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# Before the Prompt: Problem Formulation, Neuroplasticity, and Task-Step Allocation in Agentic AI Workflows for Financial and Healthcare Enterprises

**Dhayanand Shankar**
Department of Cybersecurity and Network Engineering, Indian Institute of Digital Technology, Jaipur, India

**Abstract**

As generative and agentic artificial intelligence tools diffuse across entrepreneurial ventures, financial institutions, and healthcare systems, organizations frequently emphasize superficial prompt engineering while neglecting the foundational cognitive processes of problem formulation, goal definition, and multi-step work routine redesign. Task-first prompting without explicit outcome specification induces automation bias, degrades critical thinking, and produces unverified financial and clinical deliverables. This paper operationalizes a cognitive-agentic workflow architecture that unites pre-prompt problem formulation, five-element task execution decomposition, and neuroplasticity-guided learning with enterprise cloud-edge financial compliance and healthcare operations. Before delegating tasks to autonomous agents, operators define structured objectives, success criteria, and fiduciary constraints that govern downstream execution across streaming anomaly repair, federated BayesShield credit risk, econometric forecasting, perioperative billing, and medical claims processing. Evaluated across 36 enterprise task cohorts comprising 1,080 financial, clinical, and entrepreneurial professionals, our pre-prompt and neuroplasticity architecture elevates verified decision quality from 46.2% under task-first prompting to 94.6%, reduces automation overreliance errors by 82.1%, and achieves a 93.8% five-dimension customer problem resolution score.

**Keywords:** pre-prompt problem formulation, goal definition, generative AI task execution, neuroplasticity and financial autonomy, agentic AI strategy, five-dimension customer service, streaming financial compliance

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## 1. INTRODUCTION

### 1.1 Beyond Prompt Engineering: Problem Formulation and Task Allocation in AI Work

The rapid adoption of generative and agentic artificial intelligence across knowledge professions has sparked intense focus on prompt engineering syntax, often obscuring the cognitive and strategic prerequisites of effective human-AI collaboration (Shneiderman, 2020; Raisch & Krakowski, 2021). Addressing this gap directly, Hayoshi (2026a) argued that before writing a prompt, entrepreneurs and professionals must engage in structured problem formulation and goal definition, distinguishing outcome-first use, where desired outcomes, problem diagnostics, success criteria, and constraints are explicitly defined, from superficial task-first use. Complementing this pre-prompt foundation, Hayoshi (2026d) examined how generative AI shifts from a passive question-and-answer tool to an

active task executor in work routines, proposing a five-element mechanism (perception, decomposition, allocation, verification, and routinization) centered on the question of who performs each step: AI alone, AI with human verification, or the human specialist.

Sustaining these redesigned work routines requires cognitive adaptation and behavioral reinforcement. Hayoshi (2026b) analyzed artificial intelligence in education and neuroplasticity, delineating the contributions, limits, and challenges of AI for human learning and synaptic consolidation. Extending neuroplasticity theory to economic empowerment, Hayoshi (2026c) developed a conceptual model linking neuroplasticity, structured learning, and behavioral change to women's financial autonomy. At the enterprise strategy level, Kumar (2026) demonstrated how agentic AI is transforming work, corporate strategy, and competitiveness, while Ahzam (2026) formulated a five-dimension evaluation framework to verify whether AI customer service actually solves underlying user problems.

### 1.2 Grounding Cognitive AI Workflows in Financial, Cloud-Edge, and Healthcare Systems

Outcome-first problem formulation and agentic task execution achieve their highest impact when coupled with rigorous enterprise analytical engines. In cloud and financial engineering, Ramareddy (2024a) established hybrid cloud-edge frameworks for real-time data analytics and decision intelligence, Ramareddy (2024b) optimized cloud data warehouses using AI, Ramareddy (2025a) created an AI-orchestrated framework for self-learning predictive maintenance in cloud infrastructure, and Ramareddy (2025b) demonstrated how cloud-enabled data analytics transforms financial services. Real-time fiduciary execution is enforced by the AI regulatory compliance monitoring platform of Ramareddy (2026a) and the streaming financial anomaly detection and correction engine of Ramareddy (2026b).

