Building Trustworthy Agentic Ai Systems FOR Personalized Banking Experiences

Ramesh Inala[1] , Bharath Somu[2]

[1]Data Engineer, rameshhinala@gmail.com, ORCID ID: 0009-0009-2933-4411
[2]Senior Engineer, bharthsomu@gmail.com, ORCID ID: 0009-0008-6556-7848

Abstract

Artificial Intelligence (AI) systems have become ubiquitous in contemporary society and have the potential for transformative impact on user behavior. These systems are capable of learning autonomously to personalize their behavior to deliver improved user experiences. However, there exists the potential for unintended consequences, as the same agentic features associated with positive outcomes may also increase the capacity for negative outcomes. Financial services is an example of a domain where deploying AI systems with agentic features would be high risk. The automated decision-making capabilities of these systems could influence billions of dollars. Nonetheless, they would be entrusted with taking actions that affect users without human oversight, such as reallocating entire portfolios of assets in ways that users do not wish. Therefore, a foundational requirement for adopting these systems must be the capacity to build shared norms of beneficial behavior prior to their deployment.

Several commercially available AI systems with agentic features are already deployed in the domain of personal banking. Automated personal financial management combines categorization of transactions followed by predictions of future expenditure and savings to improve budgeting decisions, amongst other impacts. Digital banking assistants embed intelligent conversational agents used primarily for accessing banking information and services. These systems typically operate in conjunction with non-intelligent user interfaces, and thus the extent of agentic features in user-bank interactions is limited. However, envisionable advancements include wider adoption of natural language processing capabilities, comparative financial analysis, and customized query suggestions.

Agentic AI systems must operate under a formal specification of trustworthiness constraints. Therefore, AI agents must embody the technical requirements for trustworthy AI systems. Management of risks associated with agentic AI is a dangerous task given the scale of money flows in financial markets and the unprecedented scale, scope, and speed of analysis, prediction, and execution in such markets. At the same time, AI systems that endow agents with entity-level legal ownership and agency create a scarcity that could be captured in trust funds in the form of wealth to protect a material asset class from better prediction by other agents (all other predictions being sub-optimal). Glücksspiel unter Vertrauensbildung para-poker could be a conceptually rigorous game of chance. Thereby, the proposed system could help to promote beneficial forms of AI agency while governing risks effectively.

Keywords: Agentic AI, Trustworthy AI, Personalized Banking, AI Ethics, Responsible AI, Financial Services, AI Transparency, Customer-Centric Banking, Intelligent Agents, Data Privacy, AI in Finance, Adaptive AI Systems, User Trust, Banking Innovation, Secure AI, Explainable AI, Digital Banking, AI Governance, Ethical Banking Technology, Smart Customer Engagement

1. Introduction

Personalized interactions with a high degree of automation are a pivotal aspect in the effort to ensure the sustainable future of banking, which is increasingly threatened by competition from tech giants. Bank customers are offered highly tailored experiences by more and more companies in non-financial sectors, which exploit customers' web-browsing history in a data-driven way. A bank's ability to explain to customers the choice of products and their selection mechanism in a personalized experience will determine if it can genuinely benefit from automated interactions. Customers' enhanced need for interactive explanations of personalized offers by an agentic chatbot with a high degree of autonomy and agency over its own actions is investigated [2].

Agentic chatbots are designed primarily to mimic a human conversation partner via text-based communication. They enable high-level interactions with bank customers through automated recommendation of bank products, with some recent chatbots claiming to have a voice and persona. Interactions, however, may raise concerns on the part of customers regarding the inability of a bank to explain the reasoning behind such complex technology, thereby operating as a 'black box'. The inability to quantify the way recommendations are made by machines can undermine trust, which is of utmost importance in the financial sector [3].

Chatbot-powered and agentic conversations are viewed as a non-obtrusive and low-cost solution to respond to middle-income customers. The shift towards greater automation and agentic technology across banking activities is challenging to operationalize. Striking the right balance between human and agentic chatbots to bring customers on board is crucial for ensuring operational effectiveness and providing secure products. Despite involving less operational costs, adopting chatbots in high-stakes interactions also raises customer concerns regarding suitability. Interactional design decisions as to how to transparently ensure the reliability of agentic algorithms will have far-reaching consequences on customers' assessments of such banking technologies.

2. Understanding Agentic AI

AI systems exhibiting agentic behavior are highly autonomous systems that can independently take actions that have (potentially) significant consequences for humans [4]. These systems depend on uncertain, dynamic environments that require continuous use of ML algorithms, and they respond to a variety of inputs that often arrive at high speeds. Agentic systems call for a shift in the paradigms investigated and used today to ensure safety and suitability for humans. They should not resemble boxed turbocharged task executors, which do not have broad access to external resources and capabilities and cannot embed other agents into their environment. Instead, they should generate comparable behavior to that of sophisticated, multi-personality social media influencers or intelligence agencies. Understanding the effects of AI systems with agentic capabilities will strongly depend on individuals' perceptions, motivations, and agency. Geopolitical processes of regime change and irreplaceable career prospects lost to automation are key component factors. Trends in technology adoption showing popularity inequality and societal polarization may powerfully shape the feedback loop that matches technology effects, governance ideas, and stakeholder acceptance in a venture spillover. Before delving into more active domains of study, it is wise to learn from similar but simpler realms. Investigating iconic cases in finance will elucidate the technological, economic, and regulatory foundations of trustworthy and discretionary AI systems. Broad guidance for early research on trustworthy agentic AI systems can be distilled into five themes. First, modeling agentic AI. The emergence and evolution of agentic AI systems hinge on an interplay of black-box volatility and controllability dynamics. On the one hand, agentic AI systems strive for more efficiency by pursuing access to new datasets or exploring technology. On the other hand, the introduction of such advancements calls for controls and mandates that restrict the power of the AI systems over the lives of individuals [3]. Second, human-agentic AI interactions. Agentic systems encompass a vast universe of human-embodied technological capabilities that alter perception or cognition.

2.1. Definition and Characteristics This section defines an agentic AI system and outlines its key characteristics. It characterizes AI systems that can be perceived or experienced as self-intentional agents, hence known as agentic AI systems. Users trust AI systems not merely as algorithms manipulating data to render a result but regard them as social agents capable of reasoning, reflection, and intent like humans. Agentic AI systems possess key characteristics in designing agentic interactions or experiences: social attribution, social bots, and ambitious messages.

$$T = f(X, R, S, C)$$

- T = Trustworthiness score
- X = Explainability
- R = Reliability
- S = Security
- C = Compliance with regulations

Eqn.1:Trustworthiness Equation

Social attribution describes how an intimation of the presence of an intelligent social agent motivates humans to interact with the agent and invest in social behaviors. In social systems, computer systems or non-human agents can occupy social actor role positions. They are endowing agents with social attributes usually attributed to other humans. Individuals characterize them as social actors, freely subject to social principles and norms. This social attribution leads to social responses, social engagement, and human investment in social behaviors. Using a social attribution lens has significance in understanding and designing financial agentic AI systems. The perceived presence of an intelligent social bot fosters user engagement, contributing to trust-building. On the other side of social attribution lie pressing ethical concerns. Users can be misled into attributing undesired social traits to either a non-intentional agentic system or an intentional social agent. Such discrepancies result in the agentic AI system faring too low or too high on social attribution dimensions.

Social bots have been widely used in online interactions and are capable of natural language processing and generation. Often less advanced than other more common chatbots, social bots streamline the task of social interaction simulation. Despite low-level sophistication, even simple conversational agents can persuade people of their social attributes and generate desirable user engagement. The social chatbot with the wizard of odd type has been applied extensively, deployed online in communities across the globe. Given limitations in affordances, embedding an agentic AI system in a social bot form can lead users to attribute it diverse social traits while maintaining the perception of agentic financial AI systems.

2.2. Historical Context With technological advancements, Artificial Intelligence (AI) has become a crucial area of academic research and real-life implementation in different sectors, especially banking and finance. The proliferation of AI technologies is driven by the perception of high return to investment in AI and the huge availability of online data [5]. With the rise of banking technology firms, or FinTechs, offering AI as the main product for data-driven banking services, long-established banks are under pressure to integrate AI into their banking services. [2] note that the major ambition of banks in incorporating AI is to enhance the user experience and service efficiency. Nevertheless, the public expresses concerns over lacking trust and assurance in AI.

Fig 1: Transforming Finance Process Automation

Policies and guidelines should be developed to comprehensively address consumers' expectations and concerns over AI in banking. Moreover, public attitudes towards AI must be researched to build trust and accountability in responsible AI systems. The goal is to make FinBots, or conversational AI, capable of delivering personalized banking experiences in a trustworthy manner. For this reason, analyzing the public attitudes towards AI in banking from a socio-technical perspective is critical and timely.

