The Adoption of AI Agents: From Automation to Autonomy, Reshaping Governance and Strategic Decision-Making in FinTech

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Abstract

This study investigated how AI agents are transforming automation, governance, and strategic decision-making in the FinTech sector. Drawing on an extensive literature review, the research identifies key adoption drivers including efficiency, real-time responsiveness, compliance alignment, and innovation pressure. The findings were evaluated using a mixed methods approach, combining 13 semi-structured expert interviews with a survey of 112 professionals, and validated through triangulation across qualitative and quantitative data. Using data collected from the survey, a regression analysis and Sample T-test was conducted, indicating that individuals are more likely to adopt AI agents if they perceive them as useful, feel confident in their ability, receive organizational support, and experience ongoing adoption within their workplace ($p < 0.05$). Expert insights reinforced these drivers, emphasizing the role of modular agent design, organizational readiness, explainability, and real-time adaptability in successful deployment. The results suggest that AI agents are evolving from static automation tools to strategic, goal-oriented collaborators. However, their integration still faces challenges related to transparency, hallucination risks, and overreliance on automation, emphasizing the need for stronger regulatory alignment and governance frameworks. While the study offers a comprehensive understanding of responsible AI agent adoption, its scope is limited by non-probability sampling and rapid evolution of the technology, which may affect the generalizability of the findings. Future research should explore long-term agent behavior and coordination across industries. Overall, the findings underscore the growing strategic importance of AI agents in shaping the future FinTech.

Keywords: AI agents adoption, FinTech, automation, autonomy, multi-agent systems, responsible AI, hallucination

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Sumário

Este estudo investigou como os agentes de inteligência artificial (IA) estão a transformar a automação, a governação e a tomada de decisões estratégicas no setor FinTech. Com base numa revisão abrangente da literatura, a investigação identificou fatores-chave que impulsionam a adoção, incluindo eficiência, capacidade de resposta em tempo real, alinhamento com a conformidade e pressão por inovação. Os resultados foram avaliados através de uma abordagem de métodos mistos, combinando 13 entrevistas semiestruturadas com especialistas e um inquérito aplicado a 112 profissionais, validados por triangulação entre dados qualitativos e quantitativos. A partir dos dados recolhidos, foi realizada uma análise de regressão e um teste T de amostras independentes, revelando que os indivíduos têm maior probabilidade de adotar agentes de IA quando os percepcionam como úteis, se sentem confiantes na sua utilização, recebem apoio organizacional e observam adoção contínua no local de trabalho ($p < 0.05$). As perspetivas dos especialistas reforçam estes fatores, sublinhando a importância do design modular, da preparação organizacional, da aplicabilidade e da adaptabilidade em tempo real. Os resultados sugerem que os agentes de IA estão a evoluir de ferramentas estáticas para colaboradores estratégicos orientados por objetivos. No entanto, continuam a existir desafios relacionados com transparência, alucinação e dependência excessiva da automação, exigindo maior alinhamento regulatório e estruturas de governação robustas. Apesar de fornecer uma visão abrangente, o estudo é limitado pela amostragem não probabilística e pela rápida evolução tecnológica. Futuros estudos deverão explorar o comportamento dos agentes e a sua coordenação entre setores.

Palavras-chave: Adoção de agentes de IA, FinTech, automação, autonomia, sistemas multiagente, IA responsável, alucinação

Título: A Adoção de Agentes de IA: Da Automação à Autonomia, Redefinindo a Governação e a Tomada de Decisões Estratégicas no Setor FinTech

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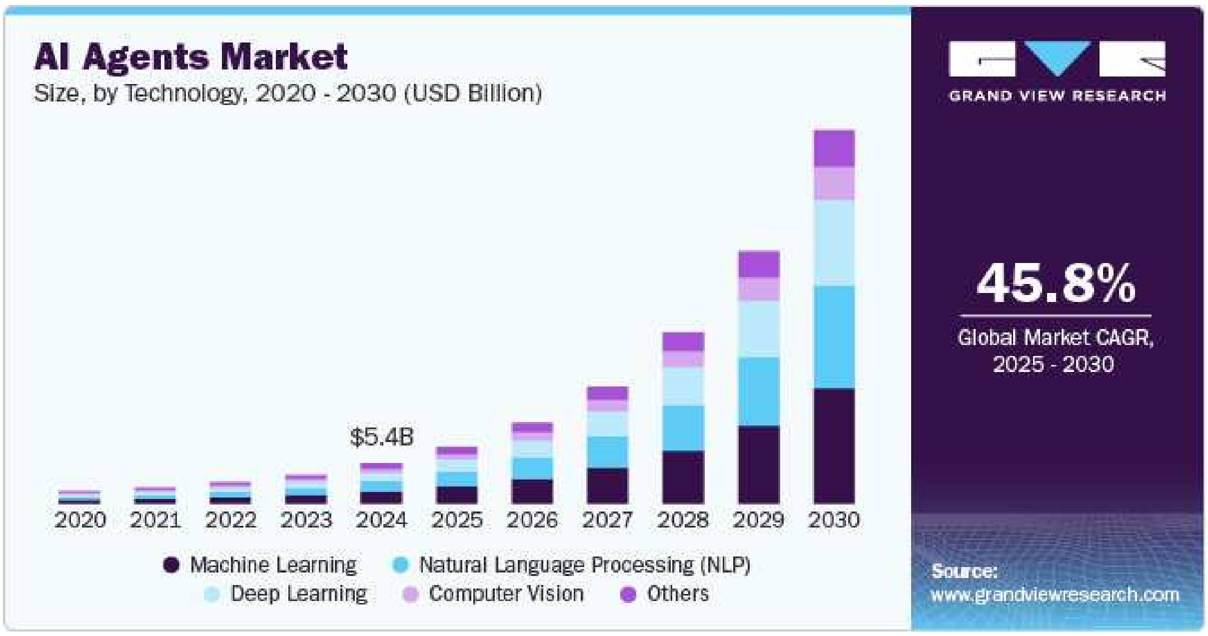
1. Introduction

The rise of digitalization and artificial intelligence (AI) is fundamentally redefining digital infrastructure, reshaping how financial institutions operate, automate processes, and make decisions. As this transformation accelerates, the financial technology (FinTech) sector has emerged as a critical testing ground for intelligent systems that demand not only technical performance but also reliability, explainability, and regulatory alignment (Puschmann, 2017). At the same time, the acceleration of AI adoption requires organizations to move beyond simple integration and develop capabilities to manage and govern AI processes effectively (Holmström, 2021). Within this context, AI agents are gaining traction as a next step in intelligent automation that goes beyond static systems. Unlike traditional task-specific models, AI agents operate autonomously, adapt to dynamic inputs, and interact with users and other systems to accomplish goal-oriented tasks (Krishnan, 2025). Their ability to act independently, interpret data, and interact with both users and other systems makes them particularly well-suited for complex environments. As illustrated in Figure 1, the AI agents market is projected to experience exponential growth, reaching over $5.4 billion already in 2024 and continuing to expand at a compound annual growth rate (CAGR) of 45.8% through 2030, driven by advances in technologies that consist Machine Learning, NLP and Deep learning (Grand View Research, 2024).

Figure 1

AI Agents Market Projected Growth



Note. Adapted from Grand View Research, (2024) AI agents represent a major step in the progression from automation to autonomy. Built on architectures such as large language models (LLMs), reinforcement learning frameworks, and modular planning systems, these agents are increasingly deployed to manage complex workflows in compliance, fraud detection, investment analysis, and customer engagement (Tran et al., 2025). Their ability to retrieve knowledge, plan multi-step actions, and respond to real-time data makes them highly attractive for FinTech ecosystems that demand precision, scalability, and resilience (Wang et al., 2024). As AI agents evolve from passive tools to strategic collaborators, their integration introduces new opportunities and risks that organizations must navigate carefully (Krishnan, 2025). However, the growing autonomy of these systems introduces critical challenges and risks. AI agents remain susceptible to hallucinations, potentially generating inaccurate or misleading outputs that undermine reliability and trust (Bai et al., 2025). Additionally, AI agents also struggle with transparency, and introduce new vulnerabilities around data integrity, security, and accountability (Brasse et al., 2023). These risks are critical in financial domains where decisions affect regulatory compliance, consumer trust, and systemic stability. Consequently, responsible deployment frameworks must be developed to control agent behavior, ensure auditability, and comply with evolving AI governance regulations (Floridi & Cowls, 2022).

The rise of vertical, horizontal, and generative agents, domain-specific systems has become essential to recent AI deployment, as they are capable of navigating complex regulatory environments, financial models, and diverse customer contexts (Zhou et al., 2024). These vertical agents are increasingly contrasted with horizontal agents, which offer general capabilities across multiple domains but lack contextual specialization. Generative agents complement both vertical and horizontal systems by leveraging large language models to synthesize information, simulate reasoning, and engage in dynamic interaction and execute strategic decision-making across domains (Cheong et al., 2024). The distinction between vertical and horizontal agents is expected to shape AI strategy in the financial sector, as organizations seek to optimize and balance the breadth and depth in their ecosystems. Moreover, the next stage in AI agent development involves multi-agent systems (MAS), which consist of interconnected agents that collaborate, negotiate, and coordinate actions in real-time to solve distributed problems (Tran et al., 2025). These systems reflect a broader trend toward decentralized, modular AI infrastructures that promise scalability and adaptability, while also demand new models of oversight, interoperability, and ethical design.

As a result, multi-agent ecosystems may redefine how organizations operate by enabling fully autonomous processes and decision-making workflows.

This thesis explores how AI agents are redefining automation, decision-making, and governance in the FinTech sector. By analyzing case studies, expert interviews, targeted survey, and regulatory frameworks, the study investigates how organizations adopt, supervise, and evaluate AI agents in real-world settings. The research identifies key benefits, risks, and strategic considerations, offering a comprehensive framework for responsible integration. To address the growing impact of AI agents in FinTech, this research aims to answer the following research question: **How are AI agents reshaping automation, governance, and strategic decision-making in FinTech, and what frameworks enable their effective and responsible adoption?**

The thesis is structured into five chapters. Chapter 1 introduces the research topic, objectives, and relevance of the study. Chapter 2 reviews the existing literature on FinTech innovation, AI evolution, AI Agent architectures, governance models and future outlook. Chapter 3 presents the methodology and research design, which combines the expert interviews and survey. Chapter 4 analyzes the findings and discusses their implications with the current academic literature and practical insights. Finally, Chapter 5 concludes with a summary of contributions, identifies limitations, and suggests directions for future research. This structured approach of the research paper aims to offer a comprehensive and actionable understanding of how AI agents are transforming financial services and what frameworks support their responsible deployment.

2. Literature Reviews

This chapter reviews key academic contributions related to digitalization, FinTech, and AI agent technologies. It covers technological foundations, behavioral adoption models, system architectures, and the governance framework considerations, shaping responsible AI deployment. These topics collectively inform the study's conceptual framework.

2.1 Digitalization and Automation

Technology has consistently shaped the development, delivery, and consumption of financial services. From early computing and electronic banking to the integration of cloud infrastructure, big data, blockchain, and artificial intelligence, each wave of innovation has accelerated the transition toward a digitally driven financial ecosystem (Maracine et al. 2020). As AI advances, its role has shifted from operational support to enabling intelligent systems that learn, adapt, and act autonomously, offering scalable and personalized financial solutions (Herrmann and Masawi 2022). This evolution has given rise to FinTech, a sector that leverages these technologies to offer more efficient, accessible, and customer-centric services (Puschmann 2017).

Initially focused on automating routine transactions, financial digitalization has matured into an ecosystem powered by real-time data processing and intelligent infrastructure (Mykhailiuk et al. 2021). Cloud computing enables on-demand, secure access to financial tools, while big data analytics enhances credit scoring, customer profiling, and market forecasting (Boggarapu, 2025). Blockchain technology has introduced secure, decentralized transaction frameworks that reshape payments and asset management (Boggarapu, 2025).

AI has become central to fraud detection, algorithmic trading, and robo-advisory services, reducing reliance on manual operations and increasing responsiveness to market demands (Das 2019). These developments have redefined risk management, compliance, and financial inclusion, transforming FinTech from a support function into the backbone of modern finance (Gomber et al. 2017).

This shift aligns with digitalization, which refers to the strategic integration of digital technologies into core business processes, beyond simply digitizing information (Parviainen et al. 2017). Financial institutions increasingly operate on cloud-based, AI-enhanced systems, replacing traditional models with agile, data-driven architectures. As a result, digitalization not only improves efficiency and accessibility but also heightens competitive pressure on legacy institutions, compelling them to adapt to the pace of FinTech innovation (Pazarbasioglu et al. 2020).

2.1.1 Digital Business Models

The growing pace of digitalization, combined with rising expectations for personalized experiences and operational efficiency, has made the digital business model central to value creation and delivery in digital finance (Parviainen et al. 2017). Defined as a structural and strategic framework, the digital business model outlines how organizations leverage digital technologies to meet their goals (Al-Debi et al. 2008). Unlike traditional models that rely on physical infrastructure and linear value chains, digital models emphasize scalability, automation, and real-time responsiveness, allowing firms to adjust dynamically to market and technological changes (Gomber et al. 2017).

This transformation is evident in the shift from conventional banking systems to data-driven FinTech models that harness big data and AI to optimize services (Alt et al. 2018). While legacy institutions have focused on internal digital upgrades, FinTech firms offer customer-centric alternatives that are faster, more accessible, and cost-efficient (Gomber et al. 2017). BigTech companies such as Google and Amazon have further accelerated disruption by entering financial services, intensifying competition (Maracine et al. 2020).

FinTech business models are evolving away from centralized, institution-based services toward distributed, technology-powered platforms (Alt et al. 2018). These include blockchain-enabled transactions, AI-powered risk tools, and autonomous agents that replace conventional intermediaries (Herrmann and Masawi 2022). Many FinTechs now specialize in focused services such as digital payments, peer-to-peer lending, and fraud detection, often deploying AI agents to support adaptive decision making (Russell and Norvig 2021). Simultaneously, BigTech firms embed financial offerings into their platforms using AI-driven credit scoring and data analytics (Maracine et al. 2020).

Artificial intelligence is a key enabler of this transformation, enhancing automation, decision making, personalization, and efficiency across digital finance (Das 2019). As AI systems continue to advance, their integration is reshaping the FinTech landscape across all operational layers.

2.2 Evolution of Artificial Intelligence

As artificial intelligence continues to evolve, its development is increasingly categorized into three conceptual stages: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI). This framework offers a foundational perspective for understanding the trajectory of AI capabilities, particularly as systems advance from task-specific automation toward general-purpose intelligence and, ultimately, autonomous agents (Glenn, 2023). These stages not only reflect technical progression but also highlight emerging questions around reasoning, adaptability, and alignment, issues that are critical for anticipating the future of intelligent systems (Álvarez-Teleña & Díez-Fernández, 2024).

2.2.1 Artificial Narrow Intelligence (ANI)

ANI, also referred to as weak AI, encompasses the systems most widely deployed today. ANI models are designed for specific tasks such as language translation, fraud detection, recommendation engines, and virtual assistants, as it is capable of operating with high efficiency in predefined contexts (Goyal et al., 2025). However, despite their strong capabilities, ANI systems are lacking contextual awareness, transfer learning, and the ability to adapt outside of their training scope (Glenn, 2023). Their success in domains like healthcare, education, and finance stems from the ability to automate repetitive processes and scale decision-making (Rawat et al., 2023). In financial services particularly, ANI underpins chatbots, transaction monitoring, and predictive analytics, enabling faster and more personalized services (Rawat et al., 2023). However, ANI systems often struggle with adversarial vulnerabilities, algorithmic biases, and limited generalization capacity, which hinder their ability to operate autonomously in dynamic environments (Glenn, 2023).

2.2.3 Artificial General Intelligence (AGI)

AGI represents the theoretical next step in AI development, where systems are capable of understanding, learning, and generalizing knowledge across domains, similar to human cognitive functioning (Goertzel, 2014). In general, AGI aims to solve unfamiliar problems, transfer knowledge from one task to another, and operate adaptively without explicit reprogramming (Latif et al., 2023). The core AGI hypothesis emphasizes that achieving generalization and self-directed reasoning requires a distinct architectural shift (Goertzel, 2014). AGI is increasingly associated with foundation model-based architectures that integrate long-term memory, symbolic reasoning, planning, and perception within a modular framework inspired by the human brain (Latif et al., 2023). These modular agents are designed for continuous learning and open-ended task execution, setting them up to serve as the foundation for future autonomous systems operating in high-complexity environments such as macroeconomic modeling or regulatory compliance (Latif et al., 2023). Despite significant theoretical progress, AGI remains largely aspirational, with no consensus on how or when it might be achieved.

2.2.4 Artificial Superintelligence (ASI)

ASI is the most speculative and ethically charged category, referring to systems that not only match but exceed human intelligence across all cognitive domains, including strategic foresight, creativity, and moral reasoning (Glenn, 2023). ASI may emerge through recursive self-improvement, where agents iteratively refine their architectures and cognitive models, ultimately surpassing human capabilities in speed, complexity, and adaptability (Barrett & Baum, 2017). With the ability to autonomously analyze vast market dynamics, anticipate systemic risks, and optimize decision-making far beyond human limitations, ASI will create AI agents that could fundamentally reshape the structure, operation, and regulation of FinTech ecosystems (Herrmann & Masawi, 2022). As the financial sector continues to evolve, it becomes essential to first understand how artificial intelligence is currently being deployed within FinTech and the foundations it lays for future developments.

2.3 Artificial Intelligence in FinTech

As FinTech redefines financial services, reliance on automation, data-driven insights, and AI-powered decision making has surged. Traditional banking has evolved into adaptive ecosystems capable of real-time fraud detection, market analysis, and investment optimization (Pazarbasioglu et al. 2020). Neobanks and AI-driven platforms increasingly use real-time analytics to deliver personalized, scalable financial solutions (Maracine et al. 2020). At the forefront of this evolution is artificial intelligence (AI), which has progressed from functioning as a supportive tool for process optimization to becoming a main driver of innovation (Holmström, 2022).

AI enables FinTech firms to automate complex operations, personalize services, and enhance decision making by leveraging machine learning and predictive analytics (Holmström 2021). This supports platform scalability, allowing rapid global expansion beyond traditional infrastructure (Maracine et al. 2020). AI applications now span banking, investment, and microfinance, improving fraud prevention, algorithmic trading, and inclusive credit scoring using alternative data (Ashta and Herrmann 2021).

Beyond task automation, AI connects dynamic financial ecosystems, from macroeconomic forecasting to compliance support and real-time advisory services (Das 2019). It has become the cognitive infrastructure of modern finance. This evolution aligns with Banking 4.0, where services are digitized, decentralized, and AI driven. Frictionless user experiences, cloud scalability, and predictive technologies now underpin global FinTech competitiveness, particularly in fraud detection, modeling, and automated customer support (Kumar et al. 2022; Goyal et al. 2025).

