MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 34 Issue 2, July-Dec 2024, Pages: 749-763

Neural Networks in Inclusive Financial Systems: Generative AI for Bridging the Gap Between Technology and Socioeconomic Equity

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Abstract

Advancing technology can improve the quality of and access to financial services for all strata of society, including the underserved. As such, countries are focusing on building inclusive financial systems – a complex network of actors, institutions, rules, and technologies that can equitably and effectively meet the financial needs of all members of society, particularly underserved populations. However, current sophisticated frontier technological applications are inaccessible to many emerging economies (EEs). At the same time, these nations are home to a large share of the global population, economic growth, and currently unbanked individuals.Access to affordable financial services is a crucial factor in improving the quality of life for communities across the world. With the continued rise of advanced technologies, emerging economies (EEs) are attempting to build inclusive financial systems capable of extending financial services to unbanked populations. On the other hand, large language models have emerged as powerful tools that enhance productivity in various aspects of work and life. Generative AI systems (GenAI) have the potential to bridge the gap between advanced technology and socioeconomic equality by allowing financial service providers in EEs to more easily deploy sophisticated and relatively expensive neural network applications. As an initial effort to explore this research space, the focus is on developing a common understanding of the problem and possible roles for generative AI in inclusive financial systems.

Keywords: Neural Networks, Generative AI, Financial Inclusion, Socioeconomic Equity, Credit Risk Analysis, Microfinance, AI Ethics in Finance, Inclusive Banking, Data Imputation for Low-Income Groups, Explainable AI (XAI) in Finance

1. Introduction

Such converging global socio-economic challenges on one hand, and on-going contestation and divergence in the technological race and approach on the other hand, put a premium on critical discourse on intelligence for society: What should be the societal ideals/values towards which intelligence and technology should be evolve and be governed? How intelligence and technology should relate to society in pursuit of such ideals/values? How to cohere and reconcile divergent sociocultural worldviews with respect to the design, development and governance of intelligence and technology? Generative Artificial Intelligence (AI) Technologies recently brought forth by deep learning based Large Language/Multimodal Models (LLMs) are capable of disrupting for good or ill socio-economic systems since these technologies operate at the infrastructure level of socio-economic systems. On the one hand, there are concerns about exacerbating socio-economic inequalities owing to the technology's disruptive affordability, accessibility and replicability. However, on the other hand, there are possibilities of ameliorating socio-economic inequalities since Generative AI Technologies can democratize the auditing, designing, development and accessibility of socio-economic systems. This research elaborates on Generative AI Technologies, focusing on the Generative AI Technological Disruption Index and possible counter measures against the proliferation of socio-economic inequalities as well as possible socio-technological pathways towards an inclusive and equitable financial system.

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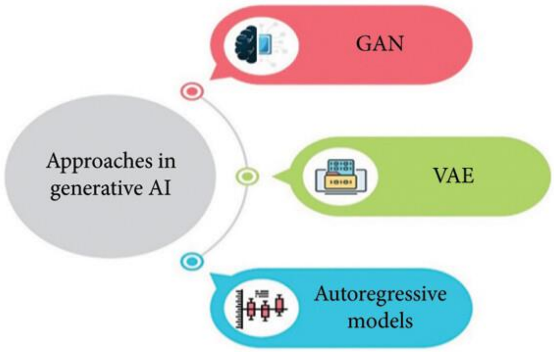

Fig 1 : Approaches in generative AI

The critical socio-economic challenges currently faced in the Western world came at the forefront of global destabilization by the COVID-19 pandemic in 2020, and the consequent disruptions of energy, supply-chain and financial markets caused by the Russia-Ukraine War in 2022. Among others, widening socio-economic inequalities leading to an economic burden of the low-income class, especially for young people, rising populism and protests against the establishment and the democracy, and increasing tensions between divergent worldviews (i.e., liberal democracies vs. authoritarian regimes) came under sharp focus. Pro-active and evolutionary responses to such global challenges emerged, for instance: the adoption of long-term visioning by the EU for the green digitization of society in 2021; the development of the Global Gateway strategy by the EU in 2021 for countering the Belt and Road Initiative by China, focusing on green and digital connectivity across the developing world; and the launch of the Partnership for Transatlantic Energy Security by the EU and the US in 2022. Global efforts to realize a Free and Open Indo-Pacific by the US, the EU and Japan, as well as the establishment of the AI Coalition by like-minded countries came, however, along a thread of divergent worldviews and contesting approach to technological development and governance (i.e., liberal/conciliatory vs. authoritarian/combatant), especially with respect to digital technologies including Artificial Intelligence (AI).