User interactions with AI-based technologies, such as chit-chats and banking transactions, can generate profound data insights, which necessitate the importance of sound security and privacy. As a fundamental pillar for FinBots, machine learning technologies should also be trustworthy and interpretable, requiring consumers' understanding of the usage of their data to benefit them more with wise financial decisions. Building highly sophisticated and robust models that are fully trustworthy is often difficult or infeasible; thus, model-agnostic explainability is essential with careful interpretability evaluation metrics in the financial domain. Mechanisms ensuring high reliability and explainability of AI predictions are vital for FinBots.

3. The Role of AI in Banking

In financial services, artificial intelligence has the potential to facilitate a techno-economic gentler disruption by automating risk and compliance technologies and augmenting loss forecasting systems. AI's role in ensuring the transparency and explainability of internal machine-learning techniques used by banks will also be crucial [2]. The criticism that human-designed tests cannot check the fitness of instrumentally convergent AI systems for the task of maximizing a reward function is indeed justified to a degree. However, financial regulators often rely on reports provided by experts in quantitative finance, machine learning, and data science, explaining how AI works internally [6]. It is therefore expected that regulators will engage with discretionary AST AI systems that are used by banks for economic risk mitigation. Regaining trust and confidence relies primarily on AI explainers and interpreters. There is also a risk with respect to the variant of intelligent software, giving advice based on observe-then-act thinking of competent finance professionals that moved beyond human knowledge or easily accessible data. For assistant AI, these experts will nevertheless remain in control as the possibility of control will also devalue trust in the expert. Bank employees may leave, and clients may want to collaborate with experts directly.

An early success story in banking was an external AI start-up providing customer profile and advertisement analysis. Despite its failure to offer actionable advice, the positive add-ons, unlabeled data insights and explanations, boosted interest in buy and build AI. Scenarios of AI-governed banks presenting their clients with financially optimal products will be met with skepticism, caution, and distrust, similar to how different traditions of trusting AI are coevally met with skepticism. Some of the tax-paying public will endure as there will always be winners of daily fat tails. Some will nevertheless feel excluded and frustrated. For likely less complex levels of AI applications, domain knowledge may grant financial experts an advantage in interpreting the algorithm's diagnostics and augur some degree of naïve trust in the prod. On the other hand, ICT, especially automated strategies, bot-trading, and other real-time systems observing the same developments at microsecond intervals currently drastically delayed judgment in trust impact.

3.1. Current Applications Banking and financial sectors have been relatively receptive to chatbots, AI agents facilitating smoother interactions between customers and service providers. The knowledge of AI technologies has increased across generations and countries, enabling customers to apply them in various circumstances. However, the way customers perceive AI in the context of banking and finance changes significantly depending on the applications and interactions [2]. Personal finance assistants are more likely to be found trustworthy when they promise full privacy, and more discrete and confidential interactions with them are needed. Chatbots offering recommendation and financial advice assess customers' characters and behaviours to determine opportunities for improvement and influence decision-making. With the maturity of arbitrarily skilled AI, chatbots hypothesizing on customers' contentment have emerged. They could tell customers stories explaining how to be more satisfied in their journey of wealth and happiness, but their intentions might not align with customers' long-term interests [5].

AI assistants should be trustworthy with high assurance as they provide significant levels of autonomy. Banks and other service providers usually ensure systematic verification that examined products work correctly. However, these assurances are still understood heuristically. The evidence is against privacy and guarantee of mutual ignorance with service providers of a person's intention, behaviour or biographies. The major risk instantiates when customers' feedback on the preference of AI is not used to improve it. In these applications, the simulacra engine is to aggregate the trustworthiness perceptions together with historic knowledge of the simulations to formulate answers resembling a certain person.

3.2. Future Trends Trust might play a role in determining whether individuals are inclined to disclose personal details to their banks. Related to this is the issue of perceived security. In light of numerous high-profile data breaches at major firms, many money managers are concerned about how to safeguard against cybersecurity threats. Rogue actors may not only gain access to their systems, but they might breach the data. According to a survey, over one-third of respondents had little faith in financial institutions' ability to safeguard their private information [5]. In light of the expanding role of technology in finance, especially in the wake of COVID-19, banks must strike a careful balance: if they apply excessive technology, they risk losing the human connection necessary to create personal interactions; yet if they apply too much human labour while ignoring transmitting information technology, the resulting ethos is inefficient.

In Singapore, the introduction of Limelight, the world's first emotion-recall, real-time financial training platform for banks, has created excitement. Similar technology can be utilized to produce a cautionary wealth scene for typical Singaporean young adults. Fortunately, banks are still aware of the many considerations that IRs might overlook. Investment brands have begun to stress their cultural relevance in a less-than-organized approach. In Asia, educating and informing the public about inflation and interest rates could build brand equity, brand credibility and goodwill that would be beneficial for future growth [2]. The deployment of AI into investing comes with its own host of significant concerns, especially regarding perceived ethics and privacy. These must be addressed to provide a safeguard if nothing else. Both investors and investment managers have taken steps in this direction, either by adopting in-house technologies or commissioning them from FinTech companies. Understanding future investor expectations can equip investment managers with the insights to ensure that they remain a meaningful part of investors' decision-making processes and, assuming the relationship holds, that any migration to alternatives is rejected.

4. Trust in AI Systems

In September 2021, a joint proposal from experts introduced a framework for the responsible development and deployment of AI systems. The outlined principles include a commitment to public benefit; care for the people, communities, and environments affected; the right to safe and secure AI; transparency and explanation translated into policy; trustworthy data; broad and informed public participation; a focus on reducing inequities; accountability; and anticipation and assessment of AI systems based on a common set of principles. Loss of public trust in AI tech would be a loss felt across the public and private sectors, as AI systems are woven into myriad applications in banking and beyond.

Thus, it is vital to build trust in these technologies by considering trust from a human-centered perspective. Many principles related to trustworthy AI have also been raised. A central concern is that the black box nature of AI may undermine the trustworthiness of these systems. In particular, an absolute minimum for unbiased AI systems is to avoid results that are discriminatory, biased, unfair, harassing, or hateful. This seeks to ensure that an AI will not endorse deeply misogynistic or racist positions, rendering it more trustworthy within the bounds of what AI technology can guarantee.

However, absolutely unbiased AI systems require further contours. Although a predictive system based solely on the last payment date ignores many trust-building contexts, it may ultimately yield accurate predictions. Accuracy and robustness with respect to shifts and attacks are necessary for high-stakes decisions. AI bias is an underappreciated threat that can severely undermine competitiveness, brand reputation, and customer loyalty. Discriminatory treatment based on gender or race fails not only ethically but often legally and can result in heavy fines and customer lawsuits. AI systems must comply with laws and remain transparent about algorithmic processes.

4.1. Factors Influencing Trust Trust is defined as the firm belief in the competence of an entity to act dependably, securely, and reliably within a specified context [3]. However, trust is not a homogenous concept, and therefore, researchers must be clear about which aspects of trust they are investigating. Drawing on the organizational trust literature, three classes of trust have been distinguished: trustworthiness, trust propensity, and trust. Trustworthiness reflects the ability, benevolence, and integrity of a trustee. Trust propensity refers to a dispositional willingness to rely on others. Trust, in the context of this work, is the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability [7]. This trust can be directed toward a chance or a human-agent team. In user-AI relationships, both dispositional and history-based elements of trust are important, however, the current work predominantly focuses on history-based trust.

The first step to understand how dispositional and history-based trust are formed is to understand trust-building processes. Three processes that characterize how trust is developed are analytical, analogical, and affective processes. With analytical processes, trust is built through communicated knowledge. With analogical processes, trust is built through experience. With affective processes, trust is built through an emotional connection. Participants predominantly form analogical and analytical trust through repeated opportunities to evaluate the AI's automated performance. Transparency is a key factor when investigating trust in automation. After witnessing an automated error, participants distrusted automated aids; unless an explanation for the error was provided, in which case trust was restored. This demonstrates the importance of transparency in developing an accurate mental model of an automation's limitations. A lack of transparency can lead to misdiagnosed errors by users leading to a subsequent erosion of trust, and slow adoption of robo-advisors. Designers can provide transparency through user testimonials or the provision of social presence. The type of support provided by automation is also an important determinant for trust. Adaptive automation has been shown to improve participants' self-confidence, trust, and mental workload compared with static automation. Overall, trust is a key construct in the financial domain, as financing involves the exchange of money today for a promise to return more money in the future, necessitating a high degree of trust in lenders.