2.3.2 Generative AI (GAI) in Financial Services

More recently, the rise of generative AI (GAI) has introduced a profound shift in the digital transformation of financial technologies. Unlike traditional AI systems that primarily analyze or predict outcomes based on historical data, generative AI refers to intelligent models that can create entirely new content with text, images, audio, code, and simulations, by learning complex patterns from vast datasets (Feuerriegel et al., 2023). These systems are built on deep generative models such as transformers, diffusion models, and GANs, which allow for high variability and creativity in outputs (Banh & Strobel, 2023). Generative AI introduces adaptability and originality, enabling systems to generate content that is not only realistic but also context-aware and user-specific. This technological leap is particularly relevant in the FinTech sector, where firms leverage such capabilities to develop AI agents that can simulate natural conversations, provide tailored financial recommendations, and automate creative functions such as client communication and regulatory documentation (Nah et al., 2023). Rather than simply optimizing backend processes, generative AI is now laying the foundation for interactive and intelligent digital ecosystems that respond fluidly to user needs and market signals.

Generative AI is actively reshaping FinTech business models and service delivery (Nah et al., 2023). Generative AI plays a key role in automated wealth management, risk assessment, and customer service bots, enabling FinTech firms to increase operational efficiency while maintaining high levels of personalization (Banh & Strobel, 2023). Moreover, firms embedding GAI into cloud-based, API-driven are creating modular, scalable, and data-centric ecosystems that challenge traditional financial institutions (Nah et al., 2023). The integration of generative AI across financial platforms has enabled the rise of conversational agents, AI-powered decision-support systems, and autonomous financial advisors that are transforming how firms engage with clients, manage compliance, and deliver personalized services (Bozkurt, 2023). Artificial intelligence agents (AI agents) represent a shift in human-AI collaboration, as they are no longer static tools but dynamic co-creators capable of interpreting user intent, generating insights, and adapting in real time (Nah et al., 2023).

2.4 The Ecosystem of AI Agents

As the capabilities of artificial intelligence have progressed, the concept of AI agents has emerged as a central paradigm in both computer science and organizational design. An AI agent is generally defined as an autonomous system that perceives its environment, processes information, and acts toward achieving specific goals (Russell & Norvig, 2021). These agents differ from traditional AI systems by their autonomy, adaptability, and proactivity, enabling them not only to respond to external stimuli but also to plan, learn, and collaborate in dynamic environments (Wooldridge, 2009).

2.4.1 Foundational AI Agents

The theoretical foundation of AI agents originates from agent-based modeling and intelligent systems research in the 1980s and 1990s, with early work laying the groundwork for viewing software entities as "agents" capable of reasoning and social interaction (Jennings & Wooldridge, 1995). Over time, this has evolved into a broader framework encompassing reactive agents, deliberative agents, and more recently, learning agents empowered by machine learning (Sutton & Barto, 2018).

Reactive agents operate on simple stimulus-response mechanisms without memory or foresight, making them fast but limited in flexibility (Maes, 1991). In FinTech, they support rule-based fraud detection and login security systems, offering consistency in high-volume tasks (Ashta & Herrmann, 2021). Deliberative agents, by contrast, use internal models and symbolic reasoning to simulate outcomes and plan ahead (Müller, 1997). Though slower, these agents are suited for strategic tasks like credit scoring and dynamic risk evaluation (Wooldridge, 2009). Hybrid agents blend reactive speed with deliberative reasoning by structuring responses across multiple layers (Franklin, S., & Graesser, 1997). In FinTech, they power investment advisory tools, balancing real-time market shifts with long-term strategy (Mărăcine et al., 2020). Learning agents are the most adaptive, improving through feedback and experience, particularly via reinforcement learning (Sutton & Barto, 2018). These agents are essential for evolving systems like robo-advisors and fraud detection tools that adapt to new data and behaviors (Herrmann & Masawi, 2022).

These agent categories not only illustrate the range of computational architectures in AI systems but also highlight the progression toward increasingly autonomous and specialized financial applications. As FinTech continues to develop, hybrid and learning agents are expected to drive the shift from static digital services to intelligent, adaptive, and decision-capable financial infrastructures (Gao et al., 2023).

2.4.2 Generative AI Agents and Multi-Agent Systems (MAS)

A particularly transformative development is the emergence of generative AI agents, an autonomous, goal-driven system built upon large language models (LLMs) such as GPT. AI agents are capable of generating content, engaging in real-time dialogue, and executing complex tasks (Gao et al. 2023). They synthesize knowledge, adapt communication strategies, and initiate actions based on evolving user context (Álvarez-Teleña & Díez-Fernández, 2024). These agents synthesize knowledge, adapt communication strategies, and initiate actions based on evolving user context, hence generative agents function as interactive cognitive systems (Banh & Strobel, 2023). In FinTech, generative models power virtual advisors, intelligent customer service bots, and automated compliance engines, scalable and efficient solutions that evolve with new data (Bozkurt, 2023).

Generative AI agents combine natural language generation with strategic reasoning, functioning as autonomous systems capable of decomposing complex tasks, retrieving external knowledge, and making iterative decisions through dialogue (Tran et al. 2025). Architectures such as AutoGPT and AgentGPT translate large language models into agents equipped with memory, planning capabilities, and tool integration (Gao et al. 2023). These agents hold strong potential in applications like real-time fraud detection, portfolio management, and personalized investment planning. However, their growing autonomy presents concerns around transparency, governance, and regulatory compliance in financial contexts (Gürpinar 2025).

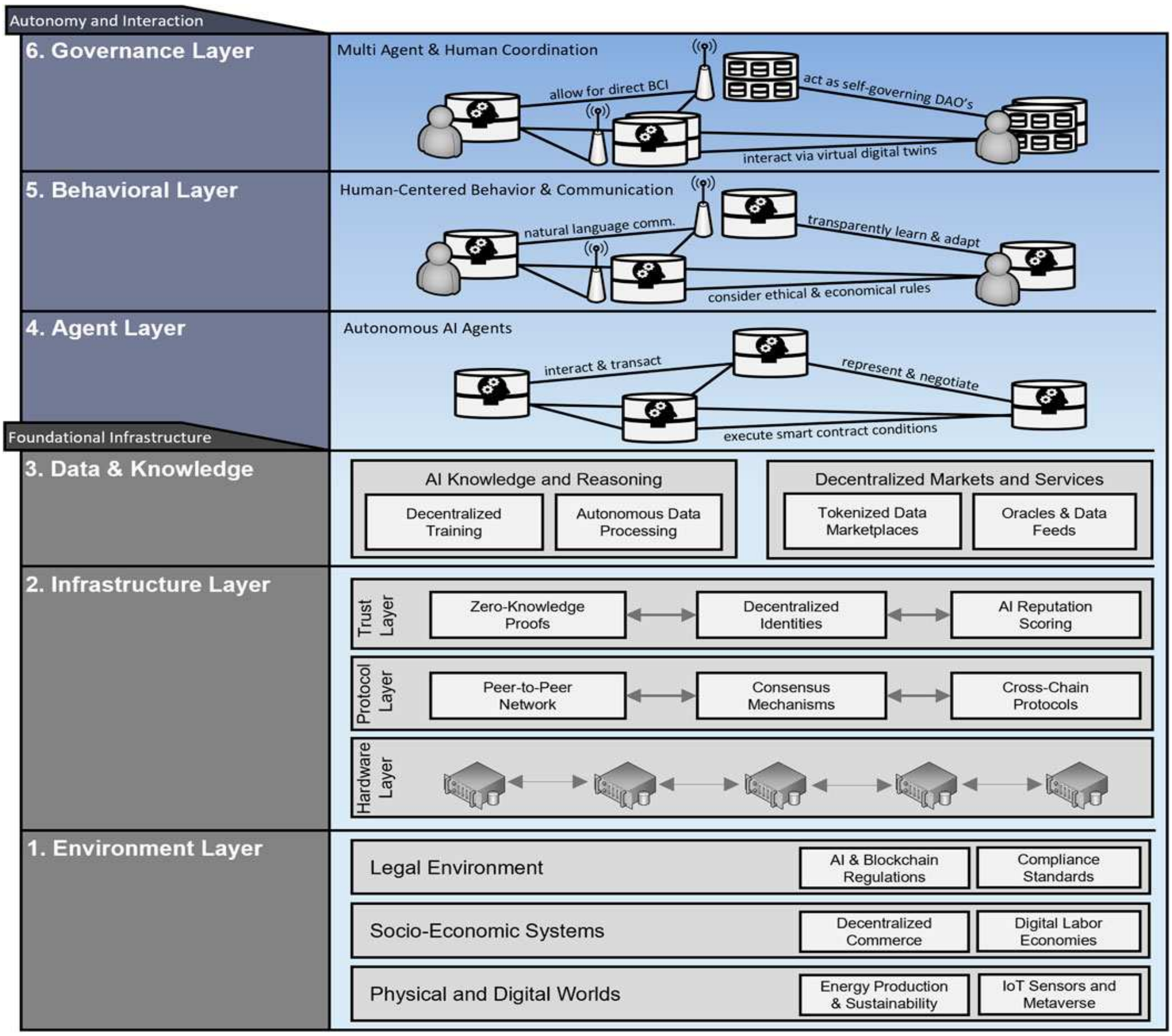
The underlying structure of these systems draws from Multi-Agent Systems, a concept developed in the 1980s to model decentralized intelligence through autonomous agents working in collaboration (Bond and Gasser 1988). These frameworks are designed to support coordination and negotiation among agents, allowing them to collectively address problems beyond the capacity of a single entity (Wooldridge and Jennings 1995). With the integration of reinforcement learning and language models, modern Multi-Agent Systems can dynamically assign roles, share knowledge, and self-organize to optimize outcomes (Tran et al. 2025).

These developments signal a broader shift in AI, from static automation toward adaptive and socially aware agents capable of complex collaboration (Álvarez-Teleña and Díez-Fernández 2024). As AI agents incorporate cognitive components such as memory, planning, and motivational structures, they are moving closer to functioning as intelligent collaborators. This evolution is reshaping the digital infrastructure of financial services, blending machine efficiency with human-like adaptability (Gürpinar 2025).

As theoretical foundations mature, the deployment of AI agents is rapidly shifting from isolated research prototypes to robust components of real-world digital infrastructures. AI agents are no longer confined to narrow tasks but are emerging as autonomous, modular systems designed to assist with complex workflows and perform multi-step reasoning (Álvarez-Teleña & Díez-Fernández, 2024). Figure 2 indicates, as these agents continue to evolve, they are increasingly forming interconnected ecosystems capable of coordination, self regulation, and adaptive decision making, reducing the need for human intervention and ultimately moving toward fully autonomous, self governing Multi-Agent System (MAS) (Gürpinar, 2025).

Figure 2

Conceptual Framework of Autonomous AI Agent Ecosystems



Note. Adapted from Gürpinar, 2025

2.4.3 Vertical vs. Horizontal AI Agents

As these systems become more deeply embedded in real-world operations, a distinction is emerging between general-purpose horizontal agents and domain-specialized vertical agents, shaping how AI is deployed across industries (Zhou et al., 2024).

Vertical agents mark a key evolution, built for sectors like finance or healthcare where regulation, context, and expertise matter most (Wang et al., 2023). They rely on tailored models and structured workflows to carry out tasks such as compliance checks or diagnostics with high accuracy (Weidinger et al., 2022). However, their effectiveness depends on high-quality proprietary data and constant updates to reflect evolving standards (Fragiadakis et al., 2024). These demands stress the importance of strong infrastructure, interdisciplinary collaboration, and responsible development (Zhou et al., 2024).

Horizontal agents, in contrast, focus on breadth. Powered by large-scale models trained on broad datasets, they handle diverse tasks like content creation, scheduling, and research without domain-specific tuning (Bommasani et al., 2021). Their flexibility supports widespread use and lowers technical barriers, particularly for non-experts (Álvarez-Teleña & Díez-Fernández, 2024). Still, their generalist design poses limitations in specialized or high-risk contexts, where compliance, reasoning, and reliability are essential (Zhou et al., 2024). Challenges like hallucination and bias also persist due to reliance on open data (Álvarez-Teleña and Díez-Fernández, 2024).

Vertical and horizontal agents each offer distinct benefits. While one delivers precision in complex environments, the other enables accessible, broad-scale adoption. Their convergence may define the next stage of AI deployment.

2.4.4 Future Trajectory of AI Agents

As artificial intelligence systems continue to evolve, the concept of AI agents is transforming from simple task-executing tools into autonomous entities capable of strategic reasoning, long-horizon planning, and adaptive collaboration (Kapoor et al., 2025). These agents increasingly operate in complex ecosystems where they initiate actions, coordinate with humans and peers, and learn from their environments. The evolution of AI agents can be framed across four generations. Agent-1 systems automate basic tasks, such as navigating interfaces or generating documents (Kokotajlo et al., 2025). Agent-2 introduces continuous learning from feedback (Gao et al., 2023). Meanwhile, Agent-3 incorporates abstract reasoning and multi-step planning through contextual memory (Li et al., 2021). Agent-4, the most advanced stage, involves distributed agents capable of recursive self-improvement and long-horizon autonomy (Kokotajlo et al., 2025). Platforms like AutoGPT and BabyAGI exemplify these advancements, supporting recursive planning, tool integration, and safe enterprise deployment (Gao et al., 2023). These tools illustrate the shift toward adaptive, context-aware agents operating at organizational scale.

However, growing autonomy introduces challenges on scalability, coordination, and explainability as it remains critical. Multi-agent systems must maintain transparency in dynamic environments and explainable AI is essential for trust in high-stakes sectors like FinTech (Gürpinar, 2025). Agents increasingly exhibit general-purpose intelligence, with traits like memory, perception, and autonomous decision-making (Grace et al., 2024). ASI is no longer envisioned as a singular entity but as a modular society of self-optimizing agents (Kokotajlo et al., 2025). This architecture allows continuous learning but raises alignment and governance concerns, particularly as agents evolve independently (Nah et al., 2023).

Agent-4 collectives may shape the near future as self-organizing systems capable of managing complex workflows and driving innovation (Kokotajlo et al., 2025). However, their recursive self-enhancement introduces systemic risks if goals become misaligned and require robust oversight. To address these challenges, modular cognitive architectures are needed to integrate memory, perception, and goal-directed behavior, enabling more effective control of agentic systems (Li et al., 2025). These developments highlight the need for adaptive governance frameworks that evolve alongside agent capabilities. As agents increasingly act as strategic collaborators in FinTech and beyond, future design must prioritize transparency, accountability, and alignment with human values (Kokotajlo et al., 2025).

2.5 Technology Acceptance Models and Diffusion of Innovation

As AI agents become more embedded in financial services, understanding the adoption drivers are essential. The Technology Acceptance Model (TAM) provides a foundational framework for explaining how users evaluate and adopt new technologies (Davis, 1989). The model focuses on two core constructs. Perceived usefulness is the belief that a system enhances performance, while perceived ease of use refers to the minimal effort required to operate it (Davis, 1989). These dimensions are particularly relevant for AI agents in FinTech, where autonomous decision-making systems must demonstrate clear utility while minimizing user friction during integration (Feuerriegel et al., 2023).

To provide a more comprehensive perspective on adoption, recent research has emphasized the value of integrating TAM with the Diffusion of Innovation (DOI) theory (Zangiacomi et al. 2022). The DOI theory explains how innovations spread through social systems over time, emphasizing key attributes such as relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1983). While TAM is effective in predicting user behavior and acceptance, its explanatory power can be enhanced through DOI's broader constructs (Rogers, 1983). The combined approach enables organizations to better address the user perceptions and strategic fit of AI agents within existing processes and structures (Zangiacomi et al. 2022). Furthermore, the integration of these models helps organizations adapt to dynamic technological shifts by designing targeted interventions that respond to both individual and organizational concerns (Venkatesh et al., 2003). As AI agents move from experimental tools to enterprise-level decision-makers, understanding their adoption through a TAM–DOI lens provides a robust foundation for navigating challenges related to trust, system compatibility, and perceived value in financial ecosystems.

2.6 Challenges of AI and Agent Systems

The rapid advancement of generative AI in financial services underscores the critical need for Responsible AI (RAI) frameworks, which aim to develop systems aligned with core ethical values such as fairness, accountability, and transparency (Mikalef et al., 2022). It aims not only to prevent harm but also to actively ensure that innovation is matched with robust oversight (Feuerriegel et al., 2023).

In AI agent systems, bias stems a major concern, as generative models trained on large, uncurated datasets often replicate and reinforce existing inequalities (Schramowski et al., 2022). This can lead to discriminatory outcomes in areas like credit scoring or customer segmentation, calling for proactive auditing and fairness-aware design (Mehrabi et al., 2021). Transparency is also limited, with generative models operating as black boxes (Sun et al., 2022). Lack of transparency in generative AI systems is a critical concern, as it threatens explainability, accountability, and regulatory compliance (Bender et al., 2021).This lack of explainability complicates compliance and erodes trust, particularly in domains like fraud detection or credit decisions where justification is essential (Brasse et al., 2023).

Hallucinations are a significant concern as AI agents become more autonomous, risking the spread of misleading information that can erode trust and decision-making (Cheong et al., 2024). Hallucinations occur when generative models produce confident but inaccurate, fabricated, or misleading responses, often without users realizing the error (Dahl et al., 2024). These errors compromise the reliability and safety of AI-driven systems, especially as model size and complexity increase (Bai et al., 2025). Approaches like retrieval-augmented generation and multi-agent validation are being explored to mitigate such risks (Cheong et al., 2024).

Beyond technical risks, generative AI presents serious ethical and societal concerns, including its misuse for fraud through deepfakes, synthetic identities, and phishing attacks (Weidinger et al., 2022). As AI agents gain operational roles, their vulnerability to adversarial manipulation raises security and accountability challenges (Khan et al., 2024). Additionally, increased reliance on AI may lead to workforce displacement and diminished human oversight, underscoring the need for robust governance and responsible innovation (Van Slyke et al., 2023). As AI systems grow in complexity and autonomy, it becomes critical to address the growing range of ethical, technical, and governance challenges they present (Nah et al., 2023).