Equation 1 : Cross-Entropy Loss Function

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

- **Purpose:** Measures the difference between predicted probabilities and true class labels in classification tasks (e.g., predicting creditworthiness).
- **Notations:**
    - N: Total number of data points (e.g., customers).
    - y_i: True label for the i-th data point ($y_i \in \{0, 1\}$, such as "eligible for credit" = 1 or "not eligible" = 0).
    - $\hat{y}_i$: Predicted probability for the i-th data point.
    - $\log$: Natural logarithm.

1.1. Defining Inclusive Financial Systems

Financial inclusion ensures that individuals have access to financial products and services that meet their needs. However, billions of people remain excluded from formal financial systems, particularly in developing economies. This makes it difficult to escape the poverty trap. Conversely, it has been shown that institutions are more profitable when they provide marginalised social groups access to financial services. This paradox has motivated the quest for inclusive financial systems. It has been shown that socioeconomically equitable, or inclusive, networks are more resistant to economic shocks and ensure higher overall profitability and lower individual-level volatility. This indicates that bridging the technology and inclusion gap is mutually beneficial. This discusses how generative artificial intelligence can bridge the technology and inclusion gap, with a specific focus on inclusive financial systems. Firstly, the concept of inclusive financial systems is elaborated on and its importance is highlighted. Secondly, current challenges in ensuring inclusivity in financial systems are discussed. Finally, generative artificial intelligence is proposed as a solution and its potential is explored.

1.2. The Importance of Socioeconomic Equity in Financial Services

A recent high-profile example of financial exclusion includes the denial of credit for odd coincidences, such as a Cambridge University professor applying for a credit card at Chase Bank and being denied due to a lack of "credit history." Similarly, a Wall Street Journal reporter had difficulties with "automated" credit decisions while using a different address. The sprawling inequities across the technology landscape, from job recruitment to policing, credit to home ownership, call for a broader agenda focused on the consequences of technology on society, illuminating pathways towards equitable and inclusive socioeconomic systems. The competitive edge of nations will increasingly depend on how well they address these inequities in technological and algorithmic systems.

Financial inclusion has been the essential focus of worldwide policymakers because of its substantial impacts on economic growth and development. It refers to the accessibility of useful and affordable financial products and services for individuals and businesses. This includes things like bank accounts, credit, insurance, and payment systems. Financial inclusion contributes to poverty elimination, inequality reduction, job growth, and financial stability. Conversely, financial exclusion refers to the inability or difficulty of individuals and communities to access financial services such as banking, credit, and insurance. This can have significant negative impacts on individuals and communities, as it can limit their ability to save and invest, access credit, and protect themselves against financial risks. Financial exclusion can be caused by a variety of factors, including lack of education and financial literacy, discrimination, and high transaction costs. It is often disproportionately experienced by marginalized and vulnerable groups. Therefore, it is imperative to consider, conceptualize, and measure socioeconomic equity when applying financial technologies.

1.3. The Potential of Artificial Intelligence in Transforming Financial Systems

Artificial Intelligence (AI) can change how financial systems operate and are governed. This will be analysed concerning inclusive financial systems using Generative AI Neural Networks. First, the potential benefits AI can provide financial systems will be discussed. Then, possible risks and challenges AI can bring will be outlined. Building on this analysis, one opportunity Generative AI can pursue to improve inclusive financial systems will be assessed. Financial systems impact almost everybody's life on earth. However, many people do not fully understand how financial systems operate, are governed, and currently fail to be inclusive. Financial literacy, access, and system design all play a role in this. Various actors have put significant resources towards building an inclusive financial system. Technological developments have also been viewed as an opportunity to improve inclusiveness, such as Fintech. Unfortunately, many of these technological solutions have exacerbated existing challenges rather than solving them. Generative AI Neural Networks are a new emerging technology. To date, they are primarily viewed and developed as consumer technologies rather than Public Good technologies that could be used to improve governance. However, Generative AI Neural Networks can bridge the gap between complex technologies and disadvantaged socio-economic groups. Generative AI offers the opportunity to explore how financial systems can better govern the intelligent use of technology to be inclusive, robust, and transparent.