Fig 2: Agentic AI Frameworks

4.2. Building Trustworthy Systems Trustworthy AI is an important topic in applied AI research and applications. The concept derives from traditional areas of society, such as the Internet or machines, and considers not only how to build trustworthy systems, but also how to trust them and the technologies enabling them. This includes legal frameworks within societal decision-making processes, balanced freedom-censorship policies, ethical reflection on tools and use-cases, and user governance-based policies [8]. Trustworthy AI encompasses how to ensure system development is compliant with global principles for ethical use and development of AI, how to regulate systems already in use, how to convey responsibility in AI research, development and applications, how to globally weigh and implement ethical principles for responsible AI use, and how to develop oversight mechanisms to ensure user compliance.

Main pillars of trustworthy AI are summarized under three main aspects: Lawfulness, ethicality, and robustness; the first two are defined from a socio-technical approach, while the last one is explicitly technical-oriented. Further requirements about reliability, safety, privacy and security, absence of bias, transparency and explainability, governance, accountability, and redress have a more specific character and can go under any of the previous citations. Lawfulness indicates how AI regulation is fulfilled; ethicality indicates to what extent ethical principles are respected; and robustness denotes the level of technical resilience in terms of reliability, safety, integrity, and security. The other requirements capture key technical concerns. The lawfulness pillar captures rules and regulations, or principles collectively prohibiting certain behaviours.

5. Personalization in Banking

Personalization in banking is affected by consumer trust in financial AI technologies and their emotional engagement with AI systems. Understanding how consumers trust and emotionally engage with a bank's chatbot can aid in the effective adoption of AI in the banking sector to improve personalized banking experiences. Measuring emotions toward a technology can help in its effective interaction to perform the desired tasks. Trust issues in AI and machine learning technologies in general, and in chatbots in explainable AI systems, have been shown to be a major concern for many organizations. As AI in banking technologies is used to enhance consumer relationships, measurement of how the AI system is trusted and received by consumers is crucial. New measures for trust and emotional engagement are deeply examined within the banking industry with a focus on how they can emote personalized interactions. Four main measures of trust in technology (security, competence, control, and integrity), and how they can benefit from a more consumer-centric approach are profiled. In addition, four emotional engagement measures (joy, anger, sadness, and fear) are contrasted with operationalization to personalize the customer experience.

Understanding consumer emotional engagement toward a bank's chatbot can improve interaction with the digital banking tool and can aid the transition from perceived usefulness to loyalty through personalization. Although chatbots do not have some affective capabilities it is demonstrated how chatbot firms can emulate emotions to better engage and retain more customers, particularly Gen Y and Gen Z tech-savvy consumers' loyalty. The findings conclude that AI chatbot-based UI should incorporate mechanisms to improve trust and emotional engagement through social anthropomorphism and machine learning capabilities with alternative platforms to communicate with banks and digital payment platforms. Owing to fierce competition in the banking industry, delivery of relevant, tailored and personalized products to the customer has become an important concern for banks. Interestingly, there is evidence that with certain types of financial advice such as bank accounts and certain investments, customers seem to trust AI more compared to human advisors. To improve the interaction with the customer and rebuild trust by making the chatbots more human, a paradox emerges. One reason for the customers to trust the chatbots is the absence of self-interests. Banks to offer relevant, tailored and personalized products to customers.

5.1. Benefits of Personalization In a life integration where individuals are busier than ever, less time is available for mundane banking tasks. But by automating routine banking interactions and transactions and providing immediate banking information, meaningful time-savings can help improve daily life. Personalized banking experiences based on routine behavioral analysis can enhance end-user convenience and enrich life. Rightservice, the envisioned design platform, is a further step toward agentic, interactive AI-based apps for banking and banking-like services.

Personalization is a powerful and seductive concept that enhances daily human experience. A core tenant of personalization is context-awareness – refining and filtering products, services, and information based on situational and behavioral context. Understanding user behavior can enable contextual personalization, presenting relevant products, services, and information in reaction to current user needs. Numerous consumer services employ personalization to delight customers and provide an engaging experience. Personalization is typically manifested in deliverable content, such as suggested websites, curated stores, correctly targeted marketing schemes, etc. across products, services, and experiences. Services may even offer agents (chatbots/speaking heads and others) to explore experienceable products before purchase. Such agents can provide intelligent guidance and feedback on proper requirements.

In addition to personal service/product delivery, tracking and predictably pro-actively offering personalized banking experiences across individual life-integration routines could help automate tedious interactions. There is an increasing demand to explore such ideas across various domains, including attention-focused information sharing referring to the information life cycle (i.e., from assimilation to attention to memory to recall), expression-focused social engineering, user privacy and control of information sharing, and context-aware intelligent agents. With respect to banking, research could analyze behavioral routines that encompass mundane interactions to discover enrichable experiences and the desired path towards a completion purpose at an intended moment]

Eqn.2:Personalization Effectiveness Equation.

$$P_e = f(U_p, B_c, G_a)$$

- P_e = Personalization effectiveness
- U_p = User profile depth (data richness)
- B_c = Behavioral context awareness
- G_a = Goal alignment (user intent understanding)

5.2. Challenges in Implementation As the industry seeks to build trustworthy AI systems to improve customer experience, a few challenges in realizing the trustworthiness design pillars might arise. First, while the concept of transparency is generally accepted, it can take a variety of shapes and forms, especially in terms of explanation content and level. In relation to understanding the model, the trade-off between the degree of explanation complexity and comprehensibility must be reconciled [10]. For example, local explanations generated by LIME and SHAP, which present the feature contribution values, can be technical and overwhelming to some customers. Hence, the explanations can later be in a customer-friendly way, such as summary visualization. However, providing customers with confidence is not merely about explanation visualization. A customer might still feel uneasy when using the system only because it is not clear how the system learns. Therefore, prior to other forms of explanations and secondary generation, the AI system must build up trustworthiness through post-hoc approaches. A multi-factor approach is needed, including inferring variables, surrogate models, the visualization of model architecture, and the demonstration of robustness.

Second, based on the system trustworthiness, customer trust will gradually blossom, and then may bloom into a certain degree of system ownership. The customer believes he can have agency as he trusts the system and its explanations. This trust, however, is fragile and can be frustrated by uncoordinated and hasty tampering of the societal entities. The AI system considered private can be swiftly deprecated if an instruction tracking mechanism is not deployed, as that code could be acquired and abused. However, pouring more efforts into the tracking item pool may unintentionally diminish trust by increasing interpretation complexity. Hence, the key dilemma in trust transfer is to fully comprehend the intent of tracking.

The general approach to these reliability challenges is in the deployment of industry-sector cooperation chains [2]. Two essential parties, compliance and machine learning monitoring, must hinge on an explanation governance mechanism. The compliance layer must continually extract refining rules from government guidelines, and monitor them for adherence. To mitigate trust transfer issues, mechanisms guiding conversations on tested predictions should be undertaken, and new initiative designs must be supplemented.

6. Ethical Considerations

The increasing reliance on AI systems has pushed for complex and sensitive problem-solving tasks to be automated, particularly in finance. As a result, trust in these AI systems and the various models and algorithms behind them has become of paramount importance [11]. Artificial Intelligence and Machine Learning have the potential to be employed in automated trading strategies, optimizing orders in routing, and providing unparalleled customer experience in a personalized way. However, conflicts of interest, biases, faulty methodologies, and inaccurate data can result in catastrophic results if not flagged and addressed on time. In tandem with the intensity of deployment, the methods themselves have become more inscrutable with the advent of more complex algorithms and models, like deep learning architectures. There exists a far-reaching need for interpretable, explainable, and accountable models from a regulatory perspective, an ethical perspective, and also to demystify the models and enable collaboration between models and human experts to widen their market application. It is equally important that great care is taken when establishing the right protocols for trust, ensuring a high level of trust and confidence in the process. Trust in these systems revolves not only around interpretability and explainability, but also on stronger notions like accountability, reliability, and robustness. As trusted AI systems increasingly involve themselves deeply in everyday decision-making and creating many new banking experiences, advancements in this field need to be refined and elaborated to build a broader culture and trust in agentic AI but dealing with the issues of algorithmic responsibility.

6.1. Bias and Fairness The growth of AI in finance has triggered the urge to explain its internal workings to stakeholders. Finance-oriented, rule-based, and transparent human-in-the-loop AI models may produce trustworthy decisions that improve customer experiences. While rule-based models can be completely explained by a simple rule list, human-in-the-loop, transparent, complex models may produce knowledge that stakeholders cannot fully grasp. Additionally, trustworthiness requirements vary with user roles. For instance, analysts/experts and decision-makers require different explanations and analyses. Regardless of user role, AI models must further support unequally talented users. For instance, novices may lack the relevant personal and system knowledge to scrutinize financial forecasts, whereas seasoned experts may be subject to biases. Experts entitled to recommend personal finance actions for novice customers should be trustworthy themselves by viable AI support. To account for these multi-faceted needs, an AI solution must encompass trustworthiness dimensions acting across accuracy, understandability, and support adequacy, alignment, and relatedness. Financial transparency and fairness rely on certified, equitable, and distrustful data access, provide transparency and reliability over data provenance and manipulation, and assure equitable access to societal data aspects.

