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Generative AI in FinTech and the challenge of explainability: Beyond algorithms

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Abstract
FinTech's incorporation of generative artificial intelligence (AI) is transforming financial services by providing individualized finance solutions with cutting-edge natural language processing (NLP) and machine learning (ML) technology. GenAI rallies decision-making and consumer engagement by offering dynamic, real-time, and adaptive financial support, in contrast to standard financial algorithms that trail preset criteria. Even yet, GenAI presents a number of difficulties, most notably the "black box" problem, which occurs when AI-driven financial decisions are opaque and difficult to comprehend. In financial ecosystems driven by AI, this presents important questions about explainability, trust, fairness, and responsibility. This study highlights the inevitability of solid regulatory frameworks and interpretable AI models to enable moral and trustworthy financial decision-making. By examining the benefits, drawbacks, and implications of GenAI in FinTech, this study emphasizes how crucial it is to deploy AI responsibly by addressing the issue of "black-box".

Keywords: AI, black box, explainability, FinTech, machine learning

1. Introduction

Robots and social AI devices have become a part of everyday life, appearing in homes, businesses, and commercial spaces (Pelau *et al*., 2021; Gursoy *et al*., 2019) [40, 19]. AI now serves consumers across industries, including education, shopping malls (Chung *et al*., 2018; Gonzalez-Jiminez, 2018) [11, 17], hospitality, and healthcare (Pelau *et al*., 2021; Mann *et al*., 2015) [40, 41]. Finance, too, has embraced AI, evolving into FinTech and now incorporating Gen-AI solutions that revolutionize personal finance management and financial advising (Yang & Lee, 2024) [4]. Unlike traditional AI systems, which relied on pres*et al*gorithms and minimal human input, Gen-AI offers highly personalized, conversational, and anthropomorphic services (Yang & Lee, 2024; Dewasiri *et al*., 2024) [4, 14]. However, while AI models achieve impressive accuracy, understanding their outputs-especially in sensitive fields like finance-is equally critical. The complexity of machine and deep learning models often makes them incomprehensible, raising concerns over transparency and interpretability. Data diversity, quantity, and quality all have a significant impact on the insights that modern machine learning programs can provide (Mehrotra, 2019) [31]. Therefore, maintaining the accuracy and trustworthiness of ML models depends on data quality and data quality monitoring (Wigglesworth, 2016) [50]. According to Mehrotra (2019) [31], one of the main problems facing quantitative analysts (quants) is "overfitting," which occurs when algorithms are too complicated or poorly written, resulting in false signals or fictitious correlations in the noise of data. Furthermore, a model may perform poorly in actual market situations even if it does well in a test environment. An algorithm for trading that is poorly developed and implemented may also have an impact on it. According to research, one major obstacle to the adoption of AI is the availability and quality of training data (Kruse *et al*., 2019) [25].

Previous research has examined FinTech evolution (Palmié *et al*., 2020) [39], its industry impact (Nalini, 2024) [36], mechanisms (Li *et al*., 2021) [28], adoption drivers (Sharma *et al*., 2024; Saadah & Setiawan, 2023) [47, 45], and business models integrating AI (Alessa & Mohammed, 2024; Zarifis & Cheng, 2024; Laidroo *et al*., 2021; Wube *et al*., 2022) [2, 56, 26, 53]. Despite its advancements and potential, AI adoption in digital payment security faces significant challenges. Nanda *et al*. (2024) [37] highlight concerns around data privacy, regulatory compliance, and the risk of algorithmic biases and false positives, which can erode user trust and lead to operational disruptions. Additionally, high implementation costs and integration issues with legacy systems hinder widespread use. Overcoming these barriers is crucial for building secure and inclusive digital payment ecosystems.

