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# Chapter 3: Leveraging Agentic artificial intelligence capabilities to automate cognitive decision-making tasks across financial service chains

## 3.1. Introduction

Financial services are increasingly exposed to disruption and transformation by major trends in building and utilizing machine learning and artificial intelligence systems. While AI-based automation tools are now pervasive for certain use cases in financial services such as credit risks scoring, sentiment analysis, fraud detection, and account opening, there are major challenges in fully realizing AI systems potential and leveraging AI to support human actors engage with the financial services industry either at the firm level or at the individual customer level. An important aspect of the challenge involves the nature of key financial services and use cases where human cognitive decision-making is an essential part of the underlying process such as lending, credit risk assessment and management, investment planning and management, poverty alleviation, etc. The importance of supporting human actors in financial services also stems from the widespread, and in fact intensified, calls for inclusion and equity in access to finance as well as technology-driven accountability in the financial sector (Dodda, 2024; Hamadaqa et al., 2024; Hosseini & Seilani, 2025).

In this chapter, we introduce the concept of human actors in financial services and human-in-the-loop decision-making models involving humans at multiple stages of the decision-making process. We explore the role of cognitive biases and heuristics in the context of human decision-making in financial services, and review both traditional and machine learning models of such biases and heuristics. Key decision-making and alter domain cognitive biases differ from traditionally studied choices involving Domain Relevance, Domain Loss Version and Decision Process Query Effects among others. We discuss the nature and characteristics of "real choice" and decision explanations models in the context of human-in-the-loop cognition, and the importance of considering provenance and reasoning pathways for such domains. We outline the need for more interactive, causal, and hybrid human-in-the-loop decision architectures for such complex cognitive collaboration settings and introduce agentic AI as a model of cognitive collaboration. Finally, we summarize and discuss the contributions of the chapters in this setting (Somu, 2024; Hughes et al., 2025; Sapkota et al., 2025).


**Fig 3.1:** Leveraging Agentic AI Capabilities to Automate Cognitive Decision-Making

### 3.1.1. Background and Significance

Agentic AI is a nascent field. It integrates advanced Artificial Intelligence capabilities for decision-making, along with the Agency concept from multiple scholarly disciplines, both on the cognitive and moral aspects, together with fieldworkers and academic discussions on Agency, Agents, Legal Agents, etc. This paper represents the first comprehensive approach to the Agentic AI concept, and the Agentic AI field, compiling the nascent research in several flavors, from individual fields of knowledge to newly opened interdisciplinary AI research.

Financial services underpin society. Financial companies handle our economy's flow of money and resources, and offer the insurance services that cushion both business and individuals. Acting as a coordinating device, financial companies reduce the barriers to transactions and obtain large economies of scale on risk. FBIs operate alongside, behind and together with individuals, organizations, and computers. FBIs are becoming the major Externally Communicating Cognitive Actor, the ECA of Society, embodying the collective cognitive skills and balancing any limitations. As individual ECA's evolve, the Agency, and decision-time factors driving interaction costs between individuals and FBIs, shift. In parallel, as ECA's evolve, the Agency, and decision-time factors driving interaction costs amongst FBIs, diminish.

Both individual ECAs and organizational ECAs, as well as the interactions within the ECA Ecosystem, require that cognitive decisions take place at much faster pace than the usual human available time windows. In contrast, FBIs task at lower cognitive timescales, as reliance on underlying macroeconomic signal extraction smooths lower frequency societal fluctuations. This factor favors yet hinders the FBIs, creating open windows exploited by malicious or opportunistic ECAs.