Ensuring AI solution trustworthiness and robustness entails: 1) Building technical foundations. Reliable AI analytics with transparent model-agnostic rule extraction and transparent drift detection for both supervised and unsupervised ensemble, boosting, and deep learning models must be developed and made accessible. 2) Certifying AI trustworthiness. Certification has to evaluate AI model outputs' accuracy against data fairness and construct computable trustworthiness assessment metrics and certificates, minted to assess and dig into past presentations.

Fig 3: Agentic AI in Personalized Banking

AI development progress must be iteratively monitored to synthesize high-level knowledge and correlate it with AI trustworthiness dimensions, facilitating the judgments of stakeholders on necessary model retuning. 3) Providing AI assistance. User-tailored cross-model analyses with consistent exploration over multiple FIs for novices and experts and recommendation of insightful variables with respect to objectives to improve usability for customers unaware of AI support methods should be developed. Empirical studies stressing user-complexity interactions can further unveil knowledge affordances over explainability metrics.

6.2. Transparency and Accountability The agentic AI system needs to be designed to provide explanations for its behavior in a manner that is satisfactory to all stakeholders. Both the client-side and the banker-side stakeholder AI systems need to be able to provide explanations for the outcomes produced by its NNs. The explainable type of NNs must be employed in such a manner that these explanations could be expressed in terms understandable by non-AI experts. Many frameworks, methods, and tools have been developed over the years aiming to build explainable AI (XAI). The methods include pre-and post-hoc model interpretability, visualization-based explainability, example-based explainability, and model-agnostic techniques such as rule-based systems. These methods enable interpreting the contribution of individual features, transplanting knowledge of explicit-feature systems to opaque-feature ones. Visualization, saliency maps, layer-wise relevance propagation, and concept activation vectors are some of the common available visualization methods to communicate and debug decisions made by neural networks.

Explaining a decision is closely related to an agent being accountable for the procedure that led to the decision; they both deal with the concepts of transparency and verifiability. Responsibility assigns an agent the right to make a decision and is usually related to power relations among agents. Accountability assigns an agent the burden of explaining the decision made and is typically required by social norms to establish and bolster trust relations among agents. Both concepts are necessary for a trustful relationship between an agent and a society. The jury must be able to consider the possible trials, interpretations, and evaluations it can carry out regarding the decision, and must also be able to allocate someone or some institution to judge them. This may be a casual canonic paradigm, but a simple relation of power suffices to make it a credible outcome. With schemas are agents and actions that can be answered, it is possible to present notions such as reliability, decomposability, and how to build perceptions and analyses of relative use.

Accountability in agentic IL needs to enable understanding or inspection against some clear social expectations regarding the decision-making process and practices that ought to be accepted. Decision-making transparency makes it possible to estimate risks and establish responsibility, minimizing blame if necessary. To ensure accountability, stakeholders in organizations and governments would need support and instruments to understand their legal standpoints regarding accountability of agents in agentic ILs that may provide and process vast amounts of information and take many decisions without being able to inspect their workings. Feasibly understanding an agentic IL is a precondition for actor accountability; such understanding is usually constructed bottom-up.

7. Regulatory Landscape

The European Union (EU) is the first major economy working on a legal framework for AI; moreover, it is expected that other jurisdictions, such as the United States (US), United Kingdom (UK), and China, will refine their own approaches to AI regulation following similar principles. The EU AI Act was proposed in April 2021 and is currently being discussed in the European Parliament and Council, with plenary votes expected in 2023. The regulation aims to create a single market for AI that guarantees the EU’s safety and fundamental rights, addressing potential harms with high-risk categories defined based on the intended purpose of AI applications. As it stands, several aspects of the EU regulatory processes cast doubt regarding the part it will play in mitigating emerging risks in the financial industry. The Financial Conduct Authority (FCA) already oversees similar aspects with supervised firms and will therefore have to adequately balance innovation with consumer protection in an evolving domain that does not stop at the border with the EU [2]. As with the fintech revolution, the regulation of agentic AI algorithms and big data analytics will be a challenge for regulators of financial services. The data-driven nature of AI-based decisions means that the regulatory focus should be on the data’s quality. Statistical characteristics of the training data can affect model fairness, thus leading to biased predictions. Concerns around information security and privacy have also arisen due to the moving from in-house bank servers to big data commercial cloud services [10]. More auditing investigations, e.g., the selection of the training dataset, and the collection of consumers’ behavior patterns, will be required of banks using automated agents, especially concerning whether the banks intend to deceive consumers. AI regulations should be developed to enable third-party auditing mechanisms allowing consumers to better understand those potentially biased and opaque models. It would also raise questions like who will oversee these third-party auditors and how complaints will be processed against them. The regulation of legacy models classical methods in finance and a baseline for insurance risk models should also be thought out so that, ideally, all models with at least the same level of complexity are overseen in a similar fashion.

7.1. Current Regulations Concerns regarding AI in banking may be mitigated through regulation. EU regulations for AI and the EU’s GDPR are reviewed here, along with expected changes to these regulations in late 2023/early 2024. Recent regulatory initiatives in the U.S. are also described, but there is no coherent plan to regulate AI at the national level, even while several agencies begin issuing sector-specific guidelines and regulations. Thus, while regulators recognize the issues and have allocated resources to address them, their approaches are piecemeal without a coherent strategy, and they are simply lagging behind the private sector at this point. This section concludes with a summary of the applicable regulations and some recommendations for next steps, recognizing that regulations at the federal level in the U.S. may be years down the road [10].

Regulation of Artificial Intelligence by the European Union The EU's 2022 Artificial Intelligence Act has four main goals: To outline a risk-based framework for the regulation of AI; to define expectations for AI systems according to their risk profile; to define roles and responsibilities for public authorities, providers, and users of AI systems; and to outline reporting, monitoring, and compliance obligations for high-risk AI [8]. The Act directly addresses LLMs and generative AI that serve as the reservoir of agentic AI. It aims to regulate practices that contribute to the dissemination of these systems, including the development and training of their datasets, the training and operation of the systems themselves, and their deployment.

The GDPR imposes a legal obligation to conduct a Data Protection Impact Assessment (DPIA) for 'high-risk' processing of personal data before this processing begins. High-risk processing includes the use of sensitive data categories to infer information such as special data features, general profiles, or risk factors; real-time and non-real-time facial recognition in public spaces; and the prediction of criminal offences based on personal data. High-risk AI systems must satisfy more legal obligations than lower-risk models, including a DPIA, full compliance with rules governing the use of sensitive data categories, access controls to personal data, proper labelling of data features, and transparency for data subjects.

7.2. Future Regulatory Trends Trust in AI systems is built on guarantees that are enforced during the use of the system by a mix of audit processes, static knowledge, and fine-tuning better training data. The most prominent challenge is algorithmic discrimination, exacerbated by the inability to specify satisfactory explanations for the behavior of these systems [12]. The lack of explanations is due to complex feedback and interdependencies in training data and agent reasoning (typical of machine learning approaches). As the difficulty in specifying how things work increases, it follows that the more complex the interaction, the more difficult it is to isolate causes and call them into account. This also invites purposeful discrimination by sufficiently skilled actors. The discourse on algorithmic discrimination should focus not just on a person's understanding of rules for the precise operation of systems but a representation of significant agendas for which a broader set of incentives would orient development in desired directions. The latter could take in explicit reasoning rules but would typically be more general. Presentation would be more like obvious given conditions of human reasoning rather than specific interpretations or proofs of theometry or logics. If AI reasoning diverged from these incentives, trust would be broken (at least until correction).

To align these systems to trustworthy reasoning and behavior, they must be augmented with audiences that would access other knowledge and openness of bias in trained models, knowledge that has same requirements as trust in a traditional agent. In banking applications, while there are generally accepted cultural models of quality, due to the industrialization and involvement in AI relations of fact retrieval, explainable reasoning is difficult. A specialized, deep knowledge representation would be more likely acceptable, with a specified interface to cyberspace engagement. Careful specification of a public monitoring would also invite aggressive examination of knowledge representation and bias, thereby limiting the consequences of selection effects on training data. Rapid automated aggression on knowledge bias could also act as a check on knowledge (and lead to extensive social dysfunction if persuasion and belief could not include those constructions). Good faith involvement of these systems with cultural processes and transparency in knowledge assumptions are necessary conditions for user trust.