Artificial intelligence has a number of drawbacks that should be considered while evaluating its application, despite the fact that it has many advantages. Two of the biggest hazards are the possibility of bias in the results obtained by employing these tools and the challenge of understanding the mathematical reasoning that the algorithms use to arrive at a particular conclusion (Fernandez, 2019) [16]. Also, Gen-AI still struggles with the "black box" problem-where decision-making processes are opaque-and faces issues of incompleteness, where essential elements are not captured in the training algorithms. These gaps contribute to broader challenges in trust, accountability, and fairness. This study seeks to extend the current literature by examining how Gen-AI is transforming FinTech through NLP, ML, IoT, and identifying the key issues that must be addressed to improve financial services. Findings reveal that Human-in-the-Loop is one of the solutions that can contribute to tackling such issues. Human-in-the-loop aims to train an accurate prediction model with minimum cost by integrating human knowledge and experience (Wu *et al*., 2022) [52].

2. Review of literature

Fintech: How Technology Transforms Finance

2.1 Evolution of FinTech

Over the past decade, the financial industry has undergone a profound transformation. The internet revolution of the early 1990s transitioned financial markets towards electronic finance, enabling services such as banking, insurance, and stock trading to be conducted digitally (Lee & Shin, 2018) [27]. Subsequent technological advancements introduced innovations including blockchain (Shahzad *et al*., 2022) [46], robo-advisors (Ansari & Bansal, 2024; Rasiwala & Kohli, 2019) [3, 43], digital payments, peer-to-peer lending (Najaf *et al*., 2022) [34], Insurtech (Cosma & Rimo, 2024; Chatzara, 2020) [13, 10], and RegTech (Muganyi *et al*., 2022) [33], collectively encompassed under the term "FinTech." These developments offer automated, artificial intelligence-driven, and cost-effective financial solutions (Shahzad *et al*., 2022; Lee & Shin, 2018; Belanche *et al*., 2019) [46, 27, 7]. In the Indian context, the government's push toward a cashless economy following demonetization, coupled with the digital acceleration prompted by the COVID-19 pandemic, significantly advanced the FinTech ecosystem. Initiatives such as the Unified Payments Interface (UPI), developed under the stewardship of the National Payments Corporation of India (NPCI), the Reserve Bank of India (RBI), and the Indian Banks' Association (IBA), alongside platforms like India Stack and schemes such as the Pradhan Mantri Jan Dhan Yojana, have collectively contributed to enhancing digital financial inclusion.

2.2 Artificial intelligence

First used by 'John McCarthy' in 1956, artificial intelligence (AI) has become a disruptive factor in many different industries (Collins *et al*., 2021; McCorduck & Cfe, 2004) [12, 30]. Natural language processing, big data analytics, machine learning, and early automation are just a few of the ways AI facilitates autonomous decision-making. At the World Economic Forum in 2023, Microsoft CEO Satya Nadella emphasized the effect of artificial intelligence and its "golden age" (Remolina, 2024) [44]. The increasing impact of AI is predicted to drive global investment to $98 billion in 2023 (Collins *et al*., 2021) [12]. According to Watson (2017) and The Global Human Capital Report (2017) [49], artificial intelligence fosters human-like interactions and integrates social and emotional intelligence into digital systems, demonstrating its function beyond efficiency. Artificial intelligence techniques can increase efficiency, lower costs, improve quality, increase customer satisfaction, and promote financial inclusion in the financial services industry. This is primarily because of the opportunities they present for automating operational procedures and boosting analytical capabilities.