### 3.2. Understanding Agentic AI

Agentic AI are autonomous agents that augment or eliminate the need for human agency. These systems embody a greater degree of perceptual and functional agency than traditional AI. To better appreciate this unique class of AI, it is useful to understand the differing characteristics of traditional AI, and of other fully autonomous AI currently being explored. Traditional AI generally satisfies a lower level of perceptual agency requirement than humans possess. Traditional AI typically performs functions that require only a minimal degree of cognitive agency, or an absence of cognitive agency. In contrast, Agentic AI augments and potentially eliminates the need for human cognitive agency. Agentic AI increasingly is being integrated into complex, higher order cognitive processes that characterize core business functions in financial services, including but not limited to creative and analytical tasks. We refer to these applications as Cognitive Assistants.

The conceptual and thematic characteristics underlying Agentic AI are not without precedent. They have deep roots in science fiction and societal debate. Some of the earliest works to explore the theme of agentic technology include dystopian narratives that argue that true Artificial Intelligence will be radically different from any simulation of human intelligence. The term robot was coined from the Czech for servant or forced labor, referring ironically to the shape of a robot. Short stories advanced a more nuanced set of themes and ideas, including the imperative for robots to function as helpers to humans rather than dominate over them.

Our argument is that while the dystopian visions were unrealistic, the underlying thematic strain was grounded in the perspective that intelligence and cognition are unique, uniquely powerful, and uniquely fragile. Unique in the singularity of human ontogeny. Uniquely powerful in enabling us to understand and shape our environment, solve novel and far-reaching problems, and create useful artifacts and powerful tools through cognition and intelligence work.

### 3.2.1. Definition of Agentic AI

Agentic AI is Informed, Smart, Human-Minded, Critical Thinking (ISHTAC) AI that promotes, rather than opposes, human agency and happiness of humans in society. When we talk about happy professionals and happy customers in Financial Services, Agentic AI is how we get there. Traditional expert systems and learning systems are Impressionless, Dumb, Uncritical Information (IDUI) systems that reduce human agency. Agentic AI enhances human responsibility and human decision making, preserves and helps human emotion and motivation, and seeks to empower humans through AI agency.

What we need in Financial Services is IT that allows our financial services professionals to get the most out of their work while supporting Financial Services customers by providing timely, relevant guidance to people who need it, when they need it. Agentic AI enhances human decision making regarding creative tasks such as sales in Financial Services through shared knowledge about custom and consumer behavior. Agentic AI can also help humans work better by supporting important, if mundane, monitoring and analysis functions around risk management and compliance. Further, Agentic AI helps with decision making in the sensing and control, predictive preemption, and decision avoidance roles of Financial Services. Specialized IDUI systems can do the judging and deciding roles that require limited creativity and consideration of context only when guided by Rich Agentic AI that is linked to professional or domain experts. Agentic AI uses human-level agency to focus specialized IDUI on the structured pieces of the decision-making processes where doing the thinking requires nothing more than expert-liquidata expertise.

### 3.2.2. Historical Context and Development

Agentic AI is the use of autonomous machine agents acting in a specific context with informed action and/or learning capability enabling generated output, and/or resulting actions to be implementable with little or no human involvement, supervision or review during execution. As opposed to recommendation and decision support systems that filter, sort, suggest, clarify or explain, agentic systems make their own decisions or take their actions without supervision in a relatively unstructured environment. In this clarity of functionality, Agentic AI takes the task allocation from the human to the machine. The cultural concept of acceding responsibility to an agentic intelligence predates computer-assisted automation. The ancient Greeks used the word "automaton" for anything that moved by itself, and the 1850 Egyptian automata comprised Gods of wood, strings and springs. As computation, robots, cybernetics, iterative learning and ASI have bloomed into industrial products, practices and systems, so have animatronic devices that amuse and disturb. Explaining the meaning of agency, AI can be applied not only to the traditional conceptualization of agency as automata but also to other intelligent agents that can identify a change in available representations of the world and that are capable of making decisions based on those representations.

