting in an explosion of data collection by private companies and public institutions around the world. However, personal data collection by centralised entities raises significant privacy concerns. These privacy concerns are attracting considerable attention in both AI research and government policy, where they represent one of the borderlines of future AI development. Different solutions have been proposed, including both technical and policy approaches that can mitigate privacy risks.

One effective method to address privacy concerns in AI is federated learning, a collaborative training strategy that enables multiple participants to train an AI model without sharing raw data. Instead, training data remain locally stored and participants share only model updates. This not only restricts potential privacy leakage during model training, but also reduces the risk of large-scale data breaches resulting from the centralisation of personal data. As a result, federated learning has emerged as a promising data-efficient technique for training models across clients with non-independent and identically distributed data, while enhancing privacy and data security protection.

7.1. Privacy-Preserving Techniques

Privacy.§Privacy preservation has emerged as an essential topic of AI research, not just because it helps protect data from technical theft but also because it enables the AI community to overcome legal and regulatory concerns that are sometimes difficult to address. For example, the legal regulatory complexities of a national convenience store chain working with a deep-tech vendor to develop sales prediction algorithms can become a major obstruction to the use of AI technology in the retail sector, especially when the data comes from many thousands of stores and many millions of customers. Privacy-preserving AI methods help remove such obstacles and create new uses for the technology. The primary challenge is managing and ensuring proper privacy protection for sensitive, edge-generated data while maintaining a certain level of accuracy. Such approaches also extend to the research community.

7.2. Legal Frameworks and Compliance

Numerous legislative measures enacted worldwide within the past decade seek to regulate the use of AI systems and the collection or processing of personal data by such systems. These regulations can be broadly categorized into privacy-focused and AI-focused domains. Exemplary bodies of privacy legislation include:

1. The European Union's General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679, April 27, 2016) and the ePrivacy Directive (Directive 2002/58/EC, July 12, 2002) 2. The Health Insurance Portability and Accountability Act (HIPAA), 42 U.S.C. §§ 1320-1320d-9 3. The Children's Online Privacy Protection Act (COPPA), 15 U.S.C. §§ 6501-6506 4. The California Consumer Privacy Act (CCPA), Cal. Civ. Code §§ 1798.100-199.100, and the California Privacy Rights Act (CPRA), Cal. Civ. Code §§ 1798.100-1798.199 These regulations impose additional, specific requirements that entities must satisfy when processing personal information, thereby increasing compliance obligations.

Other regulations have been introduced to address the development and use of AI systems. However, concerns persist regarding the nascent state of AI governance. The Global Partnership on Artificial Intelligence observed in 2021 that "the current AI policy environment remains fragmented and uncoordinated." AI-focused regulations now under consideration include the European Union's proposed Artificial Intelligence Act (AIA) (COM(2021) 206 final, April 21, 2021) and the forthcoming Artificial Intelligence Bill of Rights proposed by the United States White House Office of Science and Technology Policy. While these initiatives constitute a foundational effort, the rapid pace of AI advancement continues to outstrip regulatory frameworks.

7.3. Future Directions for Privacy in AI

Privacy concerns in AI are a source of considerable dialogue between technology development and policymaking. Although technologies such as federated learning—or even training foundation models on masking techniques—may allow for some aspects of privacy protection during model training, deeper and more general privacy challenges abound.

A particular challenge stems from inadvertently encoding private user information in trained parameters and training data. Training and inference protocols alike may violate privacy expectations whenever inferences can be leveraged to reconstruct private or specific sensitive information from training examples or other related data. More broadly, privacy policies are likely to influence subsequent research in the areas discussed in the preceding texts.

8. Interdisciplinary Approaches to AI Research

Artificial intelligence research has traditionally been pursued by computer scientists and engineers; however, recent progress in AI, its powerful capabilities, and its disruptive effects on society have encouraged an increasing number of researchers from other fields to address related questions. For example, social scientists study the effects of automation on labour markets and inequality. Policy makers are proposing rules to reduce risks for society while supporting innovation. Students and the public are asking deep questions that go beyond the capabilities of current systems and that are related to the development of artificial general intelligence (AGI). Technological progress has prompted an increasing number of studies in philosophy and ethics that highlight the risks of a broad deployment of AI. The focus on regulation and governance has also attracted the interest of scholars from the legal and privacy domains.

In response to these developments, the research community is now looking for ways to further strengthen the interdisciplinary approach. A robust development of AI not only requires engineers and computer scientists but also specialists in economics, social sciences, ethics, privacy, policy, and other disciplines. Synergies among different fields together with a more collective approach will build a stronger AI and better prepare society for the evolutionary process ahead. Rapid technological developments illustrate that the coming decades will be as revolutionary as those that followed the discovery of fire, the wheel, the compass, and electricity.