2.3 Integration of Gen Ai in Finance

The integration of artificial intelligence (AI) with financial technology (FinTech) has given rise to Smart FinTech, a new generation of FinTech solutions encompassing BankingTech, TradeTech, LendTech, InsurTech, WealthTech, RiskTech, and blockchain applications, all strongly supported by Data Science and AI (DSAI) techniques (Cao *et al*., 2021) [8]. According to Narendra Kandregula (2019) [38], the global market for AI in FinTech is projected to reach $26.67 billion by 2026, indicating a significant acceleration in its adoption, particularly in financial portfolio management. Generative AI, by creating synthetic data and analyzing historical market data, enhances market risk and volatility modeling and aids in predicting potential market disruptions. Despite these advancements, generative AI also introduces critical challenges, notably in model interpretability. Many AI models operate as "black boxes," making it difficult to understand the rationale behind their decisions, which can undermine user trust (Zhang *et al*., 2022) [58]. Additionally, data biases embedded in AI models may lead to inaccurate risk assessments or flawed financial forecasts if not carefully managed. Beyond these technical limitations, the inherent opacity of AI technologies raises substantial concerns related to client trust, regulatory compliance, and fiduciary responsibility. As Kandregula (2020) [23] aptly observes, this reflects "the fundamental paradox of modern financial technology: the most powerful predictive tools are often the least transparent." In the series of this Lui & Lamb (2018) [29], utilization of big data analytics for AI/ML-powered services like credit scoring is probably still unclear to both individual and corporate clients, despite the fact that its role is expanding. Customers might not know, for instance, that information gathered from unconventional sources, including online searches or purchases, might be used to evaluate their creditworthiness. Even though generative AI has many uses in the FinTech sector, it's crucial to think about whether the moral conundrums, data protection challenges, and potential accountability and transparency concerns have been sufficiently addressed. It is imperative that strong regulatory frameworks, data safety procedures, and the ethical and responsible use of generative AI to reduce security risks be put in place in order to guarantee the observance of legal standards, data privacy, and transparency in the application of Gen AI in the financial sector (Kaur *et al*., 2025) [24].

Table 1: Tabular compilation of related literature

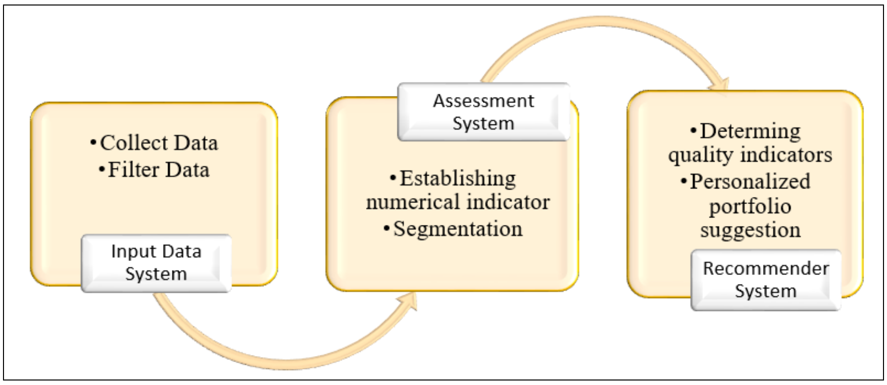
Title	Author & Year	Conclusion/Findings
AI/ML Applications and the Potential Transformation of Fintech and Finserv Sectors	Deshpande, A. (2020) [15]	Explores transformative applications of AI/ML in financial services, emphasizing analytics-driven decision-making, automation, and improved customer experiences. Highlights the integration of technology and finance.
The Future of FinTech	Das, S. R. (2019)	Discusses fintech's potential in transforming finance through technological innovation, focusing on disruption, efficiency, and future regulatory challenges.
Artificial Intelligence in Fintech	Kandregula, N. (2019) [38]	Emphasizes AI's role in transforming fintech by enabling personalized services, improving efficiency, and supporting market expansion. Highlights the importance of technology integration in finance.
AI in Finance: A Review	Cao, L. (2020)	Provides a comprehensive overview of AI's applications in finance, outlining efficiency gains, optimization benefits, and systemic risks. Discusses algorithmic bias, regulation, and trust issues. (Algorithmic bias, regulation, and trust challenges)
Artificial Intelligence: A Strategy for Financial Risk Management	Orlovskaya, T., Butusov, D., *et al.* (2024)	Emphasizes AI as a strategic tool for risk management, supporting predictive analysis and enhancing decision-making reliability. Discusses the need for responsible AI governance.
Generative AI for Financial Risk Modeling	Cao, L., *et al.* (2021) [8]	Discusses the use of generative AI for improved risk and volatility modeling. Highlights interpretability challenges and potential inaccuracies from data biases. (Opaqueness, data bias)
Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI	Arrieta, A. B., Díaz-Rodríguez, N., *et al.* (2019)	Reviews XAI methods and taxonomies, stressing the importance of interpretability and transparency to build trust. Points out black-box limitations and ethical challenges. (Explainability problem, black-box, ethical issues, trust & transparency challenges)
Explainable Artificial Intelligence Applications in Cyber Security: State-of-the-Art in Research	Sarker, I. H., Kayes, A. S. M., *et al.* (2022)	Highlights XAI's importance for transparency and interpretability in security-focused systems. Emphasizes the need to balance performance and explainability. (Explainability problem, black-box, trust & transparency challenges)