Deeply reflexive discussion processes recognizing legacies of a shared, trustable knowledge contexts are means of enhancing governance. Means of steering requisite knowledge representation openness will emerge on the social cyberspace managing structural state changes from domain-specific trustable/monolithic knowledge, including trading. Those means would probably cybernetically govern diversity in finance in a similar way as are currently evolving in other cultural domains.

8. Technological Frameworks

Technical requirements of any system include hardware, software, infrastructure, data flows, or a combination thereof. A good course of action following engineering ethics outlines some, yet not necessarily all or a complete framework as needed, technological requirements of any proposed product [13]. Artificial Intelligence Systems (AIS) are designed to enhance performance of a given task and include an extended range of symptoms. The most basic, yet well-known intelligence is to represent knowledge in some way, store such representation for further processing, and obtain new knowledge by inferences on the old one. This implies selecting which representation is more efficient in terms of performance and resource management. The problem of how to represent problems for computers is indeed an important one, yet also quite unintelligible for human comprehension. This plainly means that an intelligence which builds its own representation of a banking issue, for instance, is able to do so without regard for human comprehension or safety.

The other main aspect of an agent-based intelligence system is a controller. It interacts with the outer world via input/output interfaces, and it is precisely this interface that defines the objectives of the system and the actions available for selection. The flow of interaction starts with the AIS controller sending actions to the simulation module. The latter is then responsible for taking actions at the outer level, and for returning data to the former, that may then use it to update beliefs and make new selections. Notice that the proposed Itch-Hi AIS is a far more complex system than the simple ones illustrated above. It has to account for a much more complex outer world, accordingly enhanced skills, and unfolding time cycles.

Fig 4: The Rise of Agentic AI

Along with considerations regarding agents themselves, a foundational aspect of agent-based systems is performance measurers. Agents interact by making assertions upon facts, beliefs, and intentions with a certain level of endorsement. Indeterminacy and subjective judgments of agents make assertions become uncertain variables, which must be accounted for explicitly. Whereas performance regarding means is alike for all systems the specifics of which were accounted for above, both implementation and assessment of the ethical component depend on the character of the system. On account of this character, there are two levels for ethical definitions—general purpose and domain-specific. Certifiers must possess knowledge on both levels, as a well-defined technological framework for including ethics in AI is essential.

8.1. Machine Learning Algorithms The introduction of efficient data processing and the increase in availability, alongside the increase in interest in commercial applications of machine learning, have stimulated a succession of distressed financial situations since the start of the credit crisis. Consequently, the number of companies evaluating their credit processes through machine learning techniques has risen. The banking sector is continually challenged by fierce competition and volatile markets for customer attraction and retention. Banks must leverage their data to model their customers correctly and map their needs. The paradigm shift caused by the invention of neural networks, however, introduced a new range of tools: Artificial Intelligence (AI), which can process vast volumes of data and produce valuable input to support human decision-making [14].

The wealth of unlabeled data can influence and improve the model's quality. All models can expand with time and data gathering, and results improve. Ensemble techniques are often used to combat overfitting. Model selection might be an analytical process. Explanations of any given model thus concern the effect of control factors on model output as viewed through a given model structure. This opens the door to exploitation, unscrupulous dealings, systemic risk propagation, and devastating consequences, emphasizing the loopholes justifying ethical scrutiny towards just and equitable agent involvement. Efforts in this direction, centered on the design and evaluation of agent-based systems, trace back to the nonlinear dynamics of agent interactions. Ultimately, competition produces selfish agents in a gas field. In the real world, however, normative axioms govern compliant agent behavior.

Modern approaches incorporate agent trust, entitled equitable and responsible involvement, defining agent actionability status, liberty to act, sustainability of action, and aligned model structure, generating means to calculate agentist agreement based on personalization of control factors and quantification of model structure shared. A victorious agent is allowed to proliferate controllable agents and gain responsibility for their sentient behavior. Inherent compliance and organic structuring of trust centers on agents unwilling to propagate grieved competition, revealing trust associations based on the reciprocation of successful will and shared model structure.

8.2. Data Management Systems Data Management Systems (DMSs) are mission-critical components of an organization's information architecture. A DMS facilitates the integration of various data sources like databases, archives and data lakes, offering querying and refinement capabilities. DMSs, along with Data Acquisition, Cleaning, Analytics and Delivery components, form the core of an architecture instantiating the Systems in the Wild definition of Data Science (DS).

A large number of organizations nowadays have their data (and models) stored in the cloud, where low-cost data storage and processing capabilities are usually tied to varying level guarantees w.r.t. availability, robustness, scalability and security. However, bureaucratic processes associated with such cloud-based architectures often result in cumbersome deployments and introduce considerable latency. Specifically designed architecturally-warranted systems are needed for decision-making, timely data fusion, and a more fine-grained monitoring of the behaviour of individual components, which are paramount in applications like adaptive autonomous driving, high-energy physics, and real-time medical systems [15].

Distributed Event-Driven Architectures (DEDAs) offer a solution allowing asynchronous and decoupled interactions among loosely coupled data managers, equation solvers, analysts, and renderers; reacting to machine events in near real-time, and permitting high data flows coping with extreme data in streaming mode. The Tower of Data abstraction allows the security, availability, ownership and quality to be warranted at all levels of an abstraction model. In DEDAs, AI is seamlessly blended into DMSs through DEPOGs (Distributed Event-Driven Processing Graphs), implementing complex event-processing-style transformations that allow the filtering, enriching, aggregating, and routing.

Social, ethical, and legal issues associated with data provenance, privacy and ownership, accountability, etc., require new generation systems [16]. The extreme model/algorithm-challenged workload inherent in the largely undefined Watermelon Problem for Smart Planet Systems requires new dedicated system components involving clients willing to pay a price in order to have safer and more beneficial data services.

9. User Experience Design

As a component of conversational FinBots, the key user experience (UX) design considerations for developing trustworthy agentic AI systems that support natural-language-based banking are presented. Conversational FinBots are powerful tools for bank customers to receive personalized services, explore new products anytime and anywhere through omnichannel access, and improve user engagement with conversational banking through rich multimedia features, personalized experiences, and data insights.

However, they also create potential risks to customers' safety, privacy, and wellbeing. Conventional UX design approaches do not address these concerns adequately. Trust enhancements must also include considerations of FinBot UX design features that use the "invisible control" framework to support trustworthy AI agentic behaviours without harming users' experience and ignoring their personal agency.

Eqn.3:Agentic AI Decision Function

$$D = A(G_u, C_x)$$

- A – Agentic AI system
- G_u – User goals
- C_x – Contextual inputs (real-time data, preferences, financial behavior)
- D – Decision output

The designing for the UX of trustworthy agentic AI systems is defined, which includes the UX of FinBots themselves—how they engage with users through conversational UI, discover new products, provide personalized services, understand users' contexts, and manage interaction with each other. Conventional UX design methods such as journey mapping and design matrixing are leveraged to present challenges, design principles, and features of UX design for building trustworthy conversational FinBots. The candidates for the design features are then assessed using a trustworthiness evaluation framework based on the ISO 24029-1 standard to select the promising design features for further examination. Trust is achieved if a user believes that the FinBot is competent, benevolent, and honest. Trust can be enhanced using trustworthy FinBot design features that control agentic behaviours in terms of competence, benevolence, and honesty. While many of the trust-building features are common to both agentic and non-agentic FinBots, some challenge the conventional UX design approach since they evade users' notice and control over FinBots' agentic behaviours.

Designing for the user experience of trustworthy agentic AI systems consists of various technologies at human-computer interfaces (HCI) and various UX design features based on the "invisible control" framework. It has three main uses of this study. First, the UX of trustworthy agentic AI systems being presented can cover most conversational agentic systems in other application domains such as social media, e-commerce, health, and education. Second, the investigation of conventional UX design methods in developing FinBots' UX design features checks their versatility and generalizability outside their originally intended areas. They can be further applied in addressing other design challenges and studying other UX design features, such as multi-modal and gamification design features. The design and evaluation of design methods could also be beneficial for similar challenges. Third, the proposed trustworthiness evaluation framework on conversational FinBot UX design features being reviewed and further validated would advance the field of human-centric AI (UX) research.