Equation 2 : Autoencoder Reconstruction Loss

$$\mathcal{L}_{recon} = ||X - \hat{X}||^2 = \sum_{i=1}^{N}\sum_{j=1}^{M}(x_{ij} - \hat{x}_{ij})^2$$

- **Purpose:** Measures the reconstruction error in autoencoders, used to generate synthetic financial data or handle missing values for underserved populations.
- **Notations:**
  - X: Original input data matrix (N rows of financial data and M features, e.g., income, savings).
  - $\hat{X}$: Reconstructed data matrix.
  - x_{ij}: Actual value of the j-th feature for the i-th data point.
  - $\hat{x}_{ij}$: Reconstructed value of the j-th feature for the i-th data point.

2. Neural Networks and Generative AI: Fundamentals and Applications

Generative models can be categorized into two classes: explicit and implicit density models. Explicit density models learn a distribution representation through a parametric function mapping data samples to a probability density function. Implicit density models define a distribution with a generative process.

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Recently, advancements in generative models, including the development of Generative Adversarial Networks (GANs) and diffusion models, have greatly improved capability, usability, and accessibility. GANs consist of a generator and discriminator, with the generator creating fake data and the discriminator distinguishing between real and fake data. In diffusion models, data is gradually noised and learned to be denoised through a Markov chain, with the reverse process turned into a generative process. Notable implementations of diffusion models include Denoising Diffusion Probabilistic Models and Latent Diffusion Models.

Fig 2 : Generative AI in HR: Revolutionizing People Operations

Neural networks are computing systems inspired by biological brains. They consist of interconnected groups of neurons that process information using a connectionist approach to computation. Neural networks are classified as supervised, unsupervised, or reinforcement learning. In supervised learning, a neural network model is trained by adjusting weights through the minimization of loss functions. Unsupervised learning uses clustering and dimensionality reduction to group similar inputs. Reinforcement learning employs a reward-punishment mechanism to indicate the success of actions taken in an environment. Recently, neural networks have been applied to generative tasks such as data generation, completion, inpainting, extrapolation, and style transfer. Generative models are trained to learn the distribution of data samples so they can generate new samples from that learned distribution.

2.1. Understanding Neural Networks and Deep Learning With roots tracing back to artificial neurons in the 1940s, perceptrons in 1958, and layered networks trained by backpropagation in the 1980s, neural networks lay mostly dormant until the rise of "Deep Learning" networks in the early 2010s. Deep Learning networks have multiple hidden layers between inputs and outputs. Each layer consists of artificial neurons parameterized by weights and biases that are adjusted during training to minimize prediction error calculated by a loss function. Popular activation functions first applied in the 1980s were re-popularized from computer vision breakthroughs in 2012. Vision and language networks utilize thousands of Graphics Processing Units (GPUs) to accelerate training on large datasets. GPT-3 language model contains 175 billion parameters, necessitating immense investments for academic and lower-resourced organizations to conduct frontier research. While multinational corporations dominate training of the largest models, smaller networks can be trained on personal computers to implement Deep Learning applications. These freely available networks can be repurposed for unintended uses, as illustrated by the rapid rise of misinformation-generating bots following the release of GPT-2 language model.

Over the course of the last decade, neural networks have taken center stage in artificial intelligence (AI) research. From emphasis on "Deep Learning" networks by the industry-leading Google Brain Team in 2012, to AlphaGo defeating Lee Se-dol in 2016, to GPT-3 demonstration of massive language model capabilities in 2020, neural networks have rapidly developed into a multi-faceted tool with diverse applications. Basic neural network concepts can be dynamically explored below for global policy makers, educators, researchers, and technologists considering design interventions of dendritic-network inspired AI systems for bridging gaps between access to beneficial technology and socioeconomic opportunity.

2.2. Generative Adversarial Networks (GANs) in Finance GANs, originally developed to generate realistic images, use a pair of networks: a generator creating synthetic data and a discriminator evaluating its realism. They iteratively improve, with the generator striving to outsmart the discriminator, creating highly realistic data. GANs have notable characteristics. They are unsupervised, needing only unlabelled real data, and can capture complex distributions through deep networks. Extended GANs, like video-GANs and text-to-image GANs, successfully perform diverse data generation tasks.