Table Source: By Author

3. Objectives of the Study

- To explore the function mechanism and applications of Generative Artificial Intelligence (Gen-AI) in the FinTech industry.
- To identify and critically analyze the vulnerabilities and loopholes associated with AI-driven financial activities.

3.1 How does the Gen-Ai function in Fintech



Source: By Author

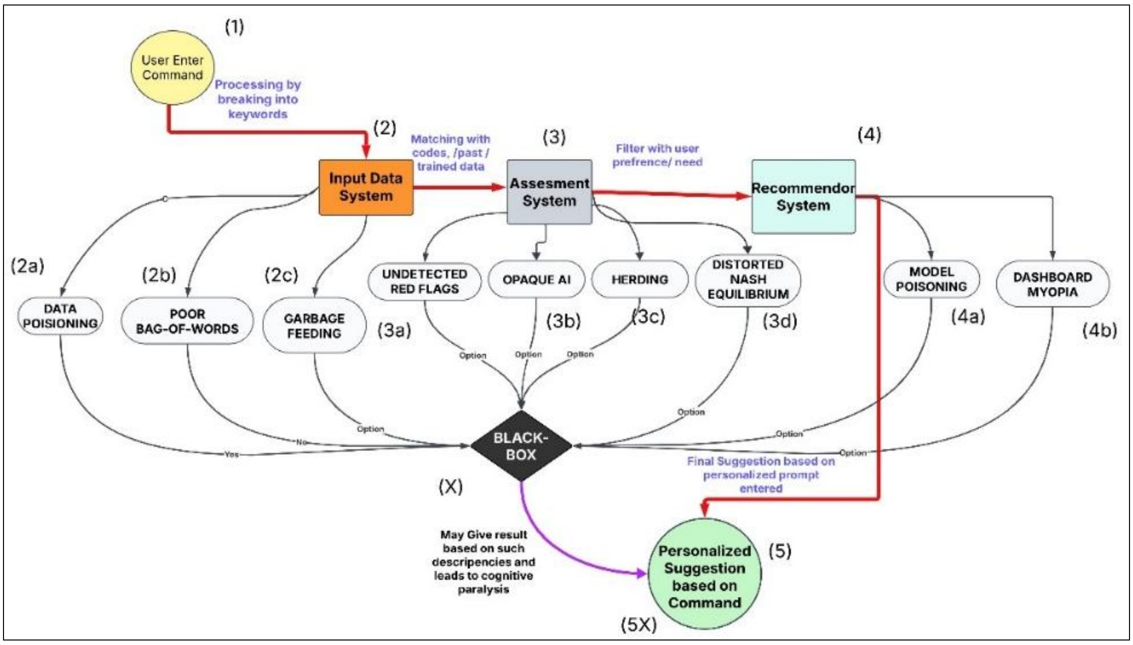
Figu 1: Working Mechanism

Table: 2: Application of Gen-AI in FinTech

FinTech Platform	Application of AI in Fintech
Digital Payments & Money Transfer	Fraud detection in real time with risk score models. Automated transaction classification for improved money management. AI-powered chatbots that help users with payment problems.
Banking & Neobanks	NLP-powered virtual assistants for automated customer service. Recommendations for individualized banking based on patterns.
Lending & Credit Technology	AI-driven alternative credit scoring for better financial inclusion. Automated loan approvals with minimal paperwork. Dynamic interest rate adjustments based on user risk profiles.
Robo Advisors / Wealth Management	Investment advice that is customized to preferences, inflation rate, and market risk. Automated rebalancing of the portfolio profits. Analyzing financial news sentiment to forecast markets.
RegTech (Regulatory Technology)	Anti-money laundering (AML) real-time transaction monitoring. AI-powered insights for automated regulatory reporting. Identity verification using AI for KYC compliance.
Blockchain & Cryptocurrency	AI-powered smart contracts to prevent fraud. By responding instantly to price adjustments, bots enable automated trading.

3.2 What are the Loop Holes in the AI, How They Create Vulnerabilities in the Ai-Driven Financial Activities

The process begins at (1), where the User inputs a prompt/query into the AI system. At (2), the Input Data System captures the user's query, filters it by breaking it down into "keywords" or "codes," and matches them with pre-fed codes in the database-using models like Word2Vec, which embeds similar meanings into vector representations. Matched data is then passed to the Assessment System (3), where further processing occurs: the system compares inputs with historical data, past queries, and coded models to align current needs. Next, the Recommender System (4) tailors personalized results by refining outputs from the assessment stage, analyzing current scenarios, trends, and even concepts like Nash equilibrium. Finally, at (5), the AI delivers personalized suggestions to the user, based on their needs and preferences, and completes the process.