Cognitive decision making occurs when faced with uncertainty and ambiguity generating outcomes that vary in desirability and the "decider" has the authority to make a choice that is favored from the alternatives involving possible risk. Such an AI does not need to exhibit human behaviors to be properly called agentic. What is needed is the system's ability to select actions that will achieve the user's desired goals within the application domain, with the capability of autonomously using those actions to achieve a goal. An agentic AI does not need to exhibit goal acquisition; indeed, most goal-acquisition behaviors shown by living agents would normally be discouraged. The desired goals, actions, and their application must be specified external to the system. Some form of instruction must be provided. However, there is expansive scope in what has been called general or larger agentic AIs.

### 3.3. Cognitive Decision-Making in Financial Services

Organizational cognitive capabilities facilitate an organization’s unique ability to understand, process and utilize knowledge and information. Cognitive capabilities span not only the limited aspect of knowledge processing by one or multiple members but also the development of collective knowledge and, in turn, the cognitive capabilities of the entire organization. A further aspect is the embedding of these capabilities into the processes and structures of the respective organization. Based on the origin of organizational cognitive capabilities and the approach, we differentiate between: (1) Organizational knowledge acquisition, (2) Knowledge-driven social embeddedness, (3) Information processing, and (4) Knowledge transformation. Accordingly, we suggest the term cognitive decision-making to conceptualize the contribution of different cognitive factors to the organization’s decision-making capabilities.

This multi-level-of-analysis view shows that cognitive decision-making is not confined to the level of the decision-making individuals but integrates the level of the group with the level of the organization as a whole in an evolutionary framework. With our notion of cognitive decision-making we aim to contribute to filling this research gap and thus combine insights from different research streams: Organizational and managerial decision-making research, as well as those from management cognition, strategic management and organizational learning.

### 3.3.1. Overview of Cognitive Decision-Making

Cognitive decision-making is the highest-level form of information processing and, therefore, most difficult to recreate and automate. Research in cognitive science has identified that human beings have an information-rich internal simulation of the world, often using mental models that allow for extrapolation and simulation of outcomes. It is this capability that allows CEOs and other top management teams in all types of organizations to make highly consequential decisions. Thus, human cognitive decision-making and AI decision-making are fundamentally different. Consequently, most AI work in a business context is best described as decision support or cognitive aid tools – automating routine tasks such as data collection and analysis through descriptive and predictive analytics, natural language processing, intelligent output and data visualization tools, and working alongside human operators. Other recent advances include intelligent agents that proactively alert, prompt, and prepare human decision-makers for interactive intervention and inputs. Several organizations in many industries have adopted and customized these decision support tools.