Equation 3 : Generative Adversarial Networks (GANs)

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Explanation:

- $D(x)$: Discriminator's probability that x is real.
- $G(z)$: Generator's output, where z is noise sampled from a distribution $p_z(z)$.
- $\mathbb{E}_{x\sim p_{data}(x)}$: Expectation over the real data distribution.
- $\mathbb{E}_{z\sim p_z(z)}$: Expectation over the noise distribution.

This equation represents the adversarial training process where D tries to distinguish real from fake data, and G tries to fool D.

2.3. Applications of Generative AI in Financial Inclusion Over the last four decades, technological advances have improved financial service accessibility for certain demographic groups, particularly for higher-income nations, but have simultaneously widened the gap between technology-haves and technology-have-nots. Most individuals and microenterprises in low-income countries and rural areas in higher-income countries still do not hold bank accounts, receive credit, or enjoy other basic financial services. Efforts to bridge this gap often focus on enhancing technology deployment in neglected areas. As a counterpoint, the new approach focuses on unmet technological goals and presents generative AI applications that could empower non-specialized individuals in developing nations to create new inclusive financial services, thus closing the currently unmet goal gap.

Generative AI, an emerging subset of artificial intelligence that generates text, imagery, music, or other media, based on user inputs, has the potential to bridge the gap between technological advancement and unmet socio-economic equity goals. In financial systems, generative AI can be used to inform, design, and evaluate the architecture of new neural networks, which can in turn be harnessed by non-specialists to create inclusive financial services customized for traditionally neglected demographic groups. To demonstrate the feasibility of this new approach, illustrative generative AI applications are presented that can help close the financial access gap between high- and low-income countries. The intent is to encourage researchers, financial technology professionals, and decision-makers in public and private organizations to explore the potential of generative AI applications.

3. Challenges and Opportunities in Implementing AI in Financial Inclusion

However, the implementation of AI generative applications in fintech companies that target the financially excluded masses presents challenges related to the local technology ecosystem, internet connectivity, language, and social customs. The development of low-cost neural network application design, development, and deployment tools can promote the growth of innovative fintech startups that utilize generative AI for inclusive financial systems.

Artificial intelligence (AI) technology, represented by neural networks, chatbots, and other generative AI applications has the potential to improve financial literacy, accessibility, and affordability of financial services for individuals who are currently underserved by the formal financial system. This is especially relevant in developing nations with low Inclusive Development Index (IDI) scores, where fast economic growth has not translated into improved conditions for vulnerable socioeconomic groups. AI-driven applications in the financial sector can enhance efficiency, security, transparency, and speed in financial service delivery. Generative AI can bridge the gap between advanced technology and individuals with low or no educational background and formal employment, providing customized, text-based financial guidance.

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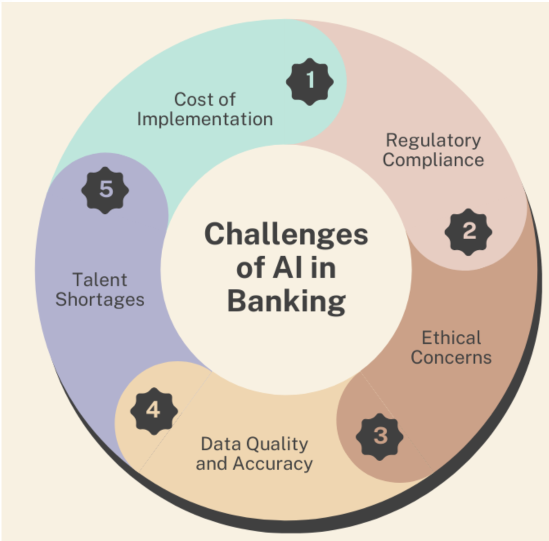