Source: By Author

Fig 1: Loopholes associated with respective system layers of the working mechanism of AI

In the diagram, there are other nodes connected with numbers (1,2,3) and raise the concern, what are they indicating as (2a, 2b, 2c, 3a, 3b….) so despite having enormous features associated with AI, there are several loopholes hidden in its processing system, they are:

4. Input Data System

a) **Data Poisoning:** In AI, data poisoning is the intentional alteration of training data to taint the learning process and produce malicious or compromised model behavior. Such attacks can have major repercussions in the financial industry, such as introducing fictitious transaction records that lead AI systems to incorrectly identify or ignore fraud. These manipulations have the potential to cause monetary losses as well as erode confidence in automated systems. Machine learning applications in finance are at serious risk from data poisoning techniques as label flipping and backdoor threats (Aljanabi *et al*., 2023) [2]. Therefore, protecting the integrity and dependability of AI-driven financial services requires combating data poisoning.

b) **Poor Bag-of-Words:** Approach in NLP, BoW model counts the frequency of words while ignoring word order and syntax. The method has significant drawbacks, particularly in intricate domains like finance, though it is efficient for other tasks. For exact interpretation in financial text analysis, like analyzing market news /annual reports, word order and context are essential (Huilgol, 2020) [21]. For instance, "increased profit" and "profit increased" have similar meanings, yet BoW handles them in the same way, possibly omitting minor distinctions. On the other hand, although having different meanings, "not profitable" and "profitable" would be regarded as comparable because they share a term. This might result in misunderstandings that impact sentiment analysis and financial decision-making.

c) **Garbage Feeding:** In artificial intelligence, the principle of "garbage in, garbage out" emphasizes that the quality of outputs is directly dependent on the quality of input data. In the financial sector, if a system is trained on inaccurate or biased financial data, it may produce unreliable analysis and predictions, leading to poor investment decisions or flawed risk assessments. like an AI-driven financial advisor relying on erroneous transaction records might misclassify spending habits, resulting in misguided budgeting advice (Zdrok, 2024) [57].