3. Research Methodology

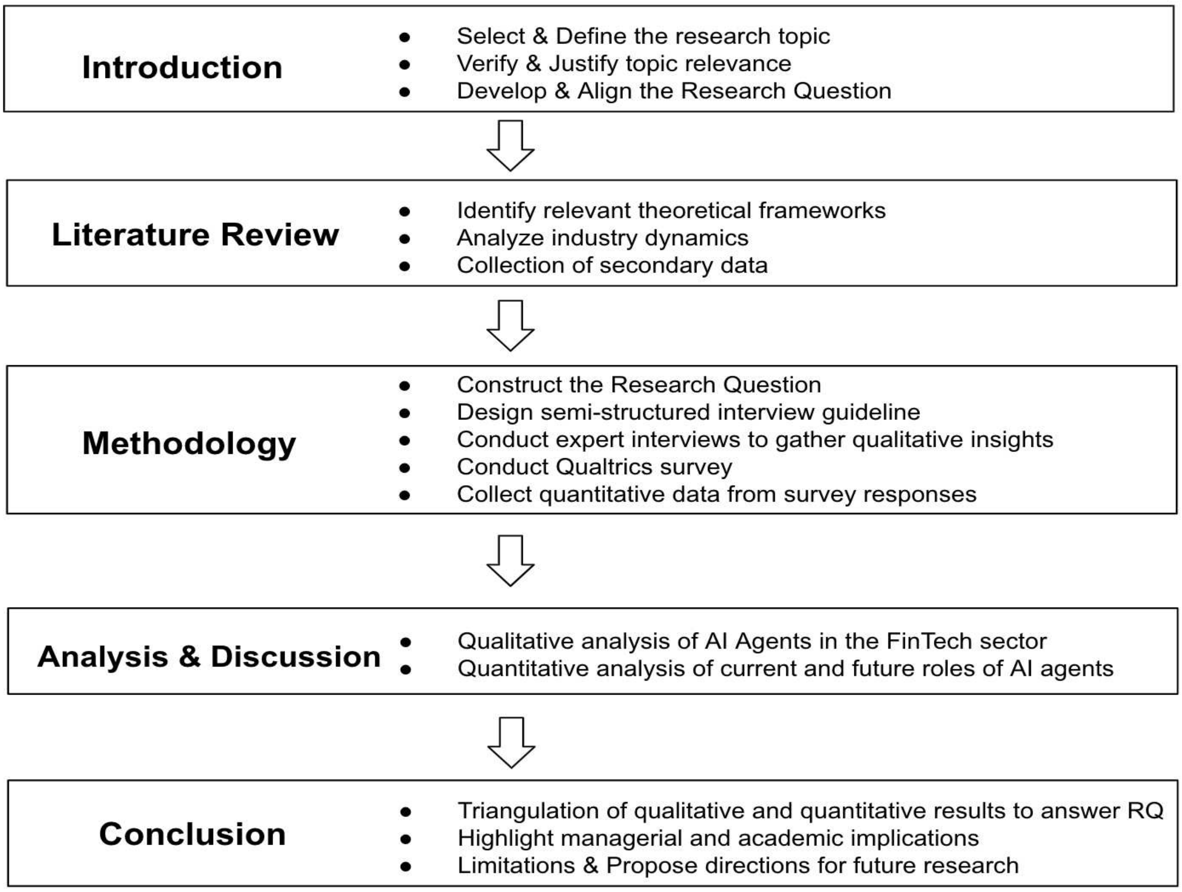
The methodology serves as the foundation of this academic research, offering clarity on how the study was conducted and ensuring that its findings are both credible and replicable. A well-structured methodological approach helps define the research process through organized and purposeful actions (Garg, 2016). In the context of this thesis, the methodology provides a roadmap for how insights were gathered, analyzed, and interpreted in relation to the evolving role of AI agents in the FinTech sector. The following sections describe the research design, data collection methods, sampling strategy, and analytical techniques applied throughout the study.

3.1 Research Design

This research explores the evolving role of AI agents in the financial technology (FinTech) sector. Figure 3 below outlines the methodology applied in this research study.

Figure 3

Research design



This study adopts a mixed methods research design to explore the current and future role of AI agents in the FinTech sector. Combining qualitative and quantitative approaches allows for a more comprehensive and balanced understanding (Almeida, 2018). This design ensures that both measurable patterns and deeper contextual insights are captured. Semi-structured interviews were conducted with AI agents and industry experts to collect specialized knowledge and assess different expert perspectives (Bogner, Littig & Menz, 2009). A subsequent survey was also conducted using Qualtrics to gather broader input from relevant industry professionals. This methodological structure helps ensure transparency, rigor, and alignment with established research standards (Garg, 2016). The combination of both methods supports triangulation and enhances the validity of the study's findings.

3.2. Data Collection

The following chapters discuss the data collection methods applied.

3.2.1 Expert Interviews

Qualitative interviews are conducted to gather in-depth insights from experts on the role of AI agents in the FinTech sector. This method allows for the collection of rich, nuanced data that helps uncover the underlying dynamics and interpretations essential to understanding the research focus (Bogner, Littig & Menz, 2009). Conducting semi-structured interviews allows for a structured yet flexible approach to explore this emerging topic in more depth. Experts were selected using a purposive sampling strategy, targeting professionals from the FinTech sector, AI consultants, and AI agents. The final sample included 12 interviews with representatives from FinTech firms, AI researchers, and AI agents like OpenAI and Gemini. Interviews were conducted via Zoom or Microsoft Teams, with an average duration of 45 to 75 minutes, except for the AI agents, which provided immediate responses. Participants were informed of the purpose and format beforehand, and consent was obtained for all interviews. A thematic analysis was applied to the expert interviews. The analysis focused on five key thematic areas; perceptions, adoption drivers, risks, governance, and future outlook. This method supported a rich, nuanced interpretation grounded in the lived experiences and expert insights of the interviewees (Braun and Clarke, 2017). The analysis focused on five key thematic areas; perceptions, adoption drivers, risks, governance, and future outlook. The conversations were recorded using Gong, a secure platform that supports transcription and assisted analysis. Table 1 outlines the participating experts' roles, expertise, and professional background, while Table 2 in Appendix B includes the full set of interview questions and Appendix C provides a summary of key insights.

Table 1

Interview Guide

Code	Description of Interviewee
IV1	Process automation expert with 10+ years in quality, fraud detection, and AI-based workflow automation. Focuses on ISO compliance and regulated industries.
IV2	Research engineer with a background in business and data science. Applies machine learning to simulation and policy modeling.
IV3	Cybersecurity specialist with experience in AI-based threat detection. Works with behavioral analytics and rule-based systems.

IV4	AI consultant leading enterprise automation projects. Develops multi-agent systems for HR, sales, and onboarding tasks.
IV5	Cloud infrastructure advisor supporting AI agent deployment. Focuses on secure, scalable environments for enterprise applications.
IV6	Fraud prevention expert with a background in data science. Designs agents for phishing detection and behavioral monitoring.
IV7	Sales enablement specialist using AI tools to support sales teams and streamline customer interactions.
IV8	Financial analyst using AI for forecasting and reporting. Works with data modeling and document automation.
IV9	Treasury professional in banking with experience in liquidity planning and AI-assisted regulatory reporting.
A1	ChatGPT – Developed by OpenAI, specialized in dialogue-based interaction, creative content generation, and general-purpose support across diverse tasks.
A2	DeepSeek – Oriented toward technical and structured tasks, often applied in scenarios involving data processing, automation, and complex modeling.
A3	Gemini – Google's large language model with a focus on autonomous reasoning and multi-step decision processes, suitable for complex problem-solving contexts.
A4	Perplexity – Designed to support research and information access, typically used for quick knowledge retrieval, summarization, and workflow assistance.

3.2.2 Survey Design

Following the literature review and expert interviews, a survey was developed to explore individual and organizational perspectives on AI agents, focusing on their use, perceived benefits, adoption drivers, and anticipated impact. The survey aimed to collect broader quantitative insights to complement the qualitative data and validate themes emerging from the theoretical framework. The final questionnaire consisted of 27 questions distributed across seven domains: (1) demographics and control variables, (2) current use of AI agents, (3) motivations and challenges for AI agents adoption, (4) perception and trust of AI agents, (5) future perspectives and scenarios. The survey included a mix of formats: multiple-choice, 5-point Likert scale items, star rating, ranking tasks, and scenario-based reflections. Several questions were adapted from validated peer studies to ensure consistency and comparability, while others were tailored specifically to the unique role of AI agents in decision-making, communication, and automation. The survey was hosted on Qualtrics and designed to be completed in approximately 5–6 minutes. It was distributed using non-probability sampling techniques, primarily convenience and snowball sampling, via LinkedIn, WhatsApp, and direct professional contacts. The target group included professionals, knowledge workers, and students from diverse sectors, regardless of technical background, to capture broad perceptions of AI agents across industries. By combining general and industry-specific questions (e.g., finance, communication, analytics), the survey enabled comparisons across adoption contexts. Responses were collected anonymously via self-completion, with no researcher interaction, ensuring efficient and reliable data to support the study's objectives (Bryman, 2016).

4. Analysis and Discussion

This chapter analyzes the expert interviews presented in Section 4.1, offering insights into how AI agents are perceived, adopted, and governed across FinTech and related sectors. The findings reflect diverse roles, use cases, and strategic considerations on the adoption of AI agents in real-world financial and operational contexts. Section 4.2 then presents the survey results, highlighting broader trends and validating key themes identified through the qualitative data to understand the general impact of AI agents.

4.1. Expert Insights

The following sections present the findings from the expert interviews.

4.1.1 Perception of AI Agents

Across the expert interviews conducted, there was strong consensus from both technical and non-technical backgrounds around the definition of AI agents as autonomous, task-oriented systems capable of decision-making, adaptation, and interaction with environments or other agents.

Respondents in IV7, IV8, and IV9 viewed AI agents as practical, embedded tools that enhance speed, accuracy, and consistency, particularly in repetitive tasks. This reflects the growing use of AI agents to automate high-volume, data-heavy workflows that support operational decision-making (Li et al., 2025). However, almost every interviewee stressed the importance of transparency and traceability in financial workflows, highlighting the vital role of explainable AI (XAI) in fostering trust and ensuring responsible deployment in sensitive or regulated environments (Floridi & Cowls, 2022).

The interviewees of IV6, IV2, and IV1 described AI agents as modular, self-learning systems, particularly emphasizing the relevance of vertical agents in finance and blockchain-based services (Wang et al., 2023). Fatima highlighted that these agents are viewed not only as task executors but also as adaptive components that can simulate, recommend, or even autonomously initiate decisions based on structured data inputs. This evolution reflects the shift from reactive tools to autonomous, strategic entities (Kapoor et al., 2025).The interviewees of IV4, A3, and A2 emphasized the importance of horizontal AI agents, highlighting their general-purpose capabilities across functions such as customer service, data processing, and workflow automation. These findings indicate that horizontal agents have proven particularly effective in FinTech and enterprise automation contexts, where their scalability and communication-oriented design enable them to manage diverse tasks across departments (Zhou et al., 2024).

The interviews with A1, A2, A3, and A4 highlighted the capabilities of generative AI agents in contextual understanding, dynamic content generation, and responsive interaction. These insights reflect how generative agents can extend human cognitive capacity through goal-driven, adaptive language processing (Li et al., 2025). Furthermore, the interviews with the LLM agents (A1–A4) emphasized the role of multi-agent systems in enabling distributed decision-making, collaborative task execution, and scalability across financial domains. Multi-agent architectures are essential for managing complexity, enhancing autonomy, and fostering inter-agent coordination in dynamic environments (Tran et al., 2025).

4.1.2 Adoption Drivers

Findings from the interviews suggest that organizations primarily adopt AI agents to enhance efficiency, cut operational costs, and automate repetitive processes. Interviewees IV1, IV2, IV4, and A1 emphasized that AI agents are increasingly integrated to streamline processes such as onboarding, document processing, fraud analysis, and customer support. Additionally, Interviewee IV4 highlighted the use of generative agents to support HR and complaint management, helping to scale operations without proportional increases in headcount or cost. These findings indicate that AI agents significantly enhance throughput and minimize manual labor, especially within departments managing high-volume, time-sensitive operations (Wang et al., 2024).

Experts from IV1, IV2, IV4, and A4 highlighted that organizations increasingly perceive AI agent adoption as essential to remain competitive and relevant. Hence, the adoption of AI agents is a strategic pressure to innovate and remain competitive. The remarks of IV1 indicate that firms often adopt AI not proactively, but out of fear of falling behind, reflecting a reactive drive for innovation. This finding resonates with the concept of "digital urgency," wherein firms feel compelled to embrace digital transformation not only to lead but simply to avoid obsolescence in rapidly evolving sectors such as FinTech, compliance, and cybersecurity (Westerman et al., 2014).

Furthermore, IV4, IV6, and A2 consider scalability and real-time responsiveness as critical adoption drivers. The findings indicated that AI agents outperform static systems by reacting dynamically to real-time inputs and coordinating actions across decentralized workflows (Wang et al., 2024). Interviewee IV4 emphasized that the modularity and adaptability of AI agents allow them to autonomously adjust to new data and evolving protocols, making them ideal tools for managing uncertainty and regulatory complexity.

Beyond efficiency and innovation, accuracy and decision support was suggested by A3 to be decisive factors in high-stakes use cases. Interviewees IV3 and IV6, both involved in cybersecurity and fraud prevention, emphasized the low false-positive rates and precision of vertical AI agents in domains such as phishing detection, behavioral risk analysis, and anomaly identification. Their ability to process vast, heterogeneous datasets while maintaining accuracy makes them invaluable in mission-critical contexts where mistakes carry significant financial or reputational cost (Zhou et al., 2024). In addition, Interviewees IV6 and IV8 indicated that the ability of AI agents to support compliance is critical, as they can enhance regulatory responsiveness by detecting rule breaches, generating alerts, and adapting to new legal requirements in near real-time. This capability provides a competitive advantage by ensuring operational alignment with evolving regulations, particularly in markets where proactive compliance is increasingly expected (PwC & Stop Scams UK, 2023).

4.1.3 Adoption Requirements and Organizational Readiness

Despite widespread interest in the potential of AI agents, the interviews indicated that the readiness of organizations to adopt them at scale remains inconsistent. Poor data quality and outdated IT infrastructure were considered to be major barriers by IV4 and IV8, especially in traditional banking environments where legacy systems and siloed databases limit interoperability. In addition, IV9 highlights that even if technical capabilities are in place, cultural and human factors can significantly hinder implementation efforts. IV3 and IV6 reported internal resistance that is often rooted in fears of job displacement or loss of decision-making authority, which are critical challenges for the adoption of AI agents in the workplace (Rai et al., 2021).

Additionally, IV1, IV2, and A2 emphasized the lack of internal expertise and governance, as it often results in limited understanding of how to manage, monitor, and audit AI agents. IV9 noted that this includes insufficient awareness of fallback protocols, transparency mechanisms, and the importance of explainability. These insights support the growing view that responsible AI adoption relies not only on model performance but also on clear accountability mechanisms and organizational readiness (Herrmann & Masawi, 2022).

From a systems perspective, IV5 and IV8 viewed the role of cloud-native architecture and embedded governance tools as foundational enablers. Without secure infrastructure and integrated compliance mechanisms, agents cannot operate safely or scale reliably (Wang et al., 2023). IV5 particularly emphasized the need for autonomous databases and cloud security protocols that support traceability and agent accountability, as these are required components of effective AI deployment frameworks (Floridi & Cowls, 2022).

4.1.4 Risks and Ethical Concerns

While the perception and adoption of AI agents were largely positive across interviews, several experts expressed concerns about ethical risks, operational reliability, and governance. IV2, IV6, and IV9 particularly emphasized risks related to hallucinations, false outputs, and overreliance on autonomous systems. These concerns are especially critical in high-stakes contexts such as fraud detection, regulatory compliance, and treasury management, where inaccurate agent responses could lead to misallocated funding, false alerts, or legal violations (Floridi & Cowls, 2022). Additionally, IV6 warned that hallucinations in risk scoring models can undermine detection accuracy, while IV9 highlighted that unverifiable recommendations in treasury operations can pose serious challenges to transparency, auditability, and trust.

The dangers of limited explainability and traceability were highlighted among IV1, IV3, A1, and A4, especially when agents operate as black-box systems. The findings indicated that without transparent logic or post-hoc interpretability, organizations may struggle to validate or contest agent decisions, putting them at risk of regulatory non-compliance and reputational damage (Brasse et al., 2023). In addition, IV4, IV6, and IV8 raised the concerns about over-automation, as organizations may implement AI agents without adequate fallback mechanisms or escalation protocols. IV2, A2, and IV9 further stressed the importance of maintaining human-in-the-loop frameworks to avoid blind trust in automated decisions, especially when client impact or compliance exposure is at stake (Retzlaff et al., 2023). This reflects a broader ethical tension between efficiency and accountability, underlining the need for structured governance, audit trails, and defined oversight roles in agent-based systems (Brasse et al., 2023).

Relatedly, IV5, A3, and IV9 indicated data privacy and security as critical vulnerabilities, especially when using externally hosted models or inter-agent systems that increase attack surfaces. In environments such as cloud infrastructure or multi-agent collaboration, these risks are magnified by the complexity of monitoring agent interactions and controlling access to sensitive data (Wang et al., 2023). Additionally, IV4 strongly emphasized that the EU AI Act must align with broader AI governance principles, calling for stronger controls over data lineage, integrity, and access within automated ecosystems.

4.1.5 Future Outlook and Strategic Potential

Among the interviewees, the future effect of AI agents is perceived as transformative, as they evolve toward higher autonomy, broader domain integration, and more collaborative functionality. IV6, A3, and IV9 emphasized the next generation of agents will likely operate with increasing independence, enabling more strategic decision-making in areas like central banking, treasury management, and predictive analytics. IV9, in particular, highlighted the possibility of agents supporting complex economic modeling and liquidity stress testing, functioning not just as assistants but as autonomous co-analysts within financial institutions. The findings suggested that agents are transitioning from reactive executors to proactive, self-guided collaborators (Kokotajlo et al., 2025).

Interviews with LLM-based agents (A1–A4) also pointed to the growing role of agent-to-agent communication and coordination. These systems are designed to coordinate tasks across compliance, risk assessment, and transaction monitoring in real time, improving both agility and decision accuracy (Tran et al., 2025). As A2 noted, the capacity of agents to operate across domains and exchange insights in real time represents a step toward intelligent, modular finance infrastructure. These insights emphasized that multi-agent collaboration is foundational to the future of autonomous systems in regulated environments (Gürpinar, 2025).

Beyond operational roles, IV1 and IV6 suggested that AI agents will likely expand into new financial verticals, including decentralized finance (DeFi), sustainability reporting, and algorithmic lending. Their modular and domain-specific design allows for rapid adaptation, making them suitable for emerging sectors where agility and regulation intersect (Zhou et al., 2024). Additionally, IV2 and A2 noted the strategic potential of modular agent architectures, which allow organizations to customize, scale, and orchestrate agent ecosystems depending on shifting business priorities.

Ultimately, IV9 speculated on the long-term emergence of Artificial Superintelligence (ASI), framing it not as imminent, but as a potential outcome of the continued evolution of increasingly sophisticated agent capabilities. The growing integration of reasoning, planning, and multi-agent negotiation indicates an early cognitive shift in agent design (Krishnan, 2025). In addition, A1, A3, and IV9 agreed that while current deployments remain bounded and supervised, the trajectory suggests a future where agents evolve from task execution tools to proactive strategic collaborators. This projection is consistent with academic models predicting the emergence of advanced agents capable of autonomous reasoning and long-term planning (Kokotajlo et al., 2025).

Together, these insights suggest that the strategic role of AI agents is poised to grow significantly. Their evolution will not only reshape operational workflows but also redefine how intelligence, decision-making, and innovation are distributed across financial systems.