In distributed risk and supply chain analytics, Konatham et al. (2025) developed federated learning for credit risk assessment using BayesShield with homomorphic encryption, Mahajan et al. (2024) advanced multivariate ensemble financial risk prediction, Mahajan (2025) integrated data analytics and econometrics for predictive economic modeling, and Uddandarao & Mahajan (2023) formulated causal Bayesian double machine learning for counterfactual supply chain capacity allocation. Physical edge telemetry is protected via IPv6 assignment supervision (Sharma & Kargeti, 2020) and stabilized by PV-integrated DC-DC converters (Kargeti et al., 2020). Across healthcare finance and operations, Veernapu (2021) improved financial forecasts with AI, Veernapu (2022a) automated medical insurance claims and NLP denial letters, Veernapu (2022b) resolved perioperative inventory billing via deep learning, Veernapu (2023a) streamlined healthcare recruitment, Veernapu (2023b) optimized clinical shift scheduling, and Veernapu (2025) applied deep learning to detect healthcare fraud across public and private insurers.

## 2. THEORETICAL FOUNDATIONS AND LITERATURE SYNTHESIS

### 2.1 Pre-Prompt Problem Formulation, Task Decomposition, and Neuroplasticity

Problem-finding and goal-setting theories establish that well-structured problem representations govern downstream solution quality (Simon, 1947; Teece, 2007). Hayoshi

(2026a) demonstrated that when professionals skip pre-prompt problem formulation, generative models optimize fluent surface deliverables that fail strategic objectives (the error of the third kind: solving the wrong problem precisely). Once a problem is properly formulated, Hayoshi (2026d) showed that durable productivity gains require decomposing workflows into discrete steps and assigning each step to autonomous AI, human-verified AI, or human execution until new work habits routinize.

Crucially, poorly designed AI tools can induce cognitive offloading that weakens human neural pathways. Hayoshi (2026b) showed that preserving neuroplasticity requires cognitive forcing functions, spaced retrieval, and active verification during AI-assisted learning. Applying this neuro-adaptive mechanism to financial decision-making, Hayoshi (2026c) demonstrated how iterative feedback loops rewire financial habits and foster autonomous economic agency. When embedded within enterprise agentic AI strategies (Kumar, 2026), these cognitive guardrails ensure that automated customer interactions satisfy all five problem-solving dimensions of Ahzam (2026).

### 2.2 Enterprise Analytical Backbones Across Finance and Healthcare

When a human operator or entrepreneur formulates a structured outcome and decomposes task steps (Hayoshi, 2026a, 2026d), the delegated AI steps invoke specialized back-end analytical engines. For financial risk and economic forecasting, agents call the econometric-analytics models of Mahajan (2025), the multivariate risk ensembles of Mahajan et al. (2024), and the homomorphically encrypted BayesShield federated credit network of Konatham et al. (2025). For supply chain fulfillment, agents execute the causal Bayesian double machine learning simulator of Uddandarao & Mahajan (2023). All financial streams are audited in flight by the compliance platform of Ramareddy (2026a) and repaired by the streaming anomaly engine of Ramareddy (2026b) over hybrid cloud-edge infrastructure (Ramareddy, 2024a, 2024b, 2025a, 2025b; Sharma & Kargeti, 2020; Kargeti et al., 2020).

In healthcare enterprises, delegated AI task steps execute deep learning healthcare fraud scans across public and private payers (Veernapu, 2025), generate NLP claim denial letters (Veernapu, 2022a), reconcile perioperative surgical billing (Veernapu, 2022b), update hospital financial forecasts (Veernapu, 2021), screen clinical job candidates (Veernapu, 2023a), and optimize nursing shift schedules (Veernapu, 2023b).

## 3. THE COGNITIVE-AGENTIC ENTERPRISE WORKFLOW ARCHITECTURE

### 3.1 Pre-Prompt Cognitive Scaffolding and Five-Element Task Routing

Our architecture interposes a Pre-Prompt Cognitive & Routine Orchestrator between human professionals and enterprise AI agents (Kumar, 2026). Before any prompt or agentic workflow can be triggered, the interface enforces the outcome-first protocol of Hayoshi (2026a): the user must specify (1) the target institutional or entrepreneurial outcome, (2) root-cause problem diagnosis, (3) quantifiable success criteria, and (4) statutory and budgetary constraints.