Fig 3 : AI in Banking: Customer Experience, Benefits, and Challenges

3.1. Ethical Considerations and Bias in AI

As the frontier of artificial intelligence advances, so do the ethics and bias considerations that accompany it. AI models produce outputs based on their training data, and concerns about how that data was gathered and the biases it may contain are paramount. The actions of artificial intelligence (AI) models generate decisions that influence the real world. In turn, information about the real world is gathered and used for training new AI models. This means that decisions biased in one direction will lead to data more biased in that direction and so on. As a result, the new generation of AI models will be more biased in that direction. Once a bias becomes recognized, a question arises; what course of action should be taken to rectify it? Two main classes of solutions have been proposed. One class of solutions tries to avoid using the biased AI model, and the other class provides methods to fix the AI model so that it is no longer biased. In many circumstances, it can be difficult to stop using the AI system as the system may already be deeply embedded. Although generally more suitable solutions to rectify biases can be devised, within many specific scenarios rectifying AI bias can be extremely challenging. It can also be pointed out that one should not completely avoid using AI as using it can bring numerous benefits and valuable insights; the key is to use AI responsibly.

3.2. Data Privacy and Security Concerns

As investments in generative AI technologies to create inclusive financial systems for unbanked populations proliferate, it is vital to ensure the privacy and security of socio-sensitive data related to financial transactions and life events. There have been notable instances in the past decade where AI models unintentionally leaked sensitive personal data due to design flaws, particularly in text-based generative AI models that rely on cloud-based system architectures. Over the past three years, several global financial institutions and banks have fallen victim to cyberattacks, resulting in substantial financial losses. In 2023, technological disruptions in financial systems undermined trust in financial regulators and raised concerns about fairness and privacy in automated decision-making systems. There is a growing apprehension that emerging generative AI technologies will amplify these risks and challenges, particularly in the context of developing economies with limited regulatory frameworks and standards.

Generative artificial intelligence (GenAI) has emerged as an innovative technology that holds great promise in addressing global challenges across diverse fields. In finance, GenAI has the potential to redefine traditional banking services, particularly in relation to incorporating unbanked populations into the financial system. It can serve as a conduit for connecting tested technologies to disadvantaged or underbanked communities. There is immense potential for generative AI technologies to close the technology-and-revenue gap between developed and developing economies. More importantly, this approach can quadruple the impact of technology on socio-economic equity, enhancing the quality of life for billions of people. However, the deployment of generative AI in inclusive financial systems, especially in developing economies, necessitates addressing a set of normative priorities to mitigate risks associated with data privacy and security concerns, environmental footprint, knowledge, and gender biases.

3.3. Regulatory Frameworks for AI in Finance

Translating lab-based experiments into real-world applications poses significant hurdles for AI and the financial system. AI models "trained" using artificial financial systems may not be instantly transferable to actual financial settings. Financial systems are shaped by human behavior, and hence are intrinsically complex and constantly evolving. There are also concerns about AI "cyber fragility" in the financial system. Alongside worries regarding potential AI misuse, the focus is on possible vulnerabilities arising from the compatibility of AI "blind spots" with the fragilities of the financial system. There is a particularly challenging "cat and mouse" dynamic regarding cyber safety in the context of AI. Sophisticated Generative Adversarial Network (GAN)-driven Artificial Intelligence (AI) attacks could become very difficult to interpret and pre-empt, hence evolving attacks could outpace defenses. Regarding the unintended consequences of AI deployment in the financial system, liquidity "black holes" could become a systemic concern. There is a growing reliance on AI technologies for decision-making regarding the allocation of resources, such as risk pricing, trading, and margining. AI algorithms typically segregate and analyze large sets of data, making decisions based on inferred models. Market participants using similar algorithms implicitly share the same understandings of the financial system, and thus act similarly in periods of stress. This could potentially generate vacuum liquidity, similar to the failed risk models during the global financial crisis.As artificial intelligence (AI) continues to evolve at a remarkable pace, the issue of regulating these technologies has rapidly gained attention. There are valid concerns about potential AI misuse, such as the threat of "deep fakes," as well as AI's ability to perpetuate, amplify, or inadvertently generate biased outcomes. Similarly, in the financial system context, there are worries regarding algorithmic trading "flash crashes," as well as potential AI-induced unwanted moral hazard in the financial ecosystem. On the other hand, AI also holds the promise of greatly enhancing financial services, thereby increasing the robustness and resilience of the financial ecosystem. For example, AI-assisted, faster, and more precise modeling of risks would facilitate better risk management both at the individual bank level and spillover effects across the whole financial system. Monitoring the financial system (the proverbial "financial weather") using machine learning techniques is much more powerful with big data analyses compared to traditional econometric implementations.