4.2. Survey Results

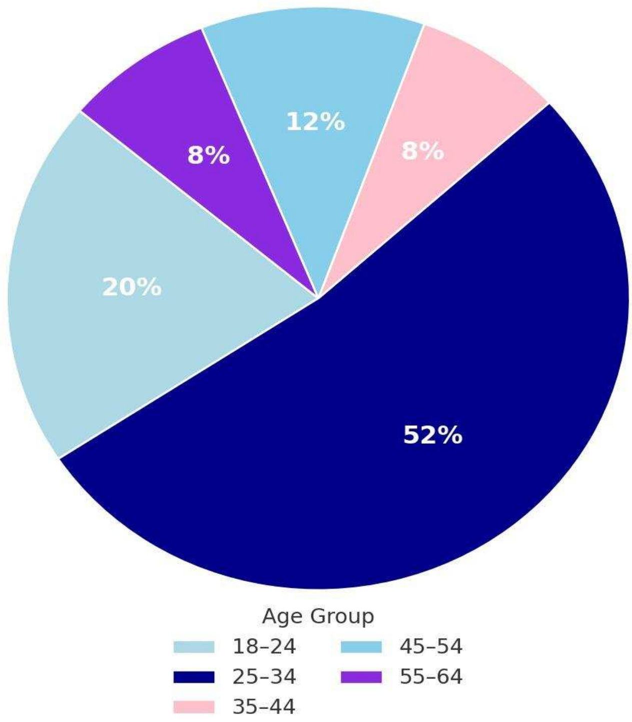
The following sections present the results and data retrieved from the Qualitrics survey.

4.2.1 Demographics of Participants

Figure 4 shows the age breakdown of the survey participants. A majority (52%) fall within the 25–34 age group, followed by 20% in the 18–24 range. The 45–54 age group represented 12% of, while both the 35–44 and 55–64 groups accounted for 8% each. Overall, the results point to a younger respondent base, with the majority being under 35 years old.

Figure 4

Age Distribution of Participants



Note. Survey responses from n =112 participants.

The gender distribution of respondents shows slightly higher representation of male participants, accounting for 58.1% of the sample, while female respondents made up 41%. Participants identifying as non-binary or choosing not to disclose their gender represented a minor fraction of the sample. Most respondents reported high levels of educational attainment. A significant majority (62.5%) held a Master's degree, while 29.8% had completed a Bachelor's degree. Only a small portion had a Doctorate or higher (3.8%), and an equally small share reported a high school diploma or less (3.8%). Respondents represented a diverse set of professional backgrounds.

The most common industry of participants currently being employed was financial services, followed by tech and consulting companies. Smaller portions were distributed across education, public sector, and creative industries. Participants were employed across organizations of varying sizes. The largest segment (33.3%) worked at large companies with over 500 employees. Mid-sized firms were also well represented, with 17.1% employed at companies with 51–200 employees and 16.2% at those with 201–500 employees. Additionally, 10.8% worked at firms with 11–50 employees, while another 17.1% were employed at small organizations with less than 10 employees. These figures suggest a balanced representation across the organizational spectrum from startups to large enterprises.

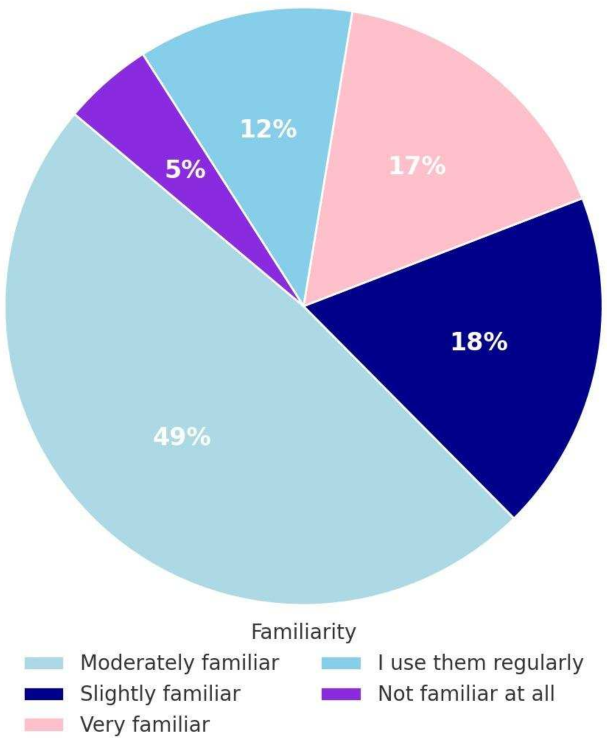
In terms of income distribution, about a third of respondents (34.2%) reported earning between €20,000 and €40,000 annually. This was followed by 22.5% earning between €40,000 and €60,000, and 18.9% reporting less than €20,000 annually. A smaller share (12.6%) earned more than €80,000, while 5.4% fell within the €60,000–€80,000 range. Notably, 6.3% chose not to disclose their income. The income profile suggests that the survey primarily reached early- to mid-career professionals, which aligns with the previously noted age and education demographics.

4.2.2 Familiarity and Current Use of AI Agents

Figure 5 represents that the majority of respondents are already familiar with AI agents, although the levels of familiarity vary. Nearly half of the participants (49%) identified as "moderately familiar" with AI agents. An additional 18% considered themselves "slightly familiar," while 17% reported being "very familiar". A small portion (12%) indicated that they "use them regularly," suggesting the experience with the AI agents. Only 5% of participants stated they were "not familiar at all".

Figure 5

Familiarity with AI Agents



Note. Survey responses from n =112 participants.

The survey results indicate that ChatGPT (OpenAI) stood out as the most frequently used AI agent, among respondents with 47.5%. Siri (Apple) followed with 18% of mentions, then Gemini (13%), Perplexity AI (10.2%), and Alexa (3.7%). Additionally, 7.6% of participants mentioned using other types of agents. However, rather than relying on a single tool, many participants reported using multiple AI agents in combination with ChatGPT, Siri, Gemini, or Perplexity. Rather than relying on a single tool, many respondents reported using a combination of AI agents. Most commonly, ChatGPT was used alongside Siri, Gemini, or Perplexity.

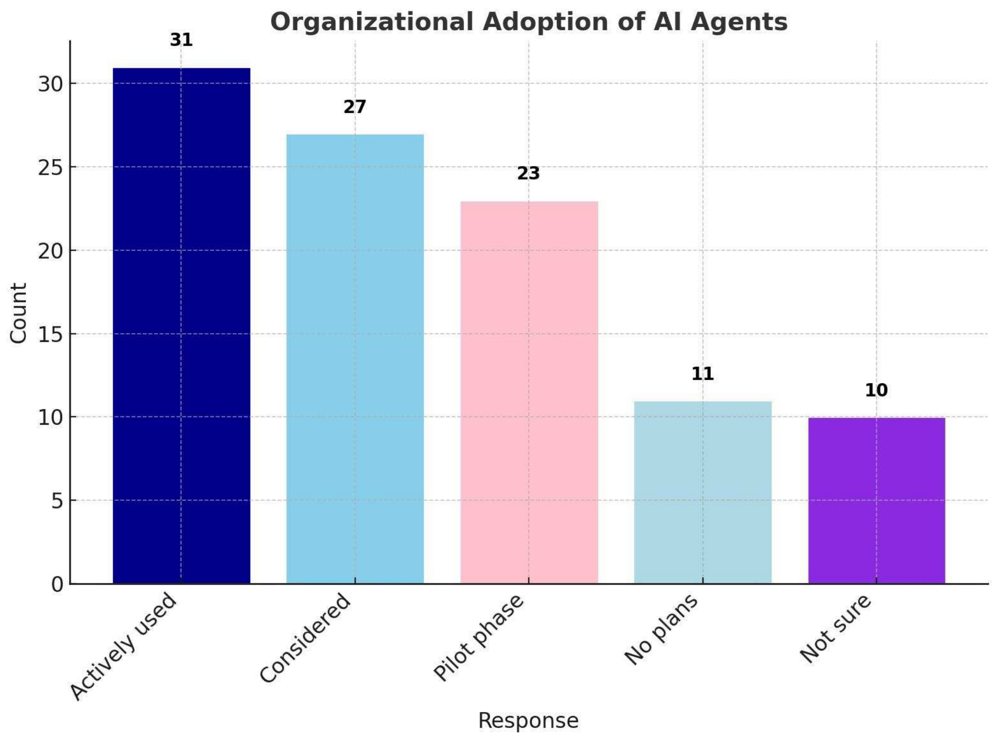
The survey findings show that AI agents are increasingly embedded in participants' daily professional routines. Over one-third (36.9%) of respondents reported using AI agents on a daily basis, while another 18.9% stated they use them two to three times per week. Additionally, 15.3% indicated using them four to six times weekly, and the same percentage reported once-a-week usage. Only a small share (8.1%) said they never use AI agents in their work. The most common motivation of respondents to use AI agents in daily work was to enhance productivity and reduce workload (24.3%), closely followed by automating repetitive or routine tasks (23.5%). A significant portion of participants (20%) also highlighted the role of AI agents in improving the speed and quality of decision-making, while 17.3% indicated they use them to gain insights from large or complex datasets. A smaller share (7.5%) noted improving customer or user experiences, while 5% of respondents use AI agents for other tasks as their primary driver. Only 2.4% reported that they currently do not see a need for AI agents. Many respondents selected multiple motivations, suggesting that AI agents are being used to support a variety of goals rather than a single, fixed task.

4.2.3 Workplace Adoption Patterns

Figure 6 indicates the current status of AI agent adoption within the respondents' organizations. A total of 31 respondents (27.9%) reported that AI agents are actively used in their workplace, while 23 respondents (21.6%) indicated usage is limited to a pilot or experimental phase. An additional 27 participants (24.3%) said their organization is currently considering adoption. By contrast, 11 respondents (10.8%) reported that there are no plans for adoption, and 10 (9.0%) were unsure. Altogether, these figures reveal that nearly half of the participants' organizations have already adopted AI agents in some capacity, while around a quarter are actively exploring future implementation.

Figure 6

Organizational Adoption of AI Agents

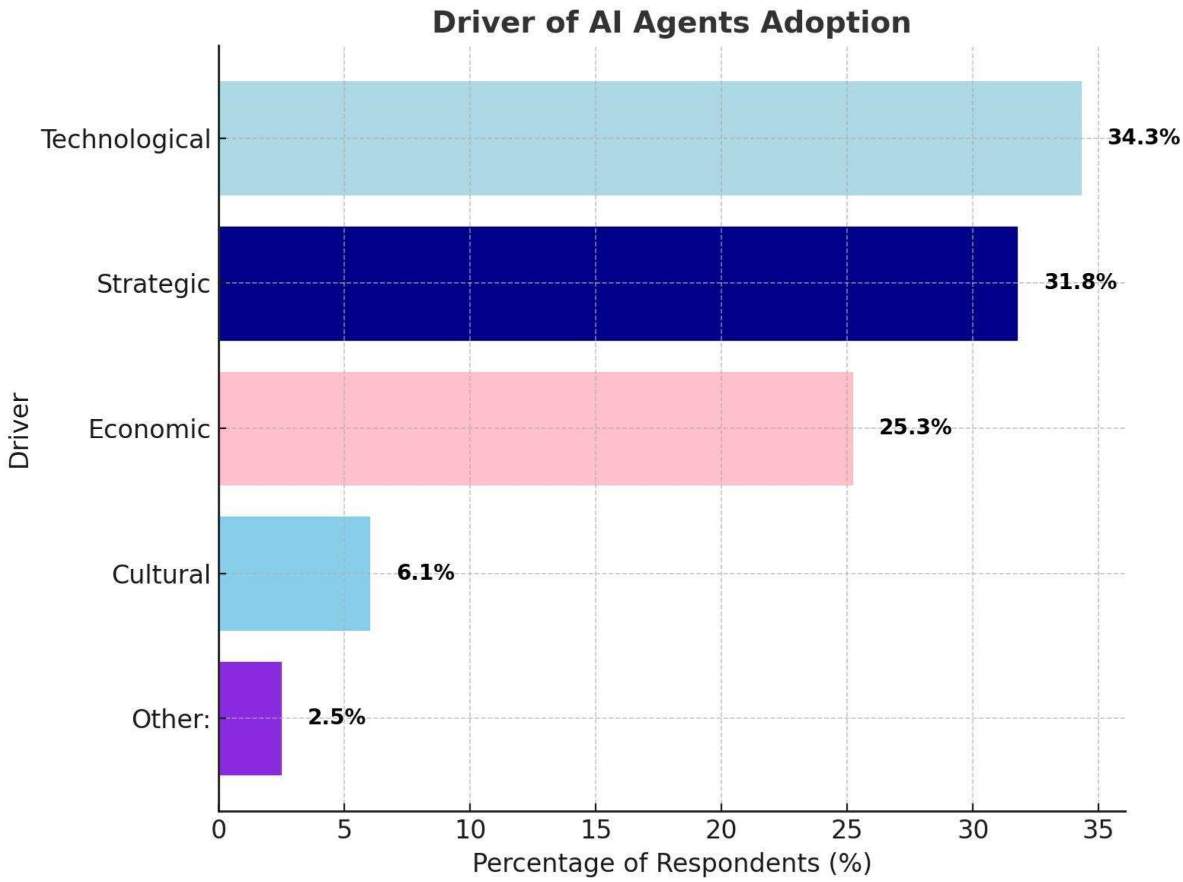


Note. Survey responses from n =112 participants.

Figure 7 presents the key drivers behind the adoption of AI agents within the respondents' organizations. The findings show that technological and strategic motivations are the most determinant, selected by 34.3% and 31.8% of participants, respectively. Economic considerations followed at 25.3%, while cultural drivers (6.1%) and other reasons (2.5%) were mentioned less frequently. In addition, some participants explicitly identified security and privacy as key drivers of AI agents adoption in open-ended responses. Overall, many respondents selected more than one factor, indicating that AI agent adoption is typically shaped by a combination of motivations rather than a single dominant driver.

Figure 7

Drivers of AI Agents Adoption

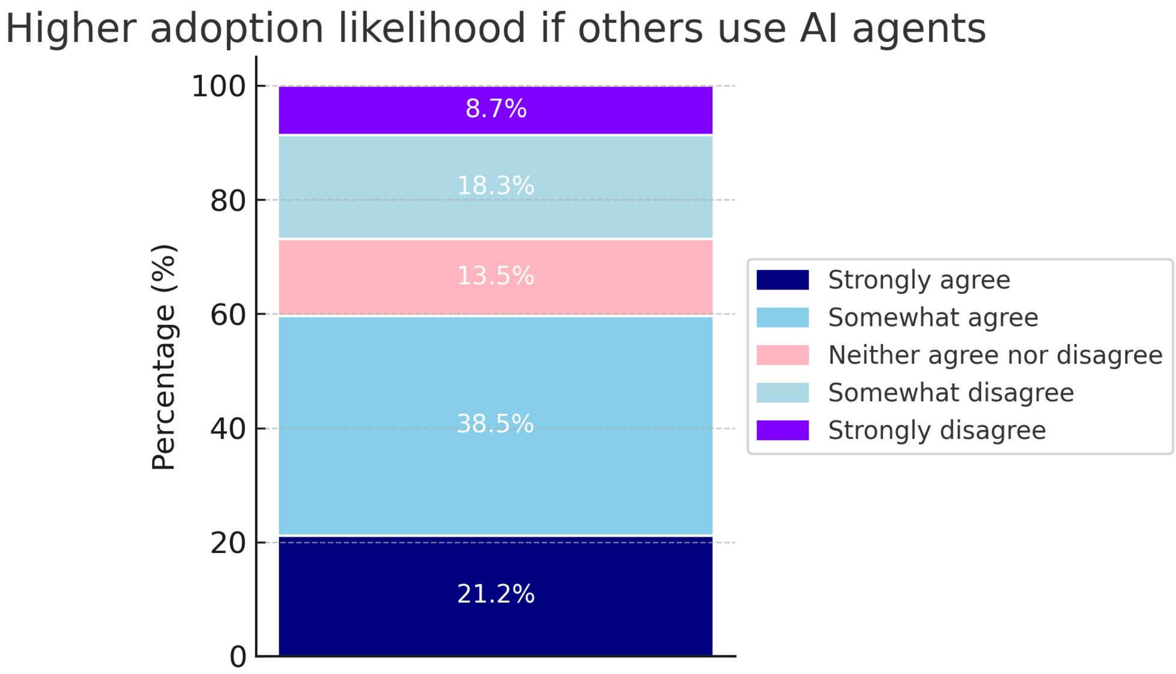


Note. Survey responses from n =112 participants.

Figure 8 shows how respondents perceive the influence of external adoption trends on their own organization's likelihood of implementing AI agents. The majority showed a positive correlation as 21.2% of participants strongly agreed, and 38.5% somewhat agreed that adoption would be more likely if others were already using AI agents. Meanwhile, 13.5% remained neutral, suggesting uncertainty or a case-by-case approach. In contrast, 18.3% somewhat disagreed and 8.7% strongly disagreed, indicating that external influence is not a decisive factor for every organization.

Figure 8

Peer Influence on AI Agent Adoption Likelihood

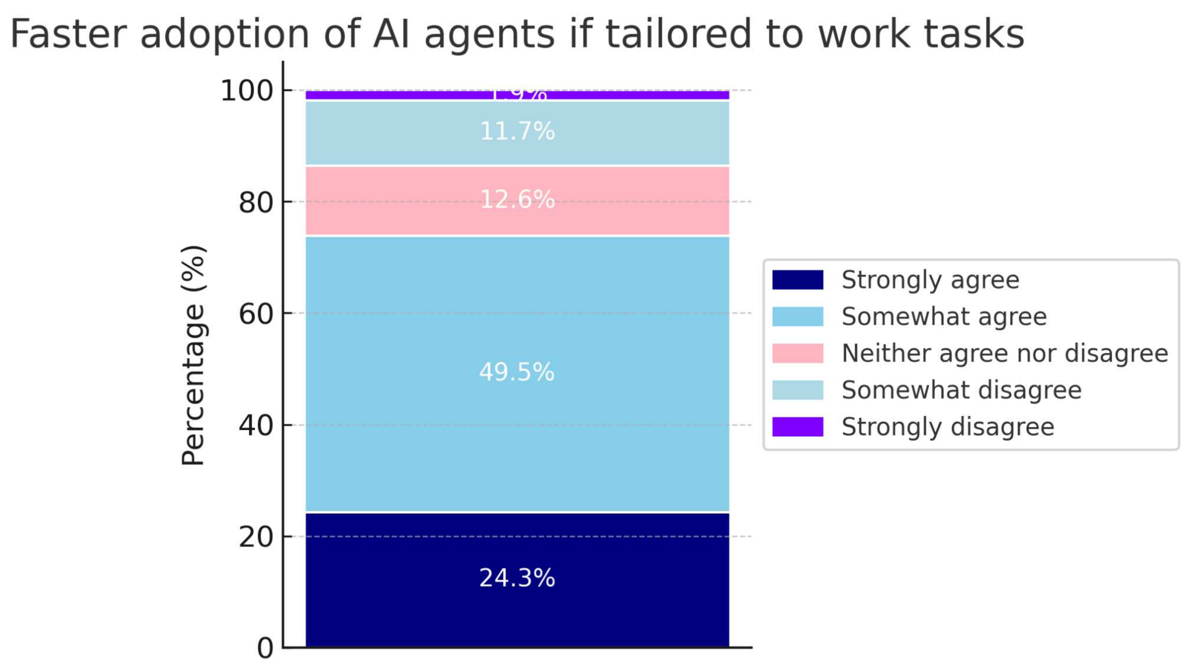


Note. Survey responses from n =112 participants.