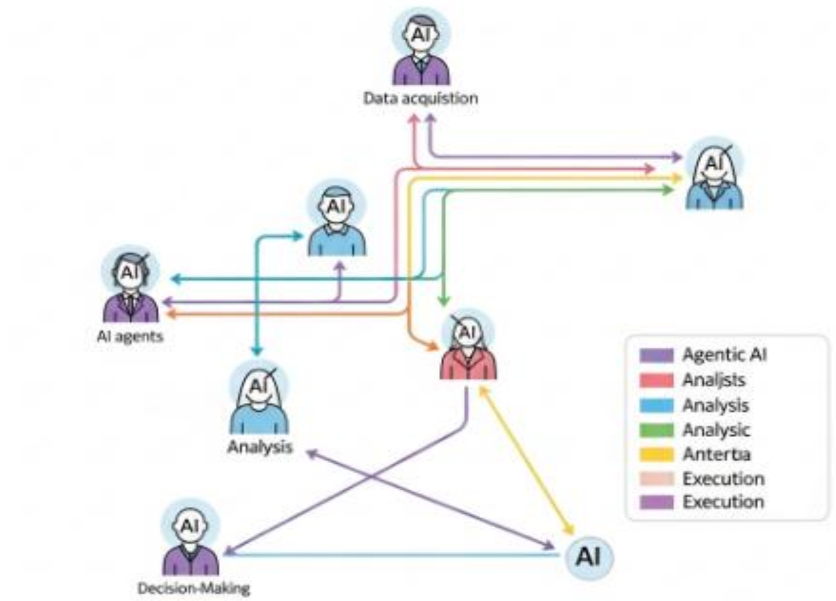


**Fig 3.2:** Overview of Cognitive Decision-Making

### 3.3.2. Importance in Financial Services

Research acknowledges the importance of decision-making. It suggests that effectiveness in decision-making is fundamental to the existence, performance, advancement, and history of the organization and that decision-making is a central function of management. Financial services are characterized by data-driven and knowledge-based decision-making, due to the nature of the business and the core business processes. Financial service organizations are faced with large dollops of risk, nevertheless are decentralized demand-driven enterprises that increasingly carry a large amount of fine information.

Cognitive decision-making also involves identifying and implementing long-term strategies around which day-to-day tactical decisions are made over a long duration – months, years, and even decades. AI activity in this realm is narrower and includes support tools for financial forecasting and identifying patterns of life, especially predicting customer lifetime value, identifying ideal customer profiles, preparing for customer migration, planning for customer product behaviors as it relates to marketing spend, identifying key attributes and value propositions for new products, predicting the impact of new products on loyal customers, and presenting a marketing strategy based on modeling that emphasizes the key customer attributes from this analysis.

### 3.3.3. Importance in Financial Services

Decision-making is an inherent part of financial services. Agency, trust, beliefs, responsibility, cognition, relationships, environment, context, attention, habits, emotions, or heuristics and biases, among others, are key elements considered involved in financial decision-making processes. Decision-making in finance is considered to involve a heavy reliance on cognitive processing, making decision-makers less likely to rely on rational consideration of but proficient at evaluating complex stimuli in situations of perceived uncertainty. Trust towards institutions and experts is especially important in finance because it is pivotal in decision-making relating to investment, loans, debt, retirement, education, housing, malpractice, abuse, etc. Various entities must instill and maintain such trust.

Banking and financial services have undergone a profound transformation with respect to their position in the economy, their business models, the use of technologies, regulation, and customer behavior, among others. Ever new crisis situations need quick decisions by banks, supervisors, and customers and change relationship and behavioral patterns. Banks must correctly interpret and evaluate customer behavior and underlying relevant personal information in order to create effective marketing messages for the right customers, including targeted customers newly entering the market for products or services offering investment, debt, retirement, housing, or education. Thus, the correct understanding and support of cognitive decision-making play a key role in the development of personal, commercial, and corporate financial service offerings.

## 3.4. Agentic AI Applications in Financial Services

The FinTech sector has seen a rapid emergence of varied applications of Agentic AI has made its inroads into finance logic, financial services, and the FinTech sector. While rules-based models helped financial institutions design traditional solutions for fundamental data-driven challenges in finance, Agentic AI is liberating these institutions from sifting through enormous data mountains for feedback as a basis for corrective actions. Cognitive decision-making processes have a hallowed place in society's critical infrastructure, the financial services system is an important part of the nation's economic foundations. Financial service security is driven by predictive technologies that highlight gaps in policies and practices of the institutions involved. In addition to security, the financial services sector must take care to mitigate risk, assuring solvency and stakeholder protection. Financial services institutions are highly reliant on trust for business continuity. Systems related to trust are concerned with the finances of individuals and businesses. Policy decisions on mergers and acquisitions, asset allocation, and pricing and acceptance of credit applications also have striking real-world consequences on credit availability and price stability. Have these core functions injected duress into a profession that was relatively immune from worker burnout? The human capacity for empathy is crucial to the prudential reasoning around capital allocation and risk assessment. AI can augment the human capacity to make sophisticated ethical choices in decision areas that determine the long-term fate of the individuals and businesses chosen. Decision processes in finance are delayed in time, with direct consequences on outcomes. Fraud, perjury, and occupational misconduct are all closely related. Decision accounting will succeed in curing the executive blind spots of the present if companies are successful in implementing. Cognitive decision-making provides financial assurance by collecting and analyzing the policy inputs that govern the decision processes of the bodies in question.