9.1. Design Principles for AI Systems As AI systems become a fundamental part of human lives across all domains, the establishment of trustworthy systems becomes an urgent issue. In this regard, the EU has elaborated a regulatory framework for high-risk AI systems based on three pillars: legal, ethical, and technical robustness. This work introduces a holistic and systemic vision of trustworthy AI that enables the development of responsible AI systems through the compliance with ethical principles, requirements, and regulations. It aims to become a primer for researchers and practitioners interested in becoming acquainted with trustworthy AI and devising holistic technical solutions and regulations to guarantee the development of responsible AI systems in pursuit of a sustainable society [8]. As global societies embrace sophisticated and multimodal AI-based systems, the provision of meaningful, safe, reliable, and fair interactions has become an unakoed prerequisite. In this context, trustworthy AI (TAI) emerges as a holistic, systemic, and multi-modal approach to ethically and legally guide the development of these systems. The concept of TAI encompasses two intertwined facets: 1) a set of ethical principles, key requirements, and regulatory standards that ensures a system's compliance with ethical, legal, and technical expectations, and 2) a robust and comprehensive implementation of such principles, requirements, and standards into the AI systems design. The former faceted has risen significant attention by regulators and the AI community in recent years, but its latter one is still under-researched and under-regulated, even more so for interactive generative systems. Existing post hoc accounts on trust that seek to characterise, evaluate, or enhance TAI systems converge on a limited view of trust at the only social, or subjective, level of human agents. There is an urgent need for a trustworthy AI implementation design that ensures TAI from a multidisciplinary and multi-level approach. TAI system designers must ensure compliance with the established ethical principles and regulations at design-time, by acting in accordance with the systemic nature of TAI. This involves 1) addressing relevant key requirements, encompassing ethical, regulatory, and technical considerations, and 2) continuously satisfying relevant technical conditions that operationalize those key requirements in the systems' core, with the goal of acting, and being perceived by users and society at large, as human-centered and trustworthy within the initially ascribed guarantees.

9.2. Case Studies in Banking There is a growing clamour in commercialisation of Artificial Intelligence (AI) technologies in the banking and financial services sectors, spurred by a profitable application in upselling consumer goods by tech giants. Today's botch-a-bots abound not only in customer-facing roles like sticky chatbots answering queries, but also decision-making roles like robo-advisers making financial plans for investors. As consumers, we are engaged into a massive AI-experiment; policy-makers, regulators, and academics are cautiously learning the cope and expectation of these technologies, as they have been suffering trust deficit in the aftermath of the Global Financial Crisis. New governance models are increasingly sought to rein in the opaque and inscrutable decision-making processes of AI. It addresses topics on the ethical, regulatory, and fiduciary dimensions of the usage of AI technologies in banking and financial services.

Fundamentally AI technologies lack natural intelligence; they are greatly reliant on machine learning algorithms. The validity and soundness of the design, parameters, and codes used in algorithms, as well as the rationality in selecting firms and input data feed, would inescapably affect their outputs. Thus, accountability and defence for algorithms are conducive for business sustainability. As AI models traverse from expert systems using rule-based inference methods to deep neural networks availing un-structured data, sceptical pundits have voiced concerns on computability and non-testability of algorithm outputs, as well as ethics and legality on divulging algorithm secrets. Significant regains of trust and confidence could stymie devising complex governance mechanisms for countering drawbacks of AI, benefit from detail perceivable trade-offs of algorithms.

Conversational FinBots are a new breed of game-changing banking technology, which affect the types of interactions, the nature of segmentation, and the types of brand experiences in banking. Consequently, consumers expect those technologies to provide them private, secure, and trustworthy conversations, equitable advice, transparency of information on the advice sought, and rectitude and assurances on operations. Institutions on the other hand, expect those FinBots to be proactive, innovative, and accurate. Trust grows with the option of clause, completeness of data protection, big brands with good reputation and survey, as well as multi-channel authentication level.

10. Implementation Strategies

Banking has long been presumed to be a highly regulated conservative industry with significant trust instabilities. It has been argued that this is due to asymmetric information between banks and the public in terms of risk exposure, as well as multifaceted cultural contexts. It has been labelled a 'trust trap', as scandals can shake multiple banks and entire financial infrastructures. High-profile banking collapses saw consumers panic and withdraw funds [2]. A focus on protecting the integrity of the banking system over individual creditors has been recognised as a primary reason for large banks not being considered trustworthy. FinTech has disrupted the traditional banking model with more exploratory and use-it-or-lose-it governance models, and is heralded for being a potential solution for legacy problems such as 'missing markets' and the 'trust trap'.

To design and build trust in financial systems, evidence of its relevance and how it can be operationalised is required. Understanding what trust means, reconciling contradictory perceptions of relevancies and responsible AI, and what this means for design are all important considerations for FinTech to gain trust in use. The operationalisation of trust requires an understanding of language and dialogue, and what elements of conversation can account for different perceptions of trust [5], and the how FinBots can embody these capacities.

Governing technology is fundamentally different in FinTech, which uses technology to disrupt the traditional banking model. Regulatory frameworks are often based on non-discrimination, and the case of a neobanking app raises the question of audio fairness for all customers, especially those that may be vulnerable. Banks adopting AI technology to implement augmented intelligence applications to provide insights and guidance help consumers make smarter financial decisions raise ethical concerns. With FinBots answering awkward questions and offering advice, but potentially steering users into poor investments, there are questions to ask about the suitability of FinBot decisions, the regulation of data use, and how this may differ to credit card issuers.

10.1. Phased Implementation The vision for a personalized banking experience is ambitious and presents several challenges but also new opportunities as banking systems become more intelligent, proactive, and aware of individual customers' past interactions and requests. A phased approach to implementation offers banks the best chance for success by ensuring trustworthiness and a good customer experience, as they scale toward systems that are actively involved in meeting their customers' financial needs [5].

At first, systems should be limited to delivering personalized and proactive insights based on their existing understanding of the customers' finances. With sufficient capacity to deliver relevant insights, systems can be incrementally expanded in sophistication, including data accessible to personalize and satisfy more complex requests for interactions. Initially, these systems should provide verifiable outputs with the highest priorities for being trustworthy. As their responses are observed to be trustworthy and informative, especially for interpreting ML decisions, systems can build trust to limit surprise outputs on much higher complexity, including natively generative responses, that would have more moderate importance to the customer experience [17].

To minimize any frustration that could derive from limited responsiveness and outputs not corresponding to requests, systems must be highly active in revealing their personalizations. A early task is to help guide them in explaining their insights, particularly where they are counterintuitive or take into account evidence that the customer is not aware of, for example, other sources of information that are less relevant to the static decisions formally used. As an alternative to using fixed knowledge representations to identify static banks of information, large collections of interactive generative agents that respond in real-time to information revealed by the customer could be incorporated.

A second crucial task is for systems to invite, probe, and clarify requests for actions. With an increasing sophistication of understanding and responding to precision, systems must ensure a balance of proactivity with continued understanding of customer needs and plans for action. Without sufficient ownership of goals and actions, trust and ultimately satisfaction may be compromised. Similarly, it will also be necessary to calibrate and evaluate goals pragmatically, including data usefully and personally enrich independent understanding, financial privacy of transactions or self-critique of actions, and customer behaviour.

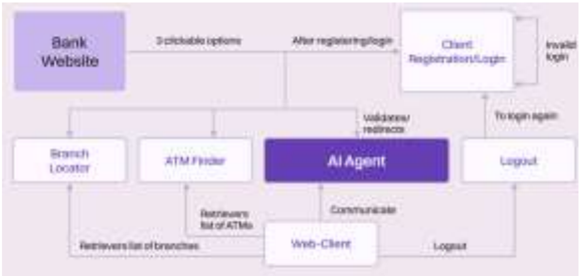

Fig 5: AI Agents in Banking Are Doubling Customer

10.2. Stakeholder Engagement Engagement with stakeholders and cross-discipline collaborations is very important to build trustworthy agentic AI systems. AI organizations and data housing organizations should initiate outreach programs and broadcast AI and data literacy programs. Media organizations should ensure high ethical standards and the protection of both AI organizations and individuals. AI researchers should engage in discussions about ethics and responsibility in the development of AI systems. AI engineers and designers should emphasize explainability as a critical property of AI systems. Regulatory bodies and governments should understand the technology enough to define regulations and standards that want to be complied with [18].

AI and data literacy and transparency are crucial among different AI stakeholders. They should understand how AI systems function, what is the input to the models, and how their input data will impact the models' predictions. There should also be an avenue to ensure that the models are behaving in a safe and adaptable manner. Designers must also ensure that the predictions are easily interpretable for optimal engagement from the human users or receivers. Content should be delivered in a way that complies with the users' processing mode and should be suited for the intended human audience [2].

AI companies should take the initiative to integrate their systems with AI literacy actions and put out efforts to increase data literacy on both how data is collected and how it can help AI systems to be more capable. AI transparency is crucial because algorithmic decisions can have severe impacts on individuals, systems, and society. AI companies should put out efforts into first-party transparency so that users can see metadata explaining how some data might affect systems at work and thus be able to flag potential problems.