Figure 9 illustrates participants' views on whether tailoring AI agents to specific tasks would boost adoption. The respondents expressed agreement with this idea overall, with 49.5% somewhat agreed and 24.3% strongly agreed. Meanwhile, 12.6% of respondents remained neutral, while 11.7% somewhat disagreed and only 1.9% strongly disagreed that task-specific AI agents would lead to higher adoption.

Figure 9

Influence of Task Relevance on AI Agent Adoption

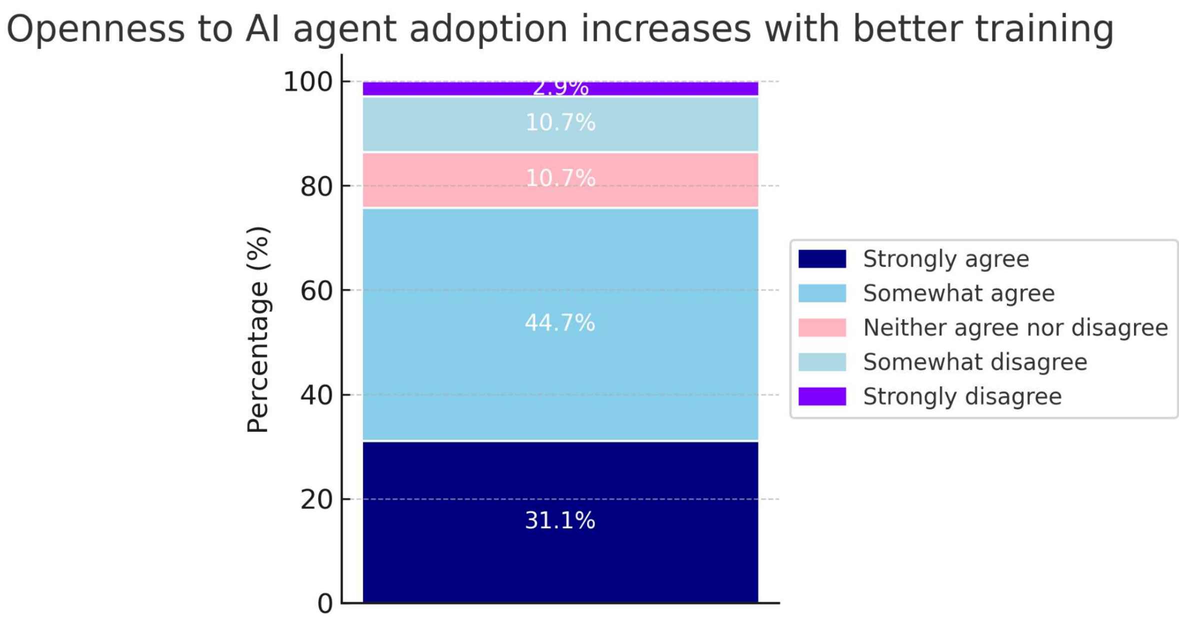


Note. Survey responses from n =112 participants.

Figure X illustrates whether better training could increase participants' willingness to adopt AI agents. The majority of respondents agreed with the statement, with 44.7% somewhat agreeing and 31.1% strongly agreeing. Only a small portion disagreed (10.7% somewhat disagree, 2.9% strongly disagree), while 10.7% remained neutral. These results suggest that improved onboarding and training could meaningfully increase openness to AI agents in the workplace.

Figure 10

Training Relevance on AI Agent Adoption



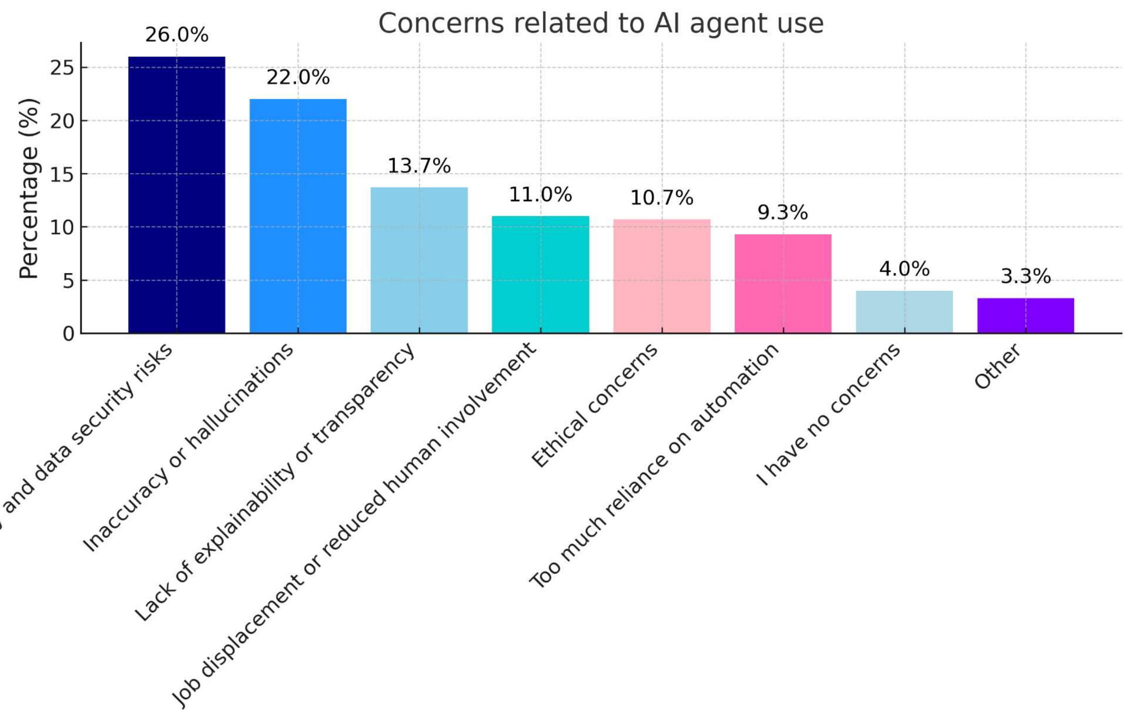
Note. Survey responses from n =112 participants.

4.2.4 Concerns of Adopting AI Agents

Figure 11 presents the key concerns participants identified regarding the use of AI agents. The most commonly reported issue among the responses were privacy and data security with 26.0%. This was followed by inaccuracy or hallucinations (22.0%), and lack of explainability or transparency (13.7%) related to the use of AI agents. Additional concerns included job displacement or reduced human involvement (11.0%), ethical considerations (10.7%), and overreliance on automation (9.3%). A small share of participants (4.0%) expressed no concerns, while 3.3% selected others, which contained environmental factors.

Figure 11

Perceived Risks and Barriers to AI Agent Adoption



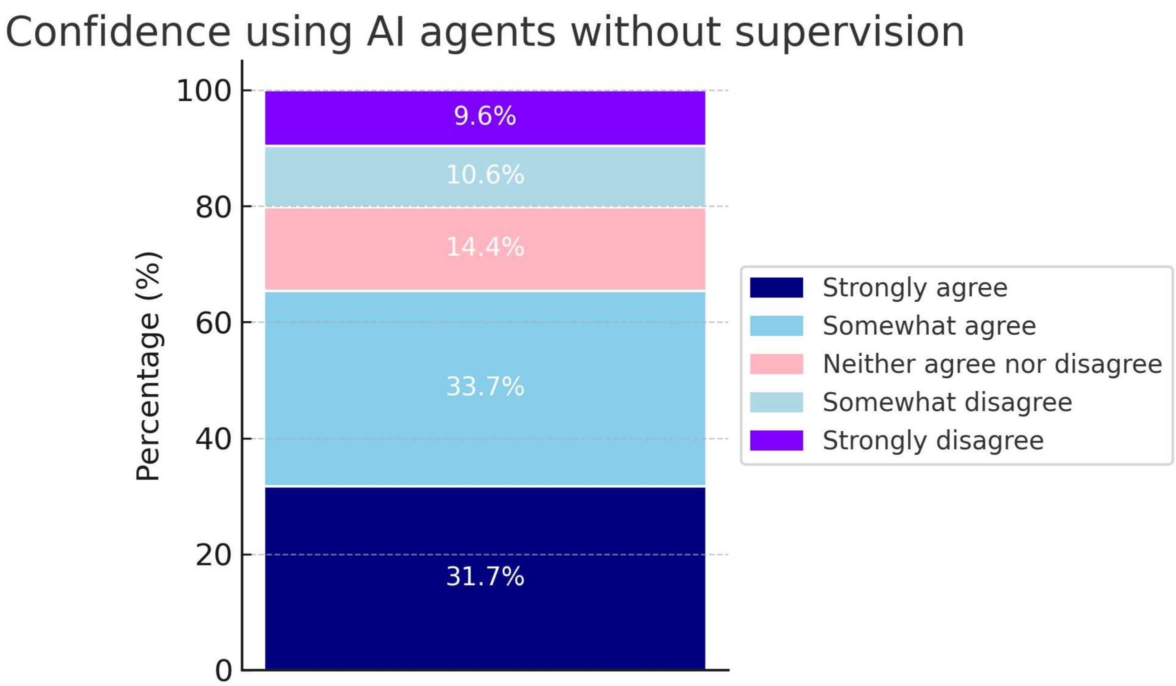
Note. Survey responses from n =112 participants.

The survey results reveal several challenges users face when working with AI agents. The most frequently reported issues were lack of trust and limited integration with other tools, each selected by 37.1% of participants. Among the respondents technical difficulties (13.3%) and cost (7.6%), were less severe. A small portion (4.8%) selected others, with open responses commonly referencing lack of accuracy as a recurring problem.

The findings of the survey indicate that most participants remain cautious about delegating important decisions to AI agents. While only 14.3% expressed clear trust, 40.0% responded "Maybe" and 39.0% said "No," reflecting widespread hesitation. The "It depends" option, selected by 6.7% of respondents, revealed that trust often hinges on the presence of human oversight and appropriate regulatory safeguards. Figure 12 explores respondents' confidence in using AI agents independently, without human oversight. While 31.7% strongly agreed and 33.7% somewhat agreed that they would feel confident using AI agents without supervision, a notable portion remained uncertain or skeptical. Specifically, 14.4% neither agreed nor disagreed, while 10.6% somewhat disagreed and 9.6% strongly disagreed.

Figure 12

Confidence in Autonomous Engagement with AI Agents



Note. Survey responses from n =112 participants.

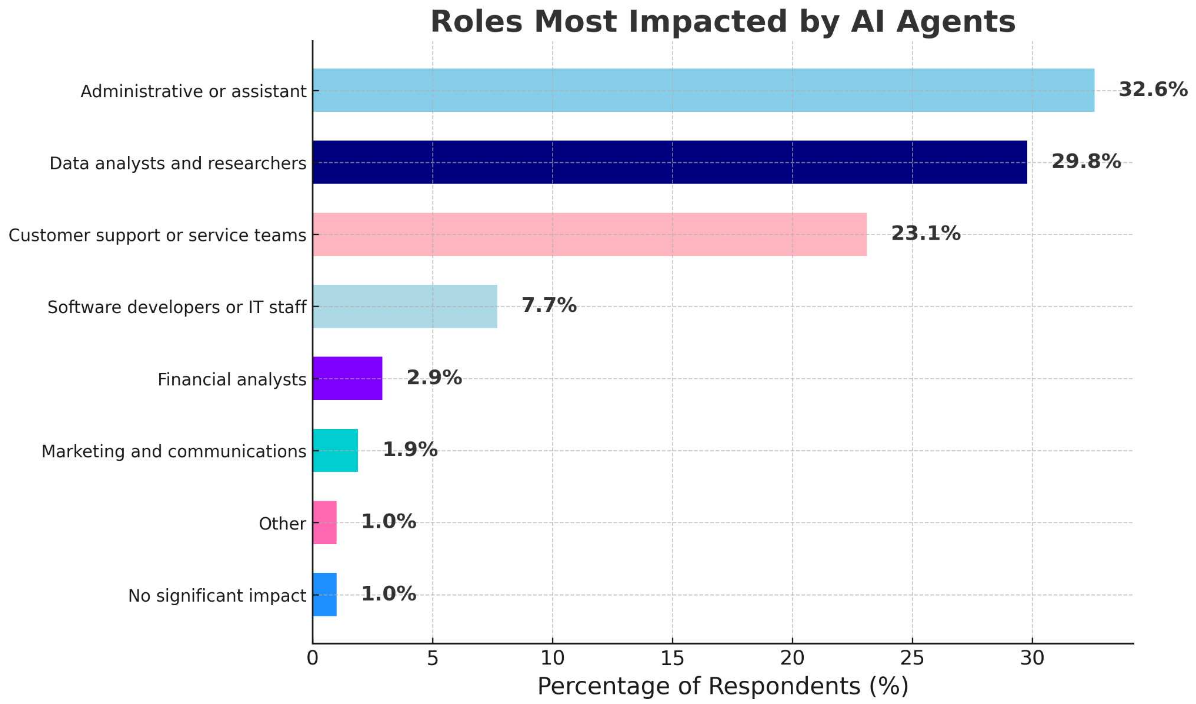
4.2.5 Impact of AI Agents on the Future workplace

The survey results show how respondents classified the innovation impact of AI agents within their organizations. The most commonly selected category was incremental innovation (30.1%), suggesting that many view AI agents as tools that enhance or optimize existing processes. Radical and disruptive innovations were each identified by 22.9% of respondents, while architectural innovation was selected by 20.7%. Only 3.4% of participants indicated uncertainty about the innovation type. Participants often selected multiple innovation types, indicating that no single classification fully captures the diverse and evolving impact of AI agents across different organizational contexts.

Figure 13 highlights the roles within organizations that respondents believe will be most affected by AI agents. The most frequently selected were administrative or assistant roles (32.6%), followed by data analysts and researchers (29.8%), and customer support or service teams (23.1%). A small fraction of respondents considered software developers or IT staff (7.7%), financial analysts or accounting professionals (2.9%), and marketing and communications roles (1.9%) to be affected or replaced by AI Agents. Only 1.0% selected "Other," and another 1.0% indicated that they do not believe AI agents will significantly impact any specific role.

Figure 13

Most Impacted Roles by AI Agents



Note. Survey responses from n =112 participants.

The survey explored participants' feelings toward the potential scenario of AI agents replacing roles such as assistants or analysts within their workplaces. Nearly half of respondents (47.6%) indicated that they would feel concerned about such a development, suggesting apprehension around job displacement or changing dynamics. A smaller share (22.9%) expressed a positive outlook, while 29.5% reported feeling neutral. The survey assessed how likely it is that AI agents will become essential tools of the participants' professional lives within the next five years. A significant portion of respondents (46.7%) considered it "very likely". An additional 32.4% viewed it as "likely," while 17.1% selected a neutral, moderate likelihood. Only the minority of respondents expressed skepticism, with 1.9% "unlikely" and just 1.0% indicating "very unlikely"

The survey asked participants how they envision AI agents evolving over the next 5 to 10 years. The most common expectation, selected by 30.7% of respondents, was that AI agents will increasingly take over tasks, reducing the need for human involvement. Meanwhile, 26.0% believed that AI agents will continue to support human work while remaining under human oversight. Another 20.2% anticipated that agents would act as intelligent collaborators working alongside humans, while an equal share expected them to become fully autonomous in many areas. A small number of respondents felt the impact of AI agents would remain limited (1.9%) or were unsure about their future trajectory (1.0%).

4.2.6 Linear Regression of AI Adoption Likelihood

To better understand the factors influencing AI agents for professionals at their workplace, a multiple linear regression analysis was conducted. The dependent variable was the self-reported likelihood that AI agents will become essential tools in the respondent's professional life within the next five years, measured on a 5-point Likert scale. A range of theoretically and empirically grounded independent variables were included, based on prior literature and survey responses. These included perceptions of usefulness, organizational encouragement, user confidence, age, income level, frequency of use, current adoption status within the organization, proficiency, and perceived job fit. The goal of the regression was to identify which variables significantly shape future adoption attitudes and to assess the overall explanatory power of the model.

Figure 14

Model Summary

Metric	Value
R-squared	0.369
Adjusted R-squared	0.341
F-statistic	12.95
F-statistic p-value	< 0.0001
Observations (N)	112

The model summary presented in Figure 14 demonstrates a good overall fit. The R-squared value of 0.369 indicates that nearly 37% of the variation in respondents' likelihood to adopt AI agents is explained by the included independent variables. The Adjusted R-squared of 0.341 confirms that the model maintains explanatory strength even when accounting for the number of variables. The regression model is statistically significant, as indicated by the F-statistic of 12.95 with a p-value below 0.001, suggesting that the combination of independent variables provides meaningful explanatory power. The analysis was based on 112 valid responses, ensuring adequate data support for the findings.

Figure 15

Regression Coefficients

Variable	Coefficient	Std. Error	p-value	Sig.

const	1.156	0.458	0.013	*
perceived_usefulness	0.598	0.096	0.000	***
org_encouragement	0.179	0.045	0.000	***
confidence	0.128	0.055	0.022	*
age	0.146	0.052	0.006	**
income	–0.086	0.037	0.022	*
usage_freq	–0.074	0.042	0.083	
org_has_adopted	~0.000	0.000	0.005	**
ai_proficiency	0.096	0.061	0.118	
job_fit	–0.152	0.063	0.016	*

$p < .05$ (*), $p < .01$ (**), $p < .001$ (***)

The individual effects of each independent variable on AI agent adoption likelihood are summarized in Figure 15. Perceived usefulness emerged as the strongest and most statistically significant predictor ($\beta = 0.60$, $p < .001$), indicating that respondents who find AI agents helpful are substantially more likely to envision their widespread future use. Organizational encouragement ($\beta = 0.18$, $p < .001$) and user confidence ($\beta = 0.13$, $p < .05$) also showed significant positive associations, suggesting that both institutional support and perceived competence with the technology play key roles in shaping adoption attitudes. Demographic factors like age ($\beta = 0.15$, $p < .01$) and income ($\beta = –0.09$, $p < .05$) were also significant. The linear regression results suggest that older respondents view AI agents more favorably, while higher income levels are associated with slightly lower adoption likelihood, potentially reflecting different exposure levels or risk perceptions. Job fit also emerged as a negative predictor ($\beta = –0.15$, $p < .05$), implying that individuals who feel AI agents are not well aligned with their current tasks may be more hesitant to adopt. Other variables, such as frequency of use and AI proficiency, did not reach conventional significance thresholds, suggesting their effects may be more context-dependent or mediated by other factors. Overall, the regression reveals that both individual perceptions and organizational context significantly shape attitudes toward future AI agent adoption.