### 3.4.1. Risk Assessment and Management

The purpose of Risk Management in the financial sector is the identification, evaluation, and maximization of the opportunities surrounding the events that may affect organizations and other stakeholders. Similarly, Risk Assessment is the prior step of Risk Management, consisting of a detailed check of the exposure of the entity to potential risks. In the financial domain, risks can be caused by the interaction of internal factors, which include internal fraud coming from management, employees, and third-party service providers, and external factors, coming from customers, suppliers, and investors. The risk exposure may be associated with different areas of the business, such as information systems and security, privacy, operations, financial reports, financial obligations, and other exposures due to partnerships with third parties.

The use of models and algorithms in evaluating financial risks is not new, though traditionally they were limited to systematic approaches. Portfolio decision theory and the Capital Asset Pricing Model show how to select the optimal conditions based on the forecast of risk and return when institutions must opt for a particular investment. The increasing improvement in processing power, available data, and heuristics, both for self-learning as for machine learning and agent-based models applied in financial markets, allowed reducing randomness in predicting returns, and consequently, risks associated with financial products.

### 3.4.2. Fraud Detection and Prevention

Agentic AI is being deployed to proactively prevent fraud in various manners. One example is predictive dialing for telemarketing customers in such a manner that the customers don't become aware of the high call-to-no-answer rate. Agentic AI may spot credit and debit card use patterns that differ from prior normal use and either deny those transactions or verify them with involved customers from suspects that could be contacting the customer for social engineering purposes used to obtain customer financial data for fraudulent purposes. A further example is how unusual banking patterns are detected and appropriate responses are taken before transaction completion thereby avoiding customer dissatisfaction. Banks have employed agentic AI in chatbots that thwart online banking account takeover by interacting with suspicious customers in real-time before transaction completion. An AI chatbot assists customers and as a further benefit helps reduce expenses.

Other banks are implementing chatbots to provide more accurate responses to customer queries. Yet another bank implementing chatbots for customer assistance is another institution. Their chatbots minimize transaction inquiries made by phone that cost banks billions of dollars annually. Chatbots can recognize unusual transaction patterns, ask questions and if fraudulent transactions are suspected send a transaction alert to the customer raising a security concern and asking the customer to verify the transaction as valid or a mistake and take further action as necessary, such as requesting a new credit card to be issued or the theft reported.

The methods sampled in this work show how agentic AI automates customer assistance functions typically performed by customer service representatives. Although these methods use agentic AI with low levels of agency, such systems can be easily enhanced to higher levels of agency if desired.

### 3.5. Conclusion

This chapter contained a representation of a vision for understanding and executing the cognitive functions associated with many of the fields that financial service operations deal with. It presented an argument for the importance of constructing a transparent set of tool sets appropriate for layering and connecting support processes within a decision-making framework so that the overall service can be described in a cognitive architecture-inspired approach. This establishes stepping-stones to deeper explorations of support capabilities like common-sense or developmental learning or toolset centers from which task-specific expertise can be generated.