4. Case Studies and Best Practices

The finance ecosystem can further support the inclusion of unbanked populations via Peer-to-Peer (P2P) Lending platforms. Even though alternative data strategies help widen the reach of credit risk models, they come with the downside of recommended loans being too similar (homophilic) to already held loans. This study proposes a mechanism that combines Generative Adversarial Networks (GAN) with the Latent Space Perturbation (LSP) technique to de-bias the credit risk model recommendations whilst maintaining their desired quality. Offering diverse recommendations is essential for financial inclusion in P2P Lending platforms. Simulations on production data from a real-world European P2P Lending platform show that the proposed approach is able to significantly increase the diversity of the recommendations whilst keeping risk levels unchanged. It can be industry-agnostic and applied to other lending contexts such as bank loans or FinTech loans. In the context of fairness in credit risk models, the art of model validation can pose challenges to meeting the expectations of regulators, other external and internal stakeholders, and the designers of potentially unfair models. Drama theory introduces the notion of social games to analyze interactions in social contexts. This work studies the use of social game models to analyze the interactions around an unfair credit risk model, as proposed in an earlier publication. In there, game-theoretic model countermeasures were proposed to mitigate the unfairness. The trained low-risk label model was found to have falsified predicted probabilities of good repayment due to its unfairness. Social games are constructed to account for the relevant actors, their strategies, payoffs, information, and interactions.

4.1. Successful Implementations of AI in Inclusive Financial Systems

Generative AI refers to artificial intelligence models that generate new data based on training inputs. Generative pre-trained transformer (GPT) models are a type of Generative AI models with neural network architecture using the transformer model. These models are trained using learner inputs, where they predict the next text in a sequence. After training, the models can

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 34 Issue 2, July-Dec 2024, Pages: 749-763

take a string of text (prompt) as input and generate a coherent continuation.

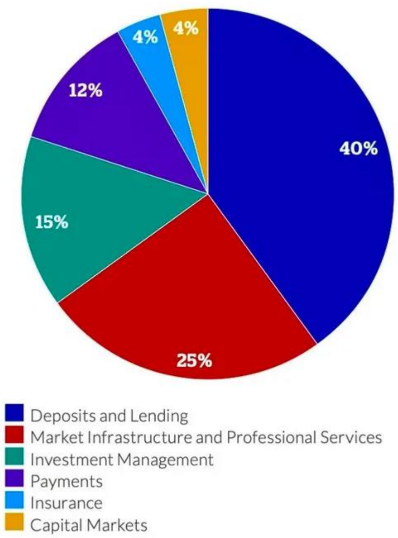

Fig : Mass Adoption Of AI In Financial Services Expected Within Two Years

Designer Generative AI tools utilizing GPT models have recently garnered interest across various fields because of their ability to generate and debug computer codes in multiple programming languages. Such tools can have a transformative impact on the development of financial technologies for fostering inclusive financial systems. However, end-users face challenges in using these tools to guarantee desired code outputs. For financial technology developers with limited expertise in computer science, it might be difficult to adopt these tools to ensure the generated code meets input requirements, thereby limiting the broader usage of the desirable Generative AI technology.

Technological advancements in computer science are aiding the development of inclusive financial systems. Artificial Intelligence, and more specifically Generative AI, could assist the design and implementation of inclusive financial systems. The challenges of implementing Generative AI can be overcome by successfully integrating designer Generative AI tools into the development processes of financial technologies. These tools harness the frontier developments in Artificial Intelligence and Machine Learning, which could help the policymakers, governments and the international organizations working towards the development and implementation of inclusive financial systems. Successful implementation of Generative AI tools can bridge the disconnect between the technology development and socio-economic equity requirements.