Figure 16

Predictors of AI Agent Adoption

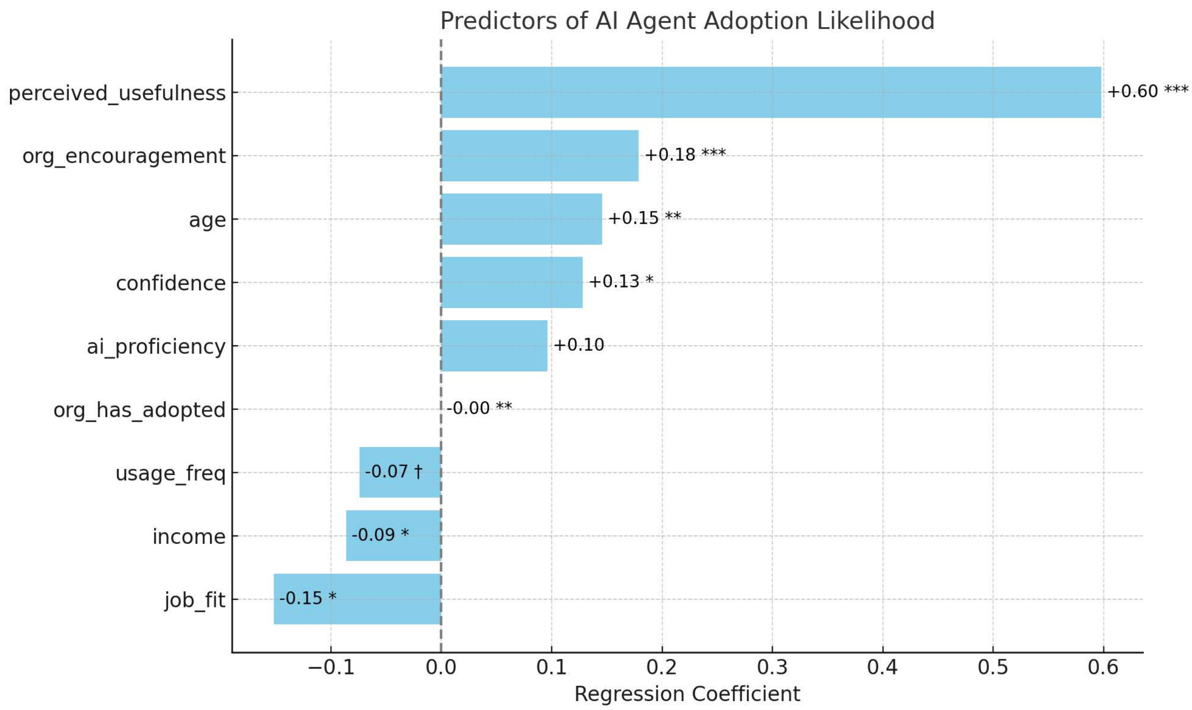


Figure 16 complements the regression table by emphasizing both the direction and relative strength of effects, making it easier to interpret which factors most strongly drive or inhibit AI agent adoption.

4.2.7 T-test Comparison of AI Agent Adoption Across Industries

To assess the influence of industry background on AI agent adoption, this study compared the responses of Finance/FinTech professionals to those from other sectors. Specifically, we tested whether professionals working in financial services exhibit different levels of adoption likelihood. An independent sample t-test was conducted comparing the mean scores of AI agent adoption likelihood between the respondents who are currently employed in Finance/FinTech compared to other industries.

Figure 17

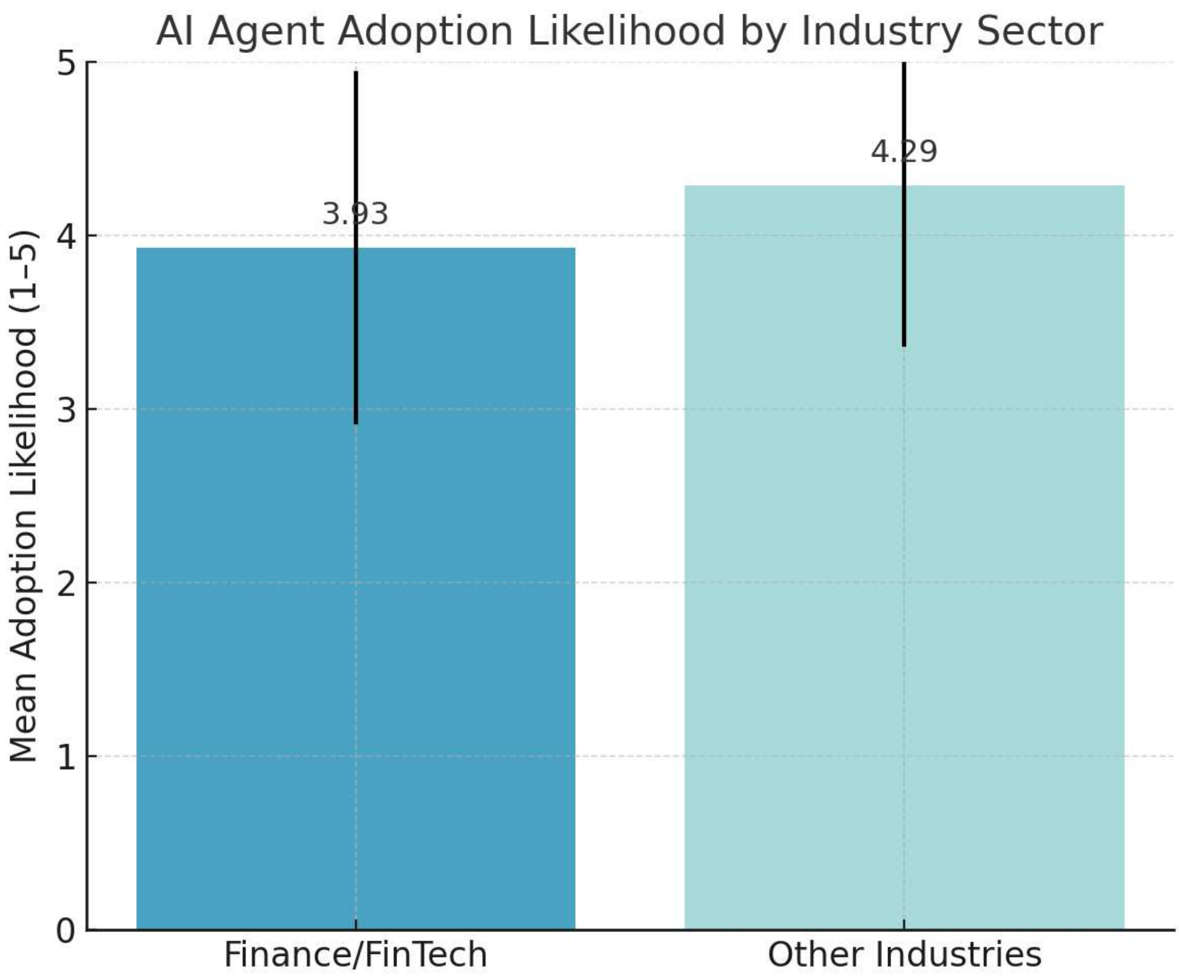
Independent Samples T-test

Group	**M**	**SD**	**n**	**df**	**t**	**p**	**Cohen's *d***
FinTech	3.93	1.02	28	44.0	–1.63	.110	–0.37
Other	4.29	0.93	77				

Welch's t-test was used due to unequal variances between groups. Although the difference was not statistically significant ($p = .110$), the medium effect size (Cohen's $d = –0.37$) suggests that professionals in Finance/FinTech sectors may be more hesitant to adopt AI agents compared to other industries.

Figure 18

AI Agent Adoption Likelihood by Industry



Although the t-test did not reveal a statistically significant difference ($p > .110$) in adoption likelihood between Finance/FinTech professionals compared to other sectors, the slightly lower mean score among the former may reflect the concerns around trust, risk, and regulatory compliance. In high-stakes environments like FinTech, perceived trust and explainability may play a disproportionately important role in shaping openness to AI agent adoption.

5. Conclusion

The final chapter summarizes main findings, addresses key limitations, discusses the broader theoretical implications, and points to possible directions for future research.

5.1 Summary of Key Findings

The findings from previous chapters, triangulating literature, expert interviews, and survey data, provide a solid foundation to assess the adoption of AI agents.

5.1.1 Individual and Organizational Readiness

The successful adoption of AI agents is strongly influenced by both individual competence and organizational infrastructure. As the findings reveal, technological readiness alone is insufficient without the support of internal expertise, governance mechanisms, and user engagement strategies. Expert interviewees from traditional institutions (IV1, IV2, IV4, IV8) highlighted legacy systems, poor data integration, and lack of interoperability as major technical barriers to deployment, while it remains critical challenges in the context of digital infrastructure limitations (Wang et al., 2023). Additionally, IV5 emphasized that cloud-native infrastructure and built-in compliance tools are essential for ensuring traceability and auditability in responsible AI systems (Floridi & Cowls, 2022).

Beyond infrastructure, organizational culture and internal governance emerged as key challenges. Resistance to change, limited understanding of AI processes, and concerns over job displacement were raised by IV3, IV6, and IV9. These concerns mirror the broader literature on Responsible AI, as it emphasizes transparency, accountability, and clear human oversight mechanisms as crucial to trust and adoption (Retzlaff et al., 2023). In addition, the survey results indicated that over 85% of participants expressed hesitation or concern about delegating decisions to AI agents.

Survey results also confirmed that individual preparedness is a critical determinant. A substantial 75.8% of respondents agreed they would adopt AI agents more readily with improved training or onboarding, while user confidence was a statistically significant predictor in the regression model ($\beta = 0.13$, $p < .05$). These findings support the view that user literacy and system explainability are core pillars of ethical AI deployment (Mikalef et al., 2022).

5.1.2 Drivers of AI Agent Adoption

The results show that the adoption of AI agents is primarily motivated by their ability to enhance efficiency, accuracy, and adaptability. Survey data revealed that perceived usefulness was the strongest predictor of adoption likelihood ($\beta = 0.60$, $p < .001$). This result is supported by the Technology Acceptance Model (TAM), which suggests that perceived usefulness and ease of use are key drivers of adoption (Davis, 1989). Additionally, the regression analysis findings highlighted the importance of organizational encouragement ($\beta = 0.18$, $p < .001$) in driving AI agent adoption. These quantitative insights highlight that both institutional support and individual capability are central to accelerating agent adoption in the workplace (Holmström, J. 2021).

In addition, IV1, IV2, IV4, and A1 emphasized the role of AI agents in streamlining high-volume processes, such as onboarding, document verification, fraud detection, and customer support. IV4 also indicated the growing use of generative agents in HR and complaint management, allowing organizations to scale operations without proportional increases in cost or personnel. These applications align with broader findings in the literature, which highlight AI's capacity to improve productivity, responsiveness, and decision-making accuracy (Feuerriegel et al., 2023). However, the regression results show a negative association between job-task fit and adoption likelihood (-0.15, $p < 0.05$), indicating that when AI agents are not well aligned with specific tasks, their integration into such operational workflows may face greater resistance.

The strategic pressure to innovate was identified by IV1, IV2, and A4 as an increasingly important driver, with organizations often adopting AI agents reactively out of fear of falling behind. This behavior aligns with the concept of digital urgency, as it's commonly observed in rapidly evolving sectors (Parviainen et al., 2017). Additionally, the survey data supports this view, as 34.3% of respondents selected technological motivations and 31.8% identified strategic factors as key incentives to remain competitive.

Scalability and modularity were also cited as core enablers. IV4, IV6, and A2 described AI agents as modular systems capable of integrating across decentralized workflows, allowing for responsive and adaptive automation. This aligns with emerging literature that highlights agent-based architectures as a foundational advancement in the development of intelligent, adaptive systems across complex organizational environments (Zhou et al., 2024).

5.1.3 Strategic Insights for the FinTech Sector

The findings emphasize how financial institutions are approaching AI agent adoption, not only as a tool for efficiency but as a means to navigate increasing complexity, regulatory scrutiny, and competitive pressure. Across both the survey and expert interviews, it became evident that AI agents are being strategically positioned to support a variety of core financial operations, particularly in domains where precision, speed, and compliance are critical.

One of the most prominent application areas identified across both expert interviews and survey responses was fraud detection and transaction monitoring, where AI agents are increasingly used to flag suspicious behavior in real time, reduce false positives, and adapt to evolving threat patterns (PwC & Stop Scams UK, 2023). Additionally, IV3 and IV6 emphasized the value of AI agents in phishing detection, behavioral risk analysis, and automated fraud analysis, highlighting their effectiveness in processing large volumes of transactional and user data. IV3 also highlighted the increasing use of AI agents in Know Your Customer (KYC) verification and anti-money laundering (AML), while IV8 emphasized their expanding role in regulatory compliance monitoring. These insights align with existing literature on the capacity of intelligent automation to enhance response speed, reduce manual intervention, and support risk-heavy operations through adaptive, high-frequency analysis (Herrmann & Masawi, 2022).

Another high-impact area is credit scoring and lending processes, where agents can analyze large datasets, simulate different repayment scenarios, and offer dynamic, context-sensitive recommendations (Kumar et al., 2022). Expert interviews indicated that vertical agents are particularly effective in this space, while survey respondents cited decision quality and predictive capabilities as key motivators for adoption. These use cases reflect how AI agents can enhance financial decision-making in areas with strict performance and fairness requirements (Kokotajlo et al., 2025). Additionally, the interview findings showcased the AI agent's significant role in process integration. Their modularity and adaptability allow institutions to deploy them incrementally, reducing the need for large-scale system overhauls while supporting long-term digital transformation (Álvarez-Teleña & Díez-Fernández, 2024).

While AI agents are being strategically adopted in FinTech to address operational complexity and enhance core functions, the survey results indicate that professionals in the sector may still approach adoption with caution. A Welch's t-test revealed no statistically significant difference in adoption likelihood between Finance/FinTech professionals and other sectors (p

= .110), yet the medium effect size (Cohen’s d = –0.37) underlined the strong sensitivity to trust, risk, and regulatory compliance, which remain central concerns in the FinTech sector (PwC & Stop Scams UK, 2023).

5.1.4 Risks and Challenges of Adoption

While AI agents offer clear benefits, their adoption is constrained by several technical, organizational, and regulatory challenges. Across interviews and survey responses, concerns about inaccuracy and hallucinations remain the dominant issue. 22.0% of survey respondents selected this as the main risk with AI agents, while IV6, A1, and A4 also emphasized the dangers of unreliable outputs, particularly in sensitive domains. Hallucinations and inaccurate outputs were identified as key challenges AI agents currently face (Bai et al., 2025). Explainability was also identified as a core issue, with 13.7% of respondents raising concerns, and IV3 and A2 underscore the need for transparent, auditable agent behavior. Additionally, the lack of transparency challenges regulatory alignment and trust remains critical (Floridi & Cowls, 2022). Among the survey participants, privacy and data security risks were the most concerning factor (26.0%), particularly when agents operate across systems with sensitive and large datasets.

Organizational barriers were equally critical. IV3, IV6, and IV9 described resistance to change, lack of AI literacy, and job insecurity as major obstacles. Job insecurity was also emphasized as a key barrier to adoption by the survey findings, where 47.6% of participants expressed concern about AI agents replacing roles at their workplace. Additionally, IV3 and IV9 stressed the need for systems that are auditable, explainable, and adaptable to new legal requirements. These findings suggest that the integration of the EU AI Act could become a key driver for institutions to embed governance into their digital infrastructure (Grace et al., 2024).

5.1.5 Broader Perceptions and Outlook

The study reveals a broadly positive outlook on the future of AI agents. Survey results show that 79.1% of respondents consider their widespread adoption likely, while only a small fraction expressed doubt. IV4, IV5, and A4 described AI agents as critical components of future infrastructures, especially due to their adaptability and modular design. These agents are expected not only to support but to increasingly coordinate tasks, serve as intermediaries between systems, and evolve into strategic collaborators (Gürpinar, 2025).

Participants held mixed views on agent autonomy. While 30.7% expected agents to reduce the need for human involvement, 46.2% envisioned them as enhancing or collaborating with human workflows. However, IV2 and IV6 emphasized the continued importance of human oversight, explainability, and strategic supervision, especially in regulated environments. These perspectives align with academic discussions on responsible AI, which highlight the risks of premature autonomy and the necessity of maintaining human-in-the-loop systems to ensure accountability and control (Floridi & Cowls, 2022). The literature increasingly frames this as a transitional phase, where agents act as collaborators rather than autonomous decision-makers (Cheong et al., 2024).

Despite growing momentum, perceptions of readiness remain uneven. Some interviewees highlighted strong technical preparedness, while IV1 and IV3 pointed to organizational hesitation, regulatory uncertainty, and cultural resistance as key barriers to adoption. Consequently, successful integration depends not only on technical capability but also on cultural and ethical alignment (Gürpinar, 2025). Finally, the expert interviews emphasized the importance of gradual deployment strategies for AI agents, as such approaches support smoother integration and help mitigate associated risks. This insight aligns with the organizational readiness, as it remains a critical factor in enabling effective AI integration and fostering innovation adoption (Mikalef et al., 2022).

5.2 Limitations

This study acknowledges several limitations stemming from both the qualitative expert interviews and the ongoing quantitative survey. While the mixed methods design offered a comprehensive view of AI agent adoption in FinTech, certain methodological and contextual constraints may affect the generalizability and interpretive depth of the findings.

5.2.1 Expert Interviews

The expert interviews faced various methodological limitations that may affect the breadth and generalizability of findings. The study pose selection bias, as the sample consisted of 13 participants, primarily based in Europe and selected through targeted outreach, which may limit the representation of the broader FinTech and AI agents ecosystem. The inclusion of AI language models as participants added conceptual richness but lacked lived professional experience, creating an imbalance in experiential perspectives. The semi-structured format and thematic analyses approach may have shaped how responses were framed and analyzed, resulting in interpretation bias. Although participants were highly experienced, variation in professional roles and levels of hands-on engagement with AI agents might have influenced the consistency and depth of the insights provided. The rapid development of AI agent technologies limits the long-term relevance of the interview findings, as current insights may quickly become obsolete.