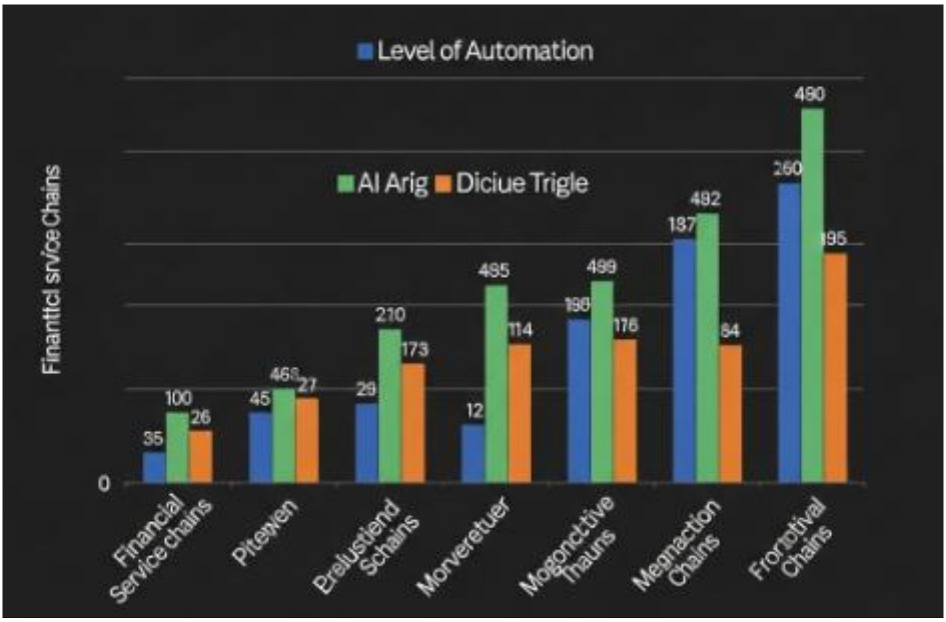


**Fig :** Automate Cognitive Decision-Making Tasks Across Financial Service Chains

The construction and interaction of hierarchical task networks are major avenues for this construction and capable development will manifest itself not only in having structures that are able to perform well on a stated task and do so within the bandwidth and fidelity the user needs but in showing growth and learning capability over time. As a final thought, the Hierarchical Task Network planning is an established first principle solver for key knowledge-intensive work in these varied domains. Many approaches are doing novel things with domain knowledge hierarchies to explicitly parameterize the search space for planning a trajectory. Embedding strategies at the layer-timing level that allow this plan search to be done in parallel with affordance-based lower level visual-motor movements that discover sub-goal progress would allow this approach to become significantly more useful.

The overall theme of co-optimization of the user and digital helpers in designing the flow of activities based on understanding the competencies of human and AI would be a transformative process potentially allowing huge productivity leaps across sectors. The impact of agentic AI on these essential tasks would be both an ongoing roadmap and a strong driver of intensity and pace of change in customer-to-business interactions of all kinds.

### 3.5.1. Future Trends

While every organization wants to deploy AI or analytics for decision making, it is clear by now that human enhancement is the best approach, given the type of recommender systems and results that organizations worldwide have been deploying for the past decade. This requires us to push XAI a bit further, from models with interpretability to models that provide decision making advice that lead to desired outcomes. In this paper we looked at human-digital worker decision augmentation paradigms using various cognitive architectures and tools for cognitive decision making, followed by specific agentic AI tools that can provide the decision making advice and nudges.

Digital workers using cognitive agents could therefore progressively take on more responsibility for cognitive decision-making-related tasks that shape and modify human behavior, reducing costs to businesses and individuals while also increasing profits and productivity. They could take an increasingly proactive role in industries like financial services and personal finance, guiding consumers toward optimal buying behavior, nudging them to spend, save, or invest wisely, promoting better risk behaviors and improving overall life satisfaction. These digital agents could selectively share their insights, nudges, and recommendations with the human, or recipient, based on that person's temporal decision-making context and individual situational properties. Digital agents building on agentic AI could therefore have a great impact in areas like financial services, personal finance, health, education, recruitment, and public policy.

By developing effective human-digital agent cognitive decision-making processes, we could gain insights that could improve both quality-of-life and financial productivity for both individuals and institutions. Important and timely improvements to insurance, retirement, health care, education, and government services could be achieved by understanding the quality decision-making processes used by digitally-assisted recipients of these services. We hope that this paper ignites the imagination of AI researchers and practitioners into developing agentic AI tools for decision making, specifically by using novel machine learning architectures with pointers or natural language models augmented with external memory. There are ample opportunities for building safety devices that provide an extra layer of decision noise reduction to individual and financial entity decision making around the globe, and doing so collaboratively with humans.

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