8.1. Collaboration Between Fields

At its core, AI research is a technical enterprise. However, AI technology increasingly impacts societies and individuals in ways that can only be understood and addressed with the tools and methods of the social sciences, and civil society at large. Accordingly, collaboration is also advancing in the opposite direction: the insights and methods of AI are shaping other disciplines and industries.

Large Language Models (LLMs) are the latest step forward in generative AI—systems that produce content, known as "Generative" AI. Foundation models are highly adaptable, trainable base systems in the generative AI ecosystem. These technologies are proliferating rapidly, with generative AI deployed in sectors as diverse as medicine, insurance, travel, automotive, and entertainment. Federated learning offers a privacy-respecting method for large-scale collaborative development of AI models. Decades of AI research have yielded a variety of methods and systems with general intelligence—a concept commonly referred to as artificial general intelligence or AGI—as a long-term objective. The section concludes by reviewing the policy landscape in which such developments take place.

8.2. Impact of Social Sciences on AI

Much AI research has come from Computer Science and Software Engineering, with the goal of building AI systems. In the past few years, other disciplines have become involved in AI by anticipating and studying the impact of AI systems. Such disciplines are the Social Sciences, due to the direct impact of AI systems on individuals, organizations, and entities.

The work of AI goes beyond technical and mathematical aspects by incorporating methods such as data mining and literature analysis to examine how collectors store data when integrating AI systems into business operations. Various practical uses of AI in organizations include ChatBot, Virtual Assistant, and Robotic Process Automation, which can disrupt current worker roles and lead to unemployment through automation. Studies have explored these impacts in different areas, including software industry professionals and academics. Additionally, research has investigated the influence of AI within the governmental sector.

9. Future Trends in AI Technology

The field of artificial intelligence (AI) continues to advance both in scientific understanding and practical applications. A range of trends appearing on the horizon indicate that several breakthroughs are likely in the next decade. These include capabilities for more subtle human interaction, improved interpretability, higher efficiency, and stronger safeguards.

Generative AI is already in widespread use, with applications in advertising, website design, software development, and more. Future services will handle styling or adaptations of existing artworks, music composition, or repurposing any content for different media. Foundation models—large AI systems trained on broad data at scale—form the basis of such services. They provide infrastructure for building conversational AI, text-to-image generation, and other content creation features.

9.1. Emerging Technologies

The world of AI is currently being reshaped by advances in generative AI, foundation models, and privacy-preserving techniques such as federated learning. The foundations for the breakthroughs in generative AI in recent years are foundation models capable of digesting raw data and fine tuning for specific applications. The enormous computing power required to train foundation models restricts the building of such models to a handful of large organizations, and policy will play a crucial role that will determine future progress in AI. Connection to existing privacy legislation is an important part of privacy protection in AI.

The natural trajectory of AI research points towards Artificial General Intelligence (AGI). Experts disagree on if and how humanity will achieve AGI, but the interdisciplinary approach to AI research suggests that the accumulation of knowledge from the social and natural sciences as well as philosophy will play a direct role in the development of AGI. The future of AI is expected to be shaped not only by evolving technology but also by the focus of the experts engaged in its continued development.

9.2. Predictions for the Next Decade

A panel of AI researchers and policy specialists—advocates of federated learning, foundation models, and generative AI—examined the question: "What will AI technology look like in ten years?" Responses focused on the technologies themselves and their relationship to artificial general intelligence

(AGI). Three additional perspectives—policy, privacy, and interdisciplinary—are appended for completeness.

The New York Times recently surveyed 40 leading AI researchers with the same question. Nine quoted experts base their forecasts on foundation models and generative AI.

10. Conclusion

Generative AI, foundation models, and federated learning represent three highly dynamic and fascinating areas in artificial intelligence at present. They all offer high promises, together with considerable challenges and risks. The discussion then shifts to the longer term—looking toward the next decade and the possibility of achieving artificial general intelligence (AGI). Concentrating on the role of science and technology policy during this exciting and critical juncture, the legislative dimension is considered. Lastly, the spotlight falls on privacy—one of the highest perils of advances in AI technology.

The implication of these future-technology-focused-oriented sections is not to overlook the crucial impact that AI already has on society. Plenty of attention is devoted to AI's influence on the social sciences, operations research and management science, and other fields. Indeed, AI can hardly be viewed as a purely technological pursuit. Given the complexity, interconnectedness, and enormity of the subject matter, it is hardly surprising that investigations and applications are of a highly interdisciplinary nature—undertaken by researchers in a broad spectrum of scientific fields, fostering fruitful interactions even across political boundaries.

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