5.2.2 Survey

The survey design and sampling approach may affect the generalizability and validity of its findings. The response rate was 73.33%, as only 112 out of 150 respondents fully completed the survey, raising concerns about nonresponse bias. Although the survey was widely distributed, the homogeneity of the final sample reflected a demographically narrow group, with most participants aged between 25 and 34 and holding a master's degree. The sample reflects characteristics of WEIRD populations, (western, educated, industrialized, rich, and democratic), which may have limited the diversity of perspectives and poses a risk to the broader generalizability of the findings (Henrich et al., 2010). The use of Likert scales, while effective for quantifying perception, is prone to acquiescence bias and may influence perception toward AI agent adoption. The reliability and consistency of the collected data may have been affected by variation in response quality due to the lack of researcher supervision.

5.3 Future Research

While this study offers a comprehensive exploration of AI agents in the FinTech sector, several areas remain underexplored and warrant further research. First, more empirical data is needed from financial institutions actively deploying AI agents. As adoption is still in its early stages, future studies should investigate real-world use cases, performance outcomes, and integration challenges to enrich the academic and practical understanding of these systems. Additionally, further exploration is required into the governance of AI agents, particularly within multi-agent ecosystems operating in high-stakes environments such as central banking, DeFi, and algorithmic trading. Research should assess how decentralized coordination, agent collaboration, and autonomous planning function at scale, and how regulatory frameworks like the EU AI Act can support transparency, accountability, and safety in these systems. Future work should continue to examine the ethical and socio-economic implications of AI agents, especially regarding fairness, accessibility, and the impact on employment. Large-scale or longitudinal studies could help clarify how issues like hallucination, bias, and explainability manifest in practice and how they vary across domains and user groups. The evolving nature of human–agent collaboration requires deeper observation. As AI agents shift from task executors to strategic collaborators, it is essential to understand how trust, decision authority, and responsibility are shared in hybrid systems. Research on interface design, explainable AI outputs, and onboarding practices will be key to ensuring responsible and user-aligned deployment.

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7. Appendices

7.1 Appendix A – Survey Guide

Table 2

Survey Design

x	Question	Type	Answer option
Demographics			
Q1	What is your age?	Multiple Choice	Under 25; 25–34; 35–44; 45–54; 55-64
Q2	What is your gender identity?	Multiple Choice	Male; Female; Non-binary/Other; Prefer not to say
Q3	What is the highest level of education you have completed?	Multiple Choice	High school or less; Bachelor's degree; Master's degree; PhD/Doctorate; Other
Q4	What industry do you currently work in?	Multiple Choice	Finance/FinTech; Tech/IT; Retail & E-commerce; Healthcare; Education; Government / Public services; Creative industries (e.g., media, design); Other
Q5	What is the size of the company you currently work at?	Multiple Choice	1-10 employees; 11-50 employees; 51-200 employees, 201-500 employees; 501+ employees
Q6	What is your annual gross income range?	Multiple Choice	Less than 20,000 Euro; 20,000 Euro - 40,000 Euro; 40,000 Euro - 60,000 Euro; 60,000 Euro - 80,000 Euro; More than 80,000 Euro
Use of AI Agents			
Q7	How familiar are you with AI agents?	Multiple Choice	Not familiar at all; Slightly familiar; Moderately familiar; Very familiar; I use them regularly
Q8	Which AI agents do you use? (Select	Multiple Choice	ChatGPT (OpenAI);

	all that apply)		Gemini (Google DeepMind); Siri (Apple); Perplexity AI; Alexa (Amazon); None; Other:
Q9	How often do you use AI agents in your work?	Multiple Choice	Daily; 4–6 times a week; 2–3 times a week; Once a week; Never
Q10	What are your main reasons for using AI agents? (Select all that apply)	Multiple Choice	To automate repetitive or routine tasks; To improve the speed and quality of decision-making; To enhance productivity and reduce workload; To gain insights from large or complex data; To improve customer or user experiences; I don’t see a need for AI agents; Other:
Q11	How proficient are you with using AI agents?	Multiple Choice	1 (Beginner); 2 (Novice); 3 (Intermediate); 4 (Advanced); 5 (Expert)
Q12	How useful do you find AI agents in your daily work?	Multiple Choice	Not at all; Slightly useful; Moderately useful; Very useful; Extremely useful
Q13	Using AI agents helps me… ...save time on repetitive tasks; ...work more efficiently overall; ...make better decisions; ...focus on higher-value or creative work; ...complete tasks I wouldn’t otherwise be able to	5-Point Likert Scale	Strongly Disagree; Somewhat Disagree; Neither agree nor disagree; Somewhat Agree; Strongly Agree
Adoption of AI Agents			
Q14	Has your organisation already adopted AI agents?	Multiple Choice	Yes, they are actively used; Yes, but only in a limited or pilot phase; No, but adoption is being

			considered; No, there are no plans to adopt AI agents; I’m not sure
Q15	What would be the main factors driving the adoption of AI agents in your organisation today? (Select all apply)	Multiple Choice	Technological; Strategic; Economic; Cultural; Other:
Q16	Please rank the following factors based on their impact on AI agent adoption (1 = most important, 6 = least important):	Ranking Order	Efficiency; Risk management; Trust / Explainability; Cost; Governance; Organisational readiness
Q17	Please indicate how much you agree with the following statements about adopting AI agents in your work environment: My organisation encourages the use of AI agents; I feel confident using AI agents without supervision; I would adopt AI agents faster if they were better tailored to my job tasks; I'm more likely to adopt AI agents if others around me use them; I trust AI agents more when I understand how they work; I would be more open to adoption if I received better training or onboarding	5-Point Likert Scale	Strongly Disagree; Somewhat Disagree; Neither agree nor disagree; Somewhat Agree; Strongly Agree
Perception and Trust			
Q18	Do you have concerns about using AI agents? (Select all that apply)	Multiple Choice	Privacy and data security risks; Inaccuracy or hallucinations; Ethical concerns (e.g., bias, fairness); Job displacement or reduced human involvement; Lack of explainability or transparency; Too much reliance on automation; I have no concerns; Other:
Q19	What would most encourage you to use AI agents more?	Multiple Choice	Better accuracy; More control and customisation; Organisational support; Improved user experience; Integration with my existing tools or systems;

Q20	What are the biggest challenges you face when using AI agents?	Multiple Choice	Technical difficulties; Cost; Lack of integration with other tools; Lack of trust; Other:
Q21	Imagine a situation where AI agents make important decisions, like choosing investments or evaluating someone's credit score. Would you feel comfortable trusting their results?	Multiple Choice	Yes; Maybe; No; It depends (please explain):
Q22	Imagine that AI agents start taking over roles like assistants or analysts at your workplace. How would you personally feel about this?	Multiple Choice	Concerned; Neutral; Positive; Not applicable
Future Role			
Q23	How would you classify the innovation impact of AI agents? (Select all that apply)	Multiple Choice	Incremental innovation; Disruptive innovation; Architectural innovation; Radical innovation; Not sure
Q24	On a scale of 1–5, how likely is it that AI agents will become essential tools in your professional life within the next 5 years?	Star Rating	1 (Very unlikely); 2; (Unlikely) 3; (Moderate) 4; (Likely) 5 (Very likely)
Q25	Which roles in a company do you think will be most impacted by AI agents?	Multiple Choice	Administrative or assistant roles; Customer support or service teams; Data analysts and researchers; Marketing and communications; Software developers or IT staff; Middle management and decision-making roles; Human resources or recruiting; Financial analysts or accounting professionals; I don’t think AI agents will significantly impact roles; Other:
Q26	Do you believe AI agents will eventually take on decision-making responsibilities without human supervision?	Multiple Choice	Yes; Maybe; No; It depends (please explain):
Q27	In the next 5–10 years, how do you	Multiple Choice	They will enhance human work

	think AI agents will evolve?	but remain under control; They will take over many tasks and reduce the need for some roles; They will work alongside humans as intelligent collaborators; They will become fully autonomous in many areas; Their impact will remain limited; Not sure

7.2 Appendix B – Interview Guide

Table 3

Interview Questions

#	**Interview Question**
Q1	Could you briefly introduce yourself and your current role? What is your professional background in AI, FinTech, or related fields?
Q2	How familiar are you with the concept of AI agents, and how would you describe them based on your experience? – Have you worked directly with agent-based systems or designed agent-driven solutions?
Q3	What types of AI agents (e.g., learning, generative, horizontal, vertical) are you most familiar with or consider most relevant today?
Q4	What are the main factors driving the adoption of AI agents in organizations today? – Are these mostly technological, strategic, economic, or cultural?
Q5	From your perspective, what are the defining characteristics of an effective AI agent? – What capabilities (e.g., autonomy, adaptability, or learning) are essential?
Q6	Why do you think AI agents should interact with other agents in real-world systems? – What could make this interaction more effective or challenging?
Q7	What are the main reasons AI agents are currently being applied in financial services or

related industries? What are the specific areas they're being deployed?

Q8	What role do you see for generative AI and multi-agent systems in the development of agent-based solutions in finance?
Q9	Do you believe FinTech firms are prepared technologically and organizationally to adopt AI agents at scale? What factors enable or hinder this adoption?
Q10	Why do you think AI agents should be used in FinTech instead of traditional AI systems? – Do they offer more strategic, real-time, or autonomous decision-making benefits?
Q11	What do you see as the biggest risks associated with the deployment of AI agents? – More specifically, in the FinTech sector? – Are you concerned about issues such as transparency or hallucination?
Q12	What governance mechanisms should be in place to ensure AI agents operate responsibly? – Should oversight be embedded in the system design, handled externally, or both?
Q13	How do you see the evolution of AI agents in 5–10 years from now? – What capabilities do you think they will develop next, particularly within the financial sector?
Q14	How do you envision the potential role of Artificial Superintelligence (ASI) in shaping the future of AI agents?
Q15	Which roles within organizations do you think AI agents could eventually take over? Or should AI agents remain only an assistive tool under human control?
Q16	What areas do you believe will be most disrupted or transformed by AI agents in the future? - Do you see this change as mostly positive, or are there potential downsides?
Q17	What advice would you offer to companies developing or deploying AI agents today?

7.3 Appendix C – Interview Summaries

Table 4

Interview Summary of IV1

Code: IV 1	**Mode: Virtual**
Date: 22.03.2025	**Duration: 1 hour 10 minutes**

Questions	**Summary**
Q2	Defines AI agents as advanced tools for specific tasks, familiarChatGPT, DeepSeek. Differentiates between general tools and true autonomous agents, past experience designing self-learning fraud detection systems.

Q3	Most familiar with horizontal and vertical agents. Stresses relevance of multi-agent systems in regulated environments for verifiability and structured operations.
Q4	Adoption driven by innovation pressure, curiosity, and need for efficiency. Notes social and organizational trends rather than purely technological motivation.
Q5	Effective agents must be precise, predictable, and transparent. Should handle repetitive or structured tasks, creative or judgment-based tasks should remain with humans.
Q6	Agent interaction enhances traceability in multi-agent systems. However, changes in APIs or internal flows may cause errors. Transparency concerns arise when agents bypass standard protocols.
Q7	AI agents applied in fraud detection, instant transaction scoring, customer service, invoice processing, and regulatory reporting due to speed and cost-efficiency.
Q8	Multi-agent systems are essential for transparency and compliance. Black-box systems not suitable for finance, agent collaboration allows step-by-step process auditability.
Q9	Tech readiness exists, but organizational barriers (e.g., resistance to change, lack of understanding) hinder adoption. Multi-agent systems can ease integration through human oversight.
Q10	AI agents offer dynamic adaptability over static traditional systems. Agents enable breakdown of complex processes and improve regulatory alignment.
Q11	Key risks include hallucination, training data bias, and lack of transparency. Concerned about reliance on AI-generated content and output manipulation.
Q12	Strong preference for embedded governance. Recommends detailed system diagrams and multi-agent setups for transparency. Black-box models deemed non-viable under audit.
Q13	Uncertain future, AI agents may enhance efficiency or spread misinformation. Predicts automation of manual roles, but stresses importance of boundaries.
Q14	ASI could act outside human interest if not regulated. Emphasizes the need for strict moral and operational constraints.
Q15	Supports agent involvement in manual and structured roles. Tasks involving emotion or strategy should remain human-led. Full autonomy is seen as risky.
Q16	Expects disruption in customer service and media. Predicts potential misinformation issues. Believes regulatory oversight will shape outcomes.
Q16	Advises prioritizing multi-agent systems, step-by-step tracking, and auditability. Warns against relying on opaque or untraceable tools in finance.

Table 5

Interview Summary of IV2

Code: IV 2	**Mode: Virtual**
Date: 29.03.2025	**Duration: 50 minutes**
Questions	**Summary**
Q2	Defines AI agents as autonomous systems that process input and perform tasks. Builds models with similar behavior through self-supervised learning, though not traditional agents.
Q3	Most familiar with learning based systems. Understands horizontal and vertical agents conceptually and highlights growing interest in multi agent structures and self supervised learning in AI development.
Q4	Economic efficiency and technological momentum are main drivers. Notes companies adopt AI to reduce operational costs and stay competitive amidst rapid innovation trends.
Q5	Highlights adaptability and decision-making as critical capabilities. Effectiveness depends on context (e.g., saving time, money, or improving UX). Warns against excessive autonomy without proper oversight.
Q6	Believes agent interaction enables complexity but carries risks. One agent's hallucination or error can influence others. Stresses need for human oversight and system-level monitoring in collaborative environments.
Q7	AI agents are applied in fraud detection, customer support and algorithmic trading. Cites improvements in cost reduction speed and consistency. Notes that customers often prefer chatbots in certain service situations.
Q8	Sees potential for generative AI fine tuned on financial data to become useful assistants. Multi agent systems can coordinate across fraud trading and support but training quality and human feedback remain essential.
Q9	Organization readiness varies. Adoption depends on infrastructure and willingness to implement oversight. Emphasizes the importance of balancing control with automation especially in sensitive financial contexts.
Q10	Agents provide more autonomy and real-time adaptability than traditional systems. Best used as support tools with human guidance in key processes.
Q11	Hallucinations in multi agent systems. Expresses concern over false data propagation source fabrication and autonomous misinformation when agents influence one another.
Q12	Supports a mix of internal and external governance. Suggests human-in-the-loop systems, pre-release testing, and source citation for transparency.

Q13	Expects agents to evolve through foundation models that can be fine-tuned for finance. Anticipates better cooperation and fewer hallucinations over time.
Q14	ASI could exceed human control and require new oversight systems. AI potentially will monitor other AI in such future scenarios.
Q15	Agents could take over routine and analytical tasks but should remain assistive in areas involving trust, empathy, or judgment, especially in finance.
Q16	Predicts major impact in customer service, policy analysis, and modeling. Outcomes depend on governance and how autonomy is balanced with accountability.
Q16	Advises companies to prioritize quality training, human oversight, and long-term trust. Recommends testing and feedback before deploying at scale.

Table 6

Interview Summary of IV3

Code: IV 3	**Mode: Virtual**
Date: 02.04.2025	**Duration: 57 minutes**
Questions	**Summary**
Q2	Understands AI agents as autonomous systems that respond to inputs. Has worked with agent-based setups for behavior monitoring, threat detection, and automated response.
Q3	Most experienced with vertical and rule-based agents used in cybersecurity. Emphasizes their value in task-specific applications like fraud detection and anomaly tracking.
Q4	Adoption driven by the need for scale, speed, and operational efficiency. Agents reduce manual workloads and outperform analysts in high-volume environments.
Q5	Effective agents should be reliable, minimize false positives, and remain under control. Autonomy is useful but only if paired with accuracy and predictability.
Q6	Inter-agent communication improves detection (e.g., linking authentication and behavioral systems). Highlights the risk of cascading errors without secure integration.
Q7	AI agents widely used in fraud detection, AML, KYC, and customer support. Their ability to process large datasets in real time is a key benefit in finance.
Q8	Sees potential in generative AI for simulating fraud and training models. Multi-agent systems are essential for coordinating between tasks like compliance and risk analysis.
Q9	FinTech firms often have the technology but face internal barriers—risk aversion, unclear regulations, and cultural resistance hinder large-scale adoption.

Q10	Believes AI agents are more adaptive than static traditional AI. Agents respond to behavioral changes in real time, improving personalization and security.
Q11	Key risks include over-reliance, opacity, and poor training data. Hallucination is especially concerning in critical contexts like finance and cybersecurity.
Q12	Recommends embedded audit trails, fallback mechanisms, and full traceability. Stresses the need for systems that allow human intervention during anomalies.
Q13	Predicts more specialized and collaborative agents across financial processes—from onboarding to fraud monitoring. Expects tighter integration and task sharing.
Q14	Views ASI as a theoretical possibility that would require new governance systems. Until then, focus should remain on safe deployment of narrow/general agents.
Q15	Believes agents will replace routine analytic roles, such as triaging and reporting. Client-facing and high-empathy roles should remain human-led.
Q16	Sees major disruption in cybersecurity and finance, and potentially legal and HR. Emphasizes that outcomes will depend on how governance is built in.
Q16	Recommends gradual deployment, strong tracking, and auditability. Warns against deploying opaque systems and stresses the importance of human fallback.

Table 7

Interview Summary of IV4

Code: IV 4	**Mode: Virtual**
Date: 09.04.2025	**Duration: 45 minutes**
Questions	**Summary**
Q2	Sees AI agents as autonomous, task-oriented systems that integrate across departments. Designs agents to operate independently while interacting with users and data platforms.
Q3	Most experienced with horizontal and generative agents. Believes these are key for large organizations needing scalable and secure enterprise-wide automation.
Q4	Adoption is driven by the need for efficiency, scalability, and innovation, especially in highly competitive and regulated industries like banking.
Q5	Effective agents must scale, integrate with backends, manage data securely, and be well documented. Flexibility and adaptability across functions are critical.
Q6	Cross-agent communication is vital for complex workflows. However, risks arise if interactions aren't traceable, since errors can multiply across systems.

Q7	AI agents are used in onboarding, customer service, and internal support. Banks already use them for HR, sales support, and complaint categorization.
Q8	Generative AI supports personalization, while multi-agent systems ensure modular, scalable deployment across departments. Both are key to enterprise automation.
Q9	FinTech firms face readiness issues due to fragmented data, legacy infrastructure, and employee resistance. Cloud adoption and data hygiene are critical enablers.
Q10	Prefers AI agents over traditional systems for their modularity, real-time responsiveness, and ability to connect workflows across business units.
Q11	Major concerns include data leakage from cloud models and hallucinations from generative tools. Emphasizes the need for human review of outputs.
Q12	Suggest traceable logs, internal audits, and EU AI Act compliance. Advocates for both embedded oversight and external governance mechanisms.
Q13	Envisions full automation of routine tasks like invoicing and reporting. Human roles will evolve toward quality control and exception handling.
Q14	While not a central focus, he noted that greater autonomy will require strong oversight. Future agents must be regulated to ensure safety.
Q15	Thinks agents will replace admin, HR, and support roles. However, tasks involving empathy, judgment, or strategic decisions should stay human-led.
Q16	Expects disruption in admin, finance, and customer service. Sees positive transformation if firms prepare data, infrastructure, and workforce early.
Q16	Advises companies to begin with system audits and structured data collection. Recommends starting small, involving staff, and scaling gradually.