5. Assessment System

a) **Undetected Red Flags:** Undetected red flags are important warning signs in AI-driven financial systems that go unnoticed because of algorithmic or data constraints, increasing financial risks. For example, AI-based credit evaluation systems could fail to notice minute irregularities in application information, granting high-risk loans and raising the default rate. According to research by the Federal Reserve Bank of Boston, while AI makes credit more accessible, it also creates risks, including pricing collusion and covert malfeasance if there is insufficient oversight. For AI systems to accurately detect and neutralize new financial risks, it is imperative that strict monitoring mechanisms be put in place.

b) **Opaque AI:** Systems with internal decision-making processes that are difficult for humans to understand are referred to as opaque AI, and they pose serious problems for the financial industry (Černevičienė & Kabašinskas, 2024) [9]. For instance, AI-powered credit risk assessment models function as making it challenging to defend loan approvals or denials. This can lead to biased results and problems with regulatory compliance. Explainable AI (XAI) frameworks are desperately needed to improve transparency, facilitate equitable decision-making, and maintain public confidence in financial institutions. This is because advanced machine learning models are inherently opaque.

c) **Herding:** The tendency of systems to mimic the actions of others or adhere to dominant patterns without independent analysis is known as herding in artificial intelligence (AI). This can happen in finance when AI-driven trading algorithms mimic other systems' techniques, resulting in coordinated purchasing or selling, heightened market volatility, and the emergence of asset bubbles or crashes. The late 1990s dotcom bubble is a prime example, in which widespread herd mentality drove up the value of technology stocks, ultimately leading to a financial meltdown. Designing AI systems to encourage autonomous decision-making and integrate various data sources is necessary to reduce such hazards.

d) **Distorted Nash Equilibrium:** Players that base their decisions on erroneous or insufficient information create a skewed Nash equilibrium in games, which produces less-than-ideal results. According to Wiszniewska-Matyszkiel (2016) [51], this happens in the financial industry when AI systems depend on inaccurate data or presumptions. AI-driven trading algorithms, for instance, could misread skewed market signals, leading to bad investment choices and losses. The idea of belief-distorted Nash equilibrium shows how distorted perceptions can deviate from the results of conventional equilibrium. Sound financial decision-making requires that AI systems be provided with complete and reliable data.

6. Recommender System

a) **Model Poisoning:** In AI, it describes malevolent attacks in which adversaries purposefully change a model's parameters to cause undesired behavior. The financial industry is at significant risk from these types of assaults. Attackers might, for instance, alter an AI system that banks employ to process handwritten checks, resulting in misunderstandings that cause monetary losses or fraud that goes unnoticed. Financial institutions must put strong security measures in place to combat these risks and guarantee the dependability and integrity of their AI systems.

b) **Dashboard Myopia:** It refers to an overreliance on simplified visual dashboards, often at the expense of deeper contextual insights. In finance, this can lead to poor decision-making; for example, an AI risk management tool may highlight strong portfolio returns while ignoring systemic risks or market volatility, resulting in losses during downturns. Studies show that AI-powered dashboards can create an illusion of control by prioritizing easily measurable metrics over complex financial patterns (2023; Bahoo *et al*., 2024; Singh *et al*., 2025) [5, 48].

c) **Black-Box:** The black box problem in AI poses a profound risk to financial stability by obscuring the decision-making processes within complex, opaque models. In the financial sector, vulnerabilities such as distorted Nash equilibria, herding behaviors, data and model poisoning, undetected red flags, dashboard myopia, and algorithmic opacity reveal how AI systems can misjudge risks, intensify market disruptions, and compromise institutional trust. In certain instances, this may result in findings that are based on erroneous connections, which could lead to biased conclusions. It goes without saying that the circumstances in which this prejudice occurs will determine its significance. For instance, bias in translation and bias in loan origination are not the same thing. Either way, it's critical to understand the causes of this prejudice (Fernandez, 2019) [16]. Without a shift toward explainable AI frameworks and stronger regulatory oversight, the unchecked adoption of opaque AI systems threatens to trigger systemic financial failures and undermine the integrity of global markets.