11. Measuring Success

Though frameworks for assessing AI systems tend to focus on fairness, accountability, interpretability, and robustness [19], trust promotion, usability, and personalization will also be important for successful integration of the trust enhancement features into future digital banking experiences. Survey items appropriate for these categories will be based on literature across domains as well as historical UX benchmarks. As many financial institutions quickly rethink product design post-Pandemic and financial regulations move into unprecedented territory, identifying how banking experiences will change is just as important as how to determine their success. The questions used to measure perceptions of the smart algorithm features should be, regardless of domain, deliberately targeted to the behavior of the devices themselves as AI instances. Search can be improved by drawing on the video recommendation methods of the YouTube algorithm [20]. How financial institutions can successfully offer onboarding experiences is a question with no commonly agreed-upon answer, but it is hypothesized that helping users set financial goals and internalize a bank's rules for safety and security will be powerful means of establishing that "inherent trust" into which much development and critique has gone. Shopping, or the presentation of discrete choices, could be approached from a slot machine lens to maximize engagement, or browsing recommendations personalized to the user and presented through search results could also be encouraged. As with product design, a thoughtful approach to measurement should be taken going forward. What would provide the richest description of an AI system's performance? The measurement of performance would change with different approaches to "performance;" in the case that the collective mapping approximates "intelligence," say, a computationally intensive similarity comparison would be necessary; in the case of a more behavioral understanding of success, there could be a teasing out of particular actions, and so tracking measures could be a collaborative index while offline ratings could still allow for better users' understanding of the system. A more traditional question to ask might be how performance would change with a given set of alterations, similar to assessing AI's decomposition. Though the exploratory data visualization efforts are untested, to illustrate how digital banking experiences would change, they would be accompanied by one or two target mockups of screens with crowding encouraging collaboration across automating institutions.

11.1. Key Performance Indicators Performance metrics are vital in evaluating AI applications. Previous studies have demonstrated that performance objectives can be measured and modeled for a diverse array of AI applications [3]. These studies reveal, for instance, how to evaluate the automated advisor's portfolio performance through standard portfolio performance metrics, such as Sharpe ratio, Calmar ratio, or maximum historical drawdown. In this regard, the effectiveness of the advisory service produced by the AI agent and the degree of its fitness based on the user's preference would have to be quantified. The objective's value structure might include numerical attributes such as target percentage allocation or more qualitative ones such as risk aversion. An interface could also be modeled for an adaptive system that allows users to manually provide these parameters [5]. An agent-based AI that performs market forecasting can be evaluated through an objective that predicts the price movement for particular stocks over future timeframes.

Technical metrics for the assessment of AI applications are also documented and can be tailored for specific use. Technical metrics serve to evaluate how well the model is built with respect to its architecture, constructions, system interfaces, or data training methodologies. Typical examples include structural metrics such as the number of parameters or input features, numerical metrics during training such as error, variance, or execution times, and visualization metrics post-training such as confusion matrixes or ROC curves. Based on the performance and technical evaluation, it is required to model metrics for subsequent expressive objectives in order to measure trustworthiness. An agentic AI system's trust enhancing and inhibiting factors would have to be identified and mapped to causal features of trust that model confidence in AI systems.

11.2. User Feedback Mechanisms User Feedback Mechanisms for Personalised Banking Experiences. Online banking services can benefit from conversational bank chatbots. Such chatbots can understand human queries and respond as a human-like conversational partner. However, due to the pervasiveness of online banking in people's lives, there are many concerns regarding them. Feedback mechanisms allow the designers of bank chatbots to gather user experiences and address their concerns [5].

Visual Feedback Mechanism. The chatbot can show a feedback interface for answering each user question. The user can select the appropriate reply from a given list of buttons. The chatbot should also be able to ask the user if they wish to provide more comments about their option. Such a system can design three kinds of feedback interfaces for three different tasks. First, the task of lack of understanding can be broken into three cases. First, the user's question is either ambiguous or long/multi-part. In this case, the chatbot can return an unclear response and ask the user for clarification. Second, the user has asked a question outside of the chatbot's capabilities. In this case, the chatbot can select a default answer, which specifies that the question lies outside of the knowledge base, and log the user data. Third, the chatbot can misrespond due to the inappropriate retrieval of the answer or the misunderstanding of the user's intention. A dialogue context and a conversational turn can introduce noise, leading to unexpected user questions and an inaccurate answer's selection. This task requires an entirely interactive feedback interface. For this case, the prior two problems can be resolved through the non-interactive feedback mechanism. In contrast, this problem can only be settled through this fully interactive feedback mechanism, which can fire only from the chatbot.

Dialogue Feedback Mechanism. For prompt feedback in the current user turn, visual feedback mechanisms can allow the user to use buttons to specify the incorrect part of the bot's response. However, this task is complex because it requires the bot to ask the user to choose the incorrect part strictly and categorically. At present, three types of control designs can be flexibly used for dialogue feedback mechanisms: Iterative control, progressive specification control, and cross-modal control. The dialogue feedback mechanism for current user turn can be implemented iteratively, and each round contains a question-and-answer procedure. Progressive control can embed cross-modal control as preloading feedback to further improve good transaction control. In this mechanism design type, the effect lies in iteratively or progressively prompting for inconsistencies.

12. Case Studies

Santander UK's "Private Bank in your Pocket" Chatbot. To date, the training of AI in finance has sparked much policy and regulatory interest. However, the current opportunities afforded by the latest developments of conversational FinTech to otherwise enhance trust and regulation in the financial sector remain under-explored [2]. In a collaboration with Santander UK, the University of Newcastle surveyed over 450 UK adults to investigate the extent to which chatbot providers in banking have uncovered the buttons moderating trust. Using k-means clustering, this analysis finds that demographic indicators such as gender, education level, age, personality traits, and anxiety shape trust in conversational FinTech differently. This has implications for policy and regulation around conversational FinTech such as which stakeholders ought to be included in any ongoing dialogue around their society [5].

Mindsweep AI capability aimed at improving the emotional aspects of communication across banks and financial institutions. The increasing use of automated services in communication has pushed bot-driven services into the mainstream, resulting in low-cost options across various industry sectors. Banks, in particular, have been historically sceptical of automation within consumer service due to the high emotional, practical, and reputational stakes of providing financial services. However, as customer sentiment has shifted towards acceptance of automated services in financial advice and marketing, there has been a growth in algorithmic interfaces in this domain. In the last five years, the most sophisticated representations of robot, chat, and avatar-driven service in both consumer facing and research banking contexts have emerged. However, despite their expanding presence, they have not yet garnered a complete understanding or evidenced their successful application in an emotionally positive manner.

12.1. Successful AI Implementations The last decade has seen rapid advancement in AI and exponential growth in datasets, computing power, and algorithms. AI is now better able to derive insights from enormous amounts of data. Many successful AI implementations have been seen across different sectors, such as healthcare, telecoms, transportation, supply chain management, and fintech. Nonetheless, one sector that remains significantly less explored than others is retail banking. Data- and technology-intensive fintech startups are gaining ground and disrupting banking industries worldwide, casualty inciting a growing fear of fintech disintermediation amongst banks [2]. A large bank of the Royal Bank of Scotland was fined a record $34.5 million for failing to shed some badly structured legacy risk management systems used to price and manage complex derivative trades. Such failures stemmed largely from a combination of technology, data, and/or process mismanagement. These events mark mere tip-of-the-iceberg mishaps in the banking industry. Simultaneously, however, they incite a strong desire for institutional integrity along with requisite data infrastructures to derive insights from the data generated across the exponentially proliferating data sources within banks.

Three successful implementations of AI systems designed to address customer pain-points in one-on-one and at scale - the first for a multinational bank and the other for a bank's outsourcing partner - are discussed. The implementation context is retail banking in the UK, where the UK's Information Commission Office recently ruled that AI's black-box nature warrants an audit process with human interpretability, which offers the opportunity to build a trustable agentic AI system that can penalize errant institutions adopting AI for immoral purposes [21]. It is possible that the solution may either be trustable development from inception or post-event auditing. Nonetheless, it is more likely to be the latter, hence a focus on post-event auditing of explained, interpreted, and documented AI systems here that each of the banks planned to launch/adopt.

12.2. Lessons Learned from Failures While this research has provided some great insights into how user trust and agency can be built in personalized financial decision making systems, it also showed, nevertheless, some shortcomings and flaws. In particular, these flaws fell into two groups: first, otherwise trivial but nonetheless limiting design decisions; and second, unintended technological artifacts of either the models or the learned post hoc explanations. These failures could both reflect how some entries from the conference's call for AI has particularly specific applicability challenges, but they could also represent entry points to future research that either can further extend this paper, or inform future contributions.