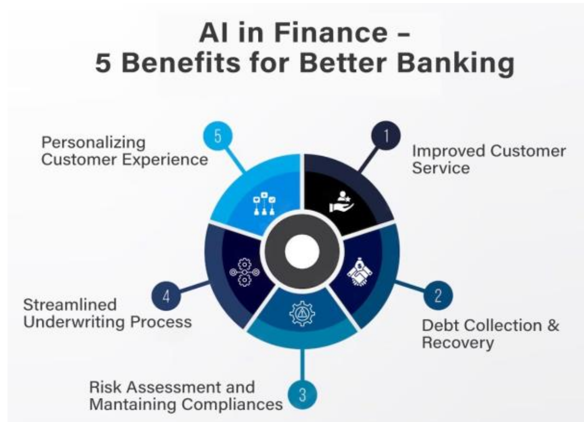

Fig 3 : AI in Finance — 5 Benefits for Better Banking

4.2. Lessons Learned and Key Takeaways

The past year has seen an extraordinary rise in policy interest—within business, government and civil society—around generative artificial intelligence (AI). In early 2023, there were 65 standalone generative AI policy initiatives globally; by September 2023 this had nearly doubled to 124. Current discussions tend to emphasize risks and mitigate harms—e.g. from AI-enabled misinformation, discrimination or job displacement. But alongside risks, generative AI also has the potential to shape more equitable, inclusive and democratic societies. A range of trends are generating possibilities for the new technologies to ameliorate rather than exacerbate existing inequalities. First, large technology companies are increasingly being viewed as part of the problem, rather than the solution. Simultaneously, trust is shifting to new, smaller players in the tech ecosystem—public universities and research institutions, non-tech companies, civil society organizations—who are advocating for the need to ensure that technology serves public interest. Second, a range of new affordances are emerging that could create more equitable opportunities to “participate, speak and influence” in generative AI development. At the societal level, the generative AI landscape features

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many open-source models and tools, which democratize access and lower barriers to entry. At the individual level, generative AI tools are emerging that can help people understand complex technical systems and support effective advocacy efforts. Third, various efforts are underway to develop larger, systemic solutions to socio-technical inequities in generative AI development. For instance, in August 2023, the United Nations launched the Generative Artificial Intelligence for Development Initiative to promote equitable access to generative AI technologies, with a particular focus on the Global South.

5. Conclusion

Generative AI systems should be designed and deployed to bridge the gap between accessibility of technology and socioeconomic equity. With increasing technological power of generative AI systems and neural networks, there are responsibilities on researchers, developers, and policymakers to ensure safety and inclusivity in their designs. Equal opportunity access and literacy education are fundamental human rights under the Universal Declaration of Human Rights, and every effort should be made to ensure access to empowering generative AI technologies.

Generative Artificial Intelligence (AI) systems have the potential to alleviate or exacerbate existing socioeconomic inequalities. The political economy of generative AI systems and other economic conversion systems, including neural networks, has been examined. Innovative ways to use generative AI systems to create new inclusive financial systems have been proposed. In particular, experiments are proposed within current large language models to create a financial literacy coach for underserved populations and monetize equity through a generative art gallery. Other experiments for future research include accessibility education systems and gamified personal banking systems.

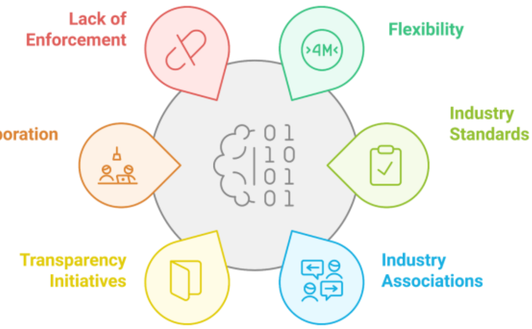

Fig 5 : The Evolution and Ethical Considerations of Generative AI in 2024

5.1. Future Directions

Neural networks were theorized in the late 1940s and early 1950s, but advances in processing speed, programming language, and the availability of data storage and collection only allowed their development in the mid-1990s. The 2010s saw the advent of contemporary generative AI. Generative AI has improved over the past three decades due to increased speed and lower costs of storage, data, computation, and network infrastructure. Generative AI systems are trained on datasets of digitalized text, images, audio, or video, and rely on programming algorithms. They analyze data to identify patterns and replicate them, generating new digital content that resembles the training data. Like prior technology waves, generative AI could profoundly impact personal, social, and economic activities. Because technology is a general-purpose tool, its impact will markedly differ based on policy choices, public awareness, education, investments, and the involvement of stakeholders, such as the private sector, civic organizations, and communities.

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