7. Human in The Loop

A method to AI known as "human-in-the-loop" (HITL) incorporates human judgment and experience into different phases of the creation and functioning of AI systems. The precision, dependability, and moral coherence of AI applications are improved by this incorporation. Human-in-the-loop (HITL) machine learning integrates human expertise into data processing, model training, and system applications to improve accuracy, interpretability, and adaptability. By involving human judgment, HITL addresses limitations of fully automated systems and enhances performance across tasks such as NLP and computer vision (Wu *et al*., 2022) [52]. According to Deshpande (2020) [15], continued human supervision is critical for the underlying data and analytical capabilities employed by AI/ML applications in "black box" systems.

- **Data Annotation:** To ensure that AI models are trained using correct and pertinent examples, humans annotate datasets. According to Settles (2009), Mosqueira-Rey *et al*. (2023, active learning (AL) uses people as oracles to annotate unlabelled data while maintaining system control over the learning process. This strategy uses human experience to tackle issues with data sparsity, model interpretability, and changing fraud trends, eventually enhancing model resilience and expediting the annotation process (Kadam, 2024) [22].
- **Model Training:** During the training stage, human input is imperative to use to improve the model's performance by correcting AI predictions. In machine teaching (MT) (Mosqueira-Rey *et al*., 2023; Simard *et al*., 2017; Ramos *et al*., 2020) [32], human domain experts limit the information they want to transmit to the machine learning model, giving them control over the learning process.

- **Continuous Monitoring:** Humans monitor AI outputs after deployment to spot and fix mistakes, preserving system integrity over time.
- **Decision Support:** Particularly in delicate or complicated situations, humans make the final judgments after AI systems have presented analysis or suggestions.AI system accountability and trust may be hampered by this lack of transparency.
  Organizations can lessen these difficulties by implementing HITL
- **Enhanced Transparency:** By allowing humans to see and analyze AI processes, the system becomes easier to comprehend by offering insights into the model's decision-making processes.
- **Bias detection:** By spotting and correcting biases in AI outputs that automated systems might miss, humans can uphold moral principles and promote justice.
- **Better Accountability:** AI-driven judgments are accountable when human monitoring is present, guaranteeing that moral principles are respected and that remedial measures can be implemented when needed.

8. Discussion & Conclusion

AI is revolutionizing the financial sector with its speed, precision, and efficiency. However, challenges around transparency, accountability, and overdependence remain significant. Blind reliance on AI can reduce human judgment, leading to risks for individuals, institutions, and economies. Though AI/ML enables innovative financial solutions, these developments still operate within existing regulatory frameworks. Emerging tools like algorithmic regulation call for continuous assessment of AI's impact on Fintech and Finserv transformations.

To mitigate risks, integrating AI as a supportive tool-alongside traditional decision-making-offers a balanced path. Moreover, embedding explainability into AI-driven workflows is no longer just a compliance need but a strategic advantage. Institutions that combine advanced analytics with transparent processes will earn greater trust and resilience in complex financial environments. Moving forward, a collaborative focus on ethical design, algorithmic fairness, and robust governance will be critical to fully realizing AI's transformative potential while safeguarding market stability and public trust.

9. Suggestion/Recommendation

Enhancing AI's cybersecurity capabilities is yet another important area that requires focus. The dangers that AI systems face is evolving along with them. To safeguard financial systems against ever-more-sophisticated attacks and preserve the integrity of AI-driven processes, strong cybersecurity measures will be essential. To create a trained workforce that can propel future innovation, the financial industry additionally has to invest in AI education and training. Integrate "Human In The Loop System", Deep Learning, and regular monitoring. With the help of this investment, the sector will be able to keep up with emerging technologies and keep pushing the limits of generative artificial intelligence.

10. Declaration of Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this research paper. No financial, professional, or personal relationships have influenced the findings, interpretations, or conclusions presented in this study.

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