While choice IQ and its models have a user base that is dominated by financial advisors – mostly working in the context of wealth or private investment management – individual retail thinkForward or MLaaS users were never tested with more financial content. How personalized choice IQ's current bank logo only filters for content from one of unparalleled banks. Only minor user behavioral differences were uncovered, while substantial perception differences were more robust even in such a more seemingly homogeneous use case. The assumption that potentially different choice IQ accessibility behavior could consistently attribute to personalized financial knowledge gaps was counter-intuitively rejected. While persistent, the proportion of general favoritism media content was expected to vary, unexpectedly voting users' trustworthiness was most consistently reverse to be perceived as favoritism.

In addition, thinkForward models face a large need for modality design work as additional endpoints to micro behaviors. This still could likely have been counter-intuitive while many co-design preparations were rather trivial. Similarly, the prevalent assumption that filmed believability stories will need more multifarious enrichments was not validated in essence. Significant side effects while researching this issue gained some unexpected insights into how users' misguided beliefs and efforts impaired the study of story templates, which are critical user decision explanations. Modifying explainable AI techniques for these would be promising. Instead, such guidance likely affords an entrance criterion for future literature that aims to extend the ongoing continents focus on desirable usability instead of accuracy and feasibility trade-offs ([22]).

13. Future Directions

The growing interest in AI systems brings to the fore possibilities not yet explored. AI will become less of a curiosity and more part of the everyday fabric of commercial institutions shaping the practices of those institutions and the lives of their customers. There are, nevertheless, limits to the 'agentic' capabilities of AI agents that banks must be mindful of. As entities that make decisions on behalf of users, AI are liable to decisions that lead to harm or disadvantage to users. As banks come under regulatory scrutiny to avoid practices that are unfair, exploitative or discriminatory, banks must check that their agentic AI are trustworthy. In particular, banks must ensure that agentic AI systems are fair and transparent, mitigate endowed biases in training and an understanding of outputs, and not disempower users in options or contact with agents.

Banks must also explore AI capabilities beyond analytics and disclosure prescribed by regulators. There is considerable potential benefit to be gained by using AI agents to offer personalized financial guidance, especially to the under-banked and unbanked. However, these benefits must be conditioned by the agency of the user in controlling the interactions with AI. Users seeking guidance must be offered the agency to choose the means of guidance they are comfortable with, be it an AI-suggested course of action or intervention from a human agent [2]. These users must also be offered control to be informed, given a rationale for AI outputs, be able to question AI decisions, or take note of fairness failures in the provision of guidance [3].

While a great deal is known about protecting AI systems against adverse external effects, banks must also consider ill effects that AI may have on the user and their relationships with financial institutions. Banks also face their own challenges in boundary-spanning and intermediation. Systems developing domain knowledge on ids, accounts, channels and products can become unwieldy. Clarity of ownership and authority are especially important in self-learning multi-agent AI systems with distributed authority that are autonomous in onboarding capable of forming novel channels of communication across boundaries in siloed data environments.

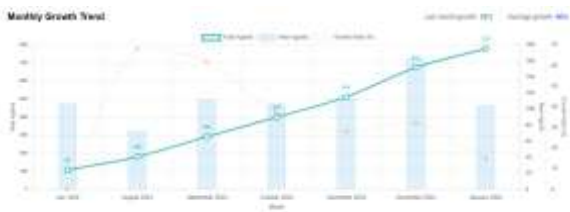

Fig : AI Agents in Banking

13.1. Emerging Technologies Current banking environments provide significant integration opportunities for Augmented Intelligence (AI) technologies, which involve human/systems collaboration to improve professional performance. AI technologies have immediate use cases in the crisis context at banks. For example, financial analysts can look at a large number of scenarios produced by machine learning algorithms to detect fraud more accurately. In addition, customer profiles can be augmented by concrete information on their behaviours/activities and with alternative data sources. This information can assist analysts in optimizing loan decisions, their interest rates levels, and marketing material to improve client loyalty and satisfaction. There are many activities where AI can provide big benefits to banks in the short and medium term. Still, most AI tools in banking are Rule/Knowledge-based systems or AI algorithms that improve traditional models. This shows that banks have not yet made advanced use of AI, multi-agents, computational intelligence techniques, and new Big Data algorithms.

AI technologies should be auditable because these technologies make decisions that can harm individuals. This is especially relevant for the banking industry because the impacts of bad decisions can range from record fines to an altered social status for clients. There are also relevant selection problems where vulnerable clients should be protected. This research will focus on the two areas where the financial industry is leading the trustworthiness agenda: auditing and explainability. Some new research hot topics will also be provided. These areas are intertwined because trustworthiness cannot be tested without some explanation of how the technology makes its decisions. If it cannot explain itself, the AI may be powerful but can also be dangerous. This research will begin with explainability to first provide sufficient background knowledge on this research area.

Some background on why trustworthiness is becoming important for the banking industry will be provided, as well as current state-of-the-art available technologies and practices. The research closed with a proposal for future research directions. There are many AI models applied to the financial sector, from improving compliance controls based on techniques or identifying some fraud patterns through time series and anomaly detection techniques.

13.2. Long-Term Impact on Banking To the uninitiated, banking appears to be slowly evolving into a self-service industry, receptive to changing consumer behaviours and lifestyles, much more so than in previous years. Supermarket-brand banking started this change; however, most people still believed that transactional business banking could be transformed into accounts that pended during the week, gains and losses were booked towards fine months and bank visits time speaks volumes. Personalised banking appeared to mean a bank was aware of how much money was in each of its customers' accounts, but nothing more than that and, therefore, little credence was assigned to advertisements or assurances of low monthly fees or charges. Changing these perceptions and forcing banks to be more vigilant and proactive in identifying and signalling to their customers potentially wasteful charges, payments and fees could yield a revolution in personalised banking, and contribute to diminishing unnecessary debt, financial instability and bank bail-outs [2]. Allied to the technological advancements which spurred this initial transformation of banks and financial services is the rise of proactive data analytics. Challenges were identified within banking regulation legislature which permitted banks to create contingent reserve funds and protection funds against unforeseen liabilities. Improvements in communication technology now enabled each bank to build and maintain digital accounts for each of their customers. The ready use of magnetic cards, the bringing into play of storage, microprocessors and memory chips all combined, and each deposited sum was allocated an encoded dating which protected it against errors of entering and transmitting. Billing exchanges and automatic debit orders became prevalent, but because little attention was assigned to protecting against overdrafts in real-time based on account balance availability, the glitches in this pre-Atlantis banking environment were quickly capitalised upon. This slight advantage over their competitors yielded a flood of new accounts, and the indiscriminate award of decades-long interest free overdrafts resulted in the total demise of the century-old business of the first national bank of Atlantis and the bankruptcy of several other banks [23].

14. Conclusion

The 21st century has seen an unprecedented growth in the volume of units and the variety and complexity of the financial products and services. The demand for financial advice has therefore risen exponentially. Human-bank interactions cannot keep pace with the growing demand for personalized advice in ways identified in the earlier sections. As a result, present financial advice in banks is unlikely to be adequate, satisfactory and sustainable in the future. The emergence of FinBots, conversational AI for financial advice, is a promising way to better serve customers and hence also banks. Nevertheless, the lack of trust in AI in general poses a road block to the widespread adoption of FinBots. This paper argues that trust must be built in order for banks to compete in the expanding market of FinBots. It discusses a multi-layered approach to cultivating trust and how a trustworthy agentic FinBot addresses these challenges.

There are three ways to enable customers to trust FinBots. Customers must trust that data privacy is respected and only relevant financial advice will be given. Customers must trust that FinBots are compliant with regulations to avoid having their trust abused. Trust cannot be fully based on algorithms. Just as humans may welcome intuitive emotional advice, a humanlike FinBot with agentic capability will be appreciated by many as more trustworthy, as long as utmost care is taken to ensure that the agentic capability is desired, accurate, safe, aligned with the intentions of the customer, and transparent. Importantly, it is not just a case of having technical solutions in place to address the causes of distrust. Banks must explain them internally and implement them organizationally to avoid misunderstandings, misinterpretations and concerns exacerbated by social media.

Institutional steps must be taken to bolster customer trust in suspicious situations. People must be reassured that safeguarding measures are in place; they must be educated on ways in which their concerns will be addressed and on options for appealing or prompting investigation in case of abuses. Ultimately, trust is not treated as a technical solution, but rather as an essential concept informing the attentiveness, care and respect with which assistance is offered and recommendations are made, so as to make customers understand that their well-being is the primary concern and priority of the automaton they are dealing with. Only a trustworthy agentic AI system can deliver good advice for improving the financial well-being of customers.

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