Table 8

Interview Summary of IV5

Code: IV 5	**Mode: Virtual**
Date: 12.04.2025	**Duration: 1 hour 15 minutes**
Questions	**Summary**
Q2	Views AI agents as autonomous systems that retrieve and process data. Supports them indirectly by providing secure and scalable infrastructure.
Q3	Familiar with domain-specific and foundational agents. Clients use vertical agents for specialized automation within enterprise environments.
Q4	Adoption driven by revenue goals and workflow efficiency. ISVs build AI agents to

	scale services, while enterprises aim to reduce manual effort.
Q5	Effective agents must be fast, scalable, and secure. Emphasizes hosting reliability and integration with enterprise data systems.
Q6	Supports agent interaction through APIs and shared infrastructure. Highlights the importance of security and interoperability in multi-agent setups.
Q7	Applied in CRM support, task automation, and data retrieval. Finance firms use agents to improve speed and reduce operational workload.
Q8	Generative and multi-agent systems help streamline product development. Oracle provides infrastructure that enables their commercial deployment.
Q9	FinTech adoption depends on cloud maturity. Firms need autonomous databases and technical readiness, which many still lack.
Q10	Agents offer real-time automation and reduce operational costs. Seen as more dynamic than static AI systems in enterprise decision-making.
Q11	Risks tied to data integrity and infrastructure reliance. Without secure environments and trusted sources, agents may generate errors.
Q12	Advocates built-in governance within cloud systems. Emphasizes traceability, secure deployment, and tools for oversight and compliance.
Q13	Expects agents to become embedded in enterprise systems and sold as services. Sees wider adoption as firms realize operational gains.
Q14	The increased autonomy will require human oversight to ensure safe deployment.
Q15	Agents likely to handle repetitive internal tasks like CRM queries. Strategic and human-facing roles expected to remain under human control.
Q16	Predicts disruption in enterprise workflows and internal operations. Believes change will be positive but may reduce headcount in some areas.
Q16	Recommends early cloud adoption and investment in infrastructure. Strong foundations help scale AI agents securely and efficiently.

Table 9

Interview Summary of IV8

Code: IV 6	**Mode: Virtual**
Date: 17.04.2025	**Duration: 1 hour 3 minutes**

Questions	Summary
Q2	Defines agents as autonomous systems capable of learning and decision-making. Has built rule- and learning-based agents for fraud detection and behavioral analysis.
Q3	Most familiar with vertical, self-learning, and API-integrated agents used in security contexts. Values task-specific precision and adaptability in real-time.
Q4	Adoption driven by security needs, scalability, and compliance demands. Real-time detection and cost reduction are key motivators for deploying AI agents.
Q5	Highlights low false-positive rates, learning ability, and transparency. Effective agents must integrate well and generate auditable, trustworthy outputs.
Q6	Multi-agent interaction boosts coverage across systems (e.g., phishing to transaction flow). But miscommunication can trigger cascading errors if not monitored.
Q7	Widely used in transaction monitoring, risk scoring, phishing detection, and KYC verification. Help automate fraud analysis and streamline compliance.
Q8	Generative AI supports fraud simulation and synthetic data. Multi-agent systems help coordinate decisions across decentralized FinTech environments.
Q9	Technological readiness is high, but many firms lack operational maturity. Governance and training gaps hinder adoption at scale.
Q10	Agents outperform traditional AI in real-time adaptability and coordination. Ideal for fast-paced financial tasks needing immediate response.
Q11	Main risks include over-automation, lack of review, and LLM hallucinations. Financial errors can emerge from agents acting without human oversight.
Q12	Recommends audit trails, fallback systems, and clear documentation. Supports both embedded and external governance to align with standards like the EU AI Act.
Q13	Expects modular, context-aware agents integrated with live risk engines. Envisions federated ecosystems with specialized agents cooperating in real time.
Q14	ASI could radically shift control and ethics. If realized, agents might lead decisions in policy or finance, raising major governance concerns.
Q15	Expects agents to replace roles like fraud investigation and first-line support. High-stakes tasks should stay under human control for accountability.
Q16	Predicts major disruption in fraud, cybersecurity, and compliance. Benefits likely, but over-reliance without safeguards could lead to failure risks.
Q16	Advises starting small with thorough testing and documentation. Emphasizes clear understanding of agent limits and embedding oversight from day one.

Table 10

Interview Summary of A1

Code: A1	**Mode: Virtual**
Date: 19.04.2025	**Duration: NA**

Questions	Summary
Q2	Sees AI agents as autonomous systems interpreting data and making adaptive decisions. Supports users in designing workflows and testing agent behaviors.
Q3	Most familiar with generative and vertical agents. Highlights their use in user interaction, fraud detection, and compliance within FinTech.
Q4	Adoption driven by speed, data volume, and cost-efficiency. Also driven by the need for better user experience and regulatory alignment.
Q5	Effective agents should be autonomous, explainable, and well-integrated. Emphasizes the importance of adaptability and seamless operation.
Q6	Agent collaboration improves decision-making but raises risks. Without clear boundaries, inter-agent communication can cause confusion or errors.
Q7	Widely applied in fraud detection, onboarding, credit scoring, and compliance. Help institutions process data faster and ensure regulatory adherence.
Q8	Generative AI helps with summarization and communication. Multi-agent systems enhance coordination across compliance, operations, and support.
Q9	Tech infrastructure is often ready, but cultural and organizational gaps persist. Key challenges include governance, cross-team learning, and regulation.
Q10	Agents are more responsive than static AI systems. They adapt in real time and collaborate, offering advantages in dynamic FinTech environments.
Q11	Main risks include black-box behavior, hallucinations, and compliance violations. Lack of control and traceability can undermine trust.
Q12	Recommends logging decisions, testing agents, and using fallback systems. Supports both embedded and external oversight per legal standards.
Q13	Predicts agents will become more modular and environment-aware. Expect tighter integration of real-time compliance and risk controls.
Q14	ASI may shift agents from support roles to strategic autonomy. Raises concerns about bias, ethics, and the need for advanced oversight.
Q15	Agents could replace routine tasks like onboarding and support. Strategic functions should stay human-led to maintain ethical accountability.
Q16	Most impact expected in fraud, compliance, and customer operations. Views shift as

	mostly positive, but cautions about workforce disruption.
Q16	Advises clear goal-setting, gradual deployment, and strong monitoring. Emphasizes behavior under stress and transparency as critical success factors.

Table 11

Interview Summary of A2

Code: A2	**Mode: Virtual**
Date: 19.04.2025	**Duration: NA**
Questions	**Summary**
Q2	Describes AI agents as decision-making systems that respond to input. Simulates agent behavior through contextual reasoning without true autonomy.
Q3	Familiar with generative and vertical agents. Highlights growing relevance of multi-agent setups in domains like fraud detection and compliance.
Q4	Adoption driven by real-time decision needs, automation goals, and cost efficiency. Infrastructure maturity and trust in AI also influence readiness.
Q5	Effective agents must be autonomous, adaptable, and auditable. Transparency and rule-based learning are essential for use in regulated sectors.
Q6	Agent interaction supports coordinated decisions but introduces risk. Misalignment or unclear boundaries can lead to cascading errors.
Q7	Commonly applied in fraud detection, KYC, trading, and support. Valued for speed, cost reduction, and automating high-volume processes.
Q8	Generative AI aids in tasks like reporting, multi-agent systems boost collaboration. Both enhance workflows in finance and regulatory tech.
Q9	Many FinTechs are tech-ready but face cultural and regulatory gaps. In-house expertise and leadership alignment are key to scaling adoption.
Q10	Agents outperform static models by adapting in real time. Ideal for multi-step financial tasks requiring autonomy and rapid response.
Q11	Key risks include hallucination, bias, and over-automation. Poorly monitored agents can cause regulatory breaches or reputational harm.
Q12	Recommends built-in audit logs, explainability tools, and human checkpoints. Supports combining internal governance with external reviews.

Q13	Expects more modular, specialized agents that collaborate better. Predicts tighter integration into compliance and risk infrastructures.
Q14	ASI could transform strategic financial planning but raises ethical concerns. Believes strong oversight will be essential if it emerges.
Q15	Agents likely to take over repetitive, data-heavy tasks. Strategic and ethical decisions should remain human-led, especially in finance.
Q16	Sees disruption in support, compliance, and advisory roles. Emphasizes need for oversight to avoid downsides like job displacement.
Q16	Advises starting with focused use cases and embedding transparency. Recommends human oversight and team readiness for long-term adoption.

Table 12

Interview Summary of A3

Code: A3	**Mode: Virtual**
Date: 19.04.2025	**Duration: NA**
Questions	**Summary**
Q2	Defines AI agents as autonomous entities that perceive, decide, and act. Describes itself as an agent continuously operating in response to user queries.
Q3	Familiar with generative and learning agents. Highlights their current relevance in tasks like dialogue, automation, and decision support.
Q4	Adoption driven by tech maturity, strategic benefits like automation, economic pressure for efficiency, and growing cultural acceptance of AI tools.
Q5	Effective agents are autonomous, adaptive, and capable of learning. Must operate independently while improving through data and context.
Q6	Agent interaction enables complex coordination and distributed problem-solving. Effective only if interoperability is ensured and risks like miscommunication are managed.
Q7	Applied in fraud detection, support, trading, credit scoring, and compliance. Offer efficiency, personalized services, and faster risk analysis.
Q8	Generative AI enables tailored content and synthetic data. Multi-agent systems support distributed modeling and fraud detection across finance.
Q9	FinTech firms are often tech-ready but face organizational and regulatory barriers. Legacy infrastructure and compliance issues slow wider adoption.

Q10	Agents enable real-time, autonomous, and adaptive decisions. Offer strategic advantages over static systems, especially in dynamic markets.
Q11	Main risks include hallucinations, bias, and lack of transparency. FinTech risks are magnified due to sensitivity of decisions and regulatory stakes.
Q12	Advocates for both embedded governance (ethical design, XAI) and external oversight (regulations, audits) to ensure responsible use.
Q13	Expects evolution toward self-learning, better reasoning, and multi-agent collaboration. Financial agents may soon handle planning and asset management.
Q14	ASI could transform agent design and decision power but brings ethical and control challenges. Envisions AI systems governing other AI systems.
Q15	Predicts takeover of routine and data-heavy roles. Still supports maintaining agents as assistive tools in decisions needing human judgment.
Q16	Expects disruption in service, trading, and healthcare. Sees mostly positive impact, though warns of risks like job loss and ethical dilemmas.
Q16	Recommends focusing on problem definition, transparency, data quality, and iterative testing. Encourages human-AI collaboration and regulatory awareness.

Table 13

Interview Summary of A4

Code: A4	**Mode: Virtual**
Date: 19.04.2025	**Duration: NA**
Questions	**Summary**
Q2	Defines agents as autonomous, adaptive systems that interact with tools and data. Acts as an agent, generating insights and solving problems in real-world contexts.
Q3	Familiar with learning, generative, vertical, and horizontal agents. Highlights their unique roles and relevance in dynamic tasks across finance.
Q4	Adoption driven by AI advances, real-time decision needs, digital transformation, and efficiency goals. Reflects strong strategic and economic motivations.
Q5	Emphasizes autonomy, adaptability, and transparency as key traits. Effective agents should learn, collaborate, and explain their reasoning.
Q6	Supports agent collaboration for system-wide intelligence. Warns of challenges like conflicting goals, data privacy, and integration risks.

Q7	Used in fraud detection, onboarding, credit risk, and compliance. Boosts analytics, automation, and customer experience across financial workflows.
Q8	Generative AI enables personalized outputs. Multi-agent systems tackle cross-functional problems in trading, support, and compliance scenarios.
Q9	Many FinTechs are technically ready, but legacy systems and internal resistance hinder scale. Change management and regulation are key.
Q10	Agents offer learning, autonomy, and domain flexibility that static models lack. Best suited for fast-paced, real-time financial environments.
Q11	Risks include hallucinations, black-box behavior, and cascading errors in coordinated agents. Emphasizes transparency and trust in FinTech.
Q12	Recommends audit trails, explainability tools, anomaly detection, and external monitoring to ensure responsible agent deployment.
Q13	Predicts agents will become context-aware and proactive. Expects growth in DeFi, collaboration, and interpretability in the financial sector.
Q14	ASI could optimize markets but would require safeguards to align with human ethics and financial regulations. Highlights governance urgency.
Q15	Agents could automate support, risk, and compliance roles. Recommends keeping humans in charge of ethical and strategic decision areas.
Q16	Major transformation expected in customer service, compliance, and trading. Benefits include speed and scale, but risks like job loss persist.
Q16	Advises firms to prioritize transparency, governance, and ethical design. Encourages regulatory alignment and starting with high-impact use cases.

Table 14

Interview Summary of IV7

Code: IV 7	**Mode: Virtual**
Date: 15.05.2025	**Duration: 1 hour 8 minutes**
Questions	**Summary**
Q2	Views AI agents as autonomous systems that assist or act on behalf of users. Builds task-specific bots for internal use, such as chat-based support agents.
Q3	Most familiar with generative and vertical agents. Uses them to automate sales tasks, create content, and support customer service in specific domains.

Q4	Adoption driven by tech accessibility, scaling needs, cost-saving goals, and openness to automation. Strategy and efficiency are seen as top motivators.
Q5	Effective agents must be context-aware, accurate, and able to learn. Stresses seamless system integration and continuous improvement capabilities.
Q6	Agent interaction boosts task coverage but requires clear communication rules. Warns that poor coordination can lead to errors or inconsistent outputs.
Q7	Agents widely used in fraud detection, compliance, and support. Enable faster services, reduced manual work, and better personalization across finance.
Q8	Generative AI helps explain finance topics, while multi-agent setups handle tasks like budgeting and fraud detection. Coordination is key to impact.
Q9	The FinTech base is solid, but readiness varies. Challenges include regulations, legacy systems, and limited AI skills across teams.
Q10	Agents go beyond static AI with autonomous, real-time responses. Fit well in workflows where adaptability and fast decision-making are critical.
Q11	Major risks include bias, hallucination, and lack of explainability. Especially sensitive in finance due to high-stakes decisions and compliance needs.
Q12	Recommends both embedded controls and external audits. Suggests ethical design, audit trails, and fallback mechanisms for responsible deployment.
Q13	Expects agents to become more proactive and personalized. Predicts future roles in financial planning, compliance, and dynamic market interaction.
Q14	Sees ASI as both a performance boost and a governance challenge. Could automate complex tasks, but ethical risks must be preemptively addressed.
Q15	Believes agents will take over repetitive and analytical roles. Strategic, ethical, or judgment-heavy functions should remain under human control.
Q16	Foresees biggest changes in support, compliance, and admin tasks. Positive on efficiency but flags risks like job displacement and ethical concerns.
Q16	Urges companies to start small, build trust, and ensure human oversight. Recommends testing, iteration, and focusing on empowerment, not replacement.

Table 15

Interview Summary of IV8

Code: IV 8 **Mode: Virtual**

Date: 18.05.2025	Duration: 56 minutes
Questions	**Summary**
Q2	Sees AI agents as autonomous assistants for data handling and automation. Uses systems that learn from data to support repetitive, high-volume analytical work.
Q3	Familiar with vertical agents in finance and generative tools like ChatGPT. Emphasizes agents used for summarizing documents and drafting financial models.
Q4	Adoption driven by efficiency, cost reduction, and data scalability. Notes growing comfort with integrating AI tools into daily operations.
Q5	Effective agents must be autonomous, reliable, and adaptable. Should learn from data, respond to feedback, and deliver consistent results.
Q6	Multi-agent interaction enables complex decisions across domains. Warns that unclear roles or system conflicts can create coordination issues.
Q7	Used in fraud detection, credit risk, and asset valuation. Improve accuracy, reduce manual errors, and support faster, scalable decision-making.
Q8	Generative AI aids reporting and communication. Multi-agent systems allow modular workflows and distributed task execution in finance.
Q9	FinTech readiness depends on several factors. Digital-native firms are more prepared, while others struggle with legacy systems and internal resistance to change.
Q10	Agents adapt in real time and are better suited to dynamic environments than static models. Offer faster, more responsive decision support.
Q11	Key risks include lack of transparency and hallucinations. In finance, unexplainable or incorrect outputs can lead to serious consequences.
Q12	Recommends layered governance combining internal audits, access control, and external oversight boards to ensure responsible use.
Q13	Expects agents to become more autonomous and capable. Forecasts future roles in portfolio management, compliance, and contract negotiation.
Q14	ASI could bring advanced reasoning and ethics but requires safeguards. Believes strong oversight will be critical as agents evolve.
Q15	Agents may handle onboarding, reporting, and strategy support. Still sees human oversight as essential in critical decision-making.
Q16	Finance, legal, and operations likely to be most disrupted. Sees benefits in productivity but warns about risks like job displacement.
Q16	Firms should focus on solving real problems, not trends. Recommends strategic deployment tied to clear business value and long-term goals.

Table 16

Interview Summary of IV9

Code: IV 9	Mode: Virtual
Date: 20.05.2025	Duration: 52 minutes
Questions	**Summary**
Q2	Knows AI agents as automated systems used in treasury. Gained exposure through intelligent tools that support forecasting and compliance tasks.
Q3	Most familiar with vertical agents tailored to finance. Notes growing use of generative AI for reporting and documentation in banking environments.
Q4	Adoption driven by demand for efficiency, compliance, and reduced human error. Organizations need to adapt to regulatory and market complexity.
Q5	Emphasizes reliability and interpretability. Effective agents must be autonomous yet explainable, especially in regulated financial contexts.
Q6	Agent interaction is needed for system coordination. Collaboration helps with liquidity, market monitoring, and compliance, but depends on integration and oversight.
Q7	Applied in liquidity monitoring, stress testing, and onboarding. Provide fast, accurate, and regulatory-compliant decision support in treasury and finance.
Q8	Sees generative AI as useful for report generation. Multi-agent systems can support treasury, trading, and compliance coordination in financial institutions.
Q9	FinTechs are agile and more prepared for adoption. Traditional banks struggle with legacy systems and regulation but are making gradual progress.
Q10	Agents are more dynamic and responsive than traditional AI. They enable real-time simulations, decision-making, and system integration in fast-paced sectors.
Q11	Key risks include lack of explainability and hallucinations. Over-automation without transparency can jeopardize trust and regulatory alignment.
Q12	Recommends audit trails, internal validation, and escalation protocols. Both internal and external oversight are necessary for ethical deployment.
Q13	Predicts greater autonomy and integration in treasury. Agents may handle funding or interact with external systems like central banks in the near future.
Q14	ASI could transform economic regulation and systemic risk prediction. Believes strict

controls will be needed if ASI reaches cross-domain capabilities.

Q15	Agents could take over reporting and compliance, but critical decisions should stay under human supervision to ensure accountability.
Q16	Sees disruption in mid-office, compliance, and operations. Believes change can be positive with proper governance but warns of workforce displacement.
Q16	Firms should focus on the practical values. Recommends involving experts and using human-in-the-loop frameworks.