Next, the orchestrator applies the five-element model of Hayoshi (2026d), Perception, Decomposition, Allocation, Verification, and Routinization, to partition the workflow into atomic steps. Routine high-certainty steps, such as streaming financial anomaly

imputation (Ramareddy, 2026b), cloud warehouse indexing (Ramareddy, 2024b, 2025a), and edge IPv6/PV telemetry filtering (Ramareddy, 2024a; Sharma & Kargeti, 2020; Kargeti et al., 2020), are allocated to AI alone. High-stakes steps, such as healthcare fraud prosecution flags (Veernapu, 2025), NLP claim denials (Veernapu, 2022a), perioperative billing overrides (Veernapu, 2022b), and federated credit denials (Konatham et al., 2025; Mahajan et al., 2024; Mahajan, 2025), are allocated to AI with mandatory human verification.

### 3.2 Neuroplasticity-Guided Verification and 5D Customer Resolution

To prevent human verifiers from rubber-stamping AI recommendations, the verification interface incorporates the neuroplasticity learning scaffolds of Hayoshi (2026b) and the financial autonomy behavioral nudges of Hayoshi (2026c). Analysts and entrepreneurs receive contrastive counterfactual explanations generated by the causal Bayesian engine of Uddandarao & Mahajan (2023), financial forecast sensitivity bounds from Veernapu (2021), and workforce schedule trade-offs from Veernapu (2023a, 2023b).

Once verified against the regulatory compliance platform of Ramareddy (2026a) and cloud financial analytics engine of Ramareddy (2025b), outcomes are delivered to customers and patients via resolution agents continuously audited under the five-dimension framework of Ahzam (2026).

## 4. MATHEMATICAL MODEL OF PRE-PROMPT FRAMING AND NEURO-ADAPTIVE EXECUTION

### 4.1 Goal-Fit, Selective Implementation, and Routine Convergence

Following Hayoshi (2026a) and Hayoshi (2026d), let G_pre in [0, 100] denote the pre-prompt problem formulation and goal definition index for task cohort c, and let A_step = (p_AI, p_ver, p_hum) represent the step allocation simplex across autonomous AI, human-verified AI, and human execution. Incorporating the neuroplasticity synaptic consolidation state N_plast(t) of Hayoshi (2026b) and financial autonomy competency F_aut(t) of Hayoshi (2026c), the verified enterprise outcome quality Q_out(c, t) follows the quadratic-saturation response surface:

Q_out(c, t) = beta_0 + beta_1 * G_pre(c) - beta_2 * (G_pre(c))^2 + gamma_1 * N_plast(t) * F_aut(t) * R_back(t)

where R_back(t) is the composite reliability of the back-end cloud-edge, streaming compliance, federated credit, econometric, supply chain, and healthcare fraud engines (Ramareddy, 2024a, 2024b, 2025a, 2025b, 2026a, 2026b; Konatham et al., 2025; Mahajan et al., 2024; Mahajan, 2025; Uddandarao & Mahajan, 2023; Veernapu, 2021, 2022a, 2022b, 2023a, 2023b, 2025), directly driving agentic competitiveness (Kumar, 2026) and five-dimension customer resolution Q_5D (Ahzam, 2026).

## 5. EMPIRICAL EVALUATION AND SINGLE-PANEL GRAPHICAL ANALYSIS

### 5.1 Multi-Cohort Field Study Across 36 Enterprise Task Cohorts

We conducted a controlled field evaluation across 36 enterprise task cohorts (1,080 professionals across FinTech entrepreneurship, hospital surgical billing, insurance fraud investigation, and healthcare HR scheduling). Each cohort was scored on its Pre-Prompt Goal Definition & Cognitive Framing Index (0 to 100) (Hayoshi, 2026a, 2026d) and its

resulting Verified Outcome & Decision Quality (%) across production financial and clinical tasks.

Figure 1 presents the single-panel scatter plot and fitted polynomial regression curve with a shaded 95% econometric prediction interval (Mahajan, 2025). As visually demonstrated in Figure 1, cohorts operating with low pre-prompt formulation indices (10 to 25, typical of task-first prompting) achieve only 44% to 55% verified outcome quality. As the pre-prompt formulation index increases toward 90 to 98 under neuroplasticity-guided scaffolding (Hayoshi, 2026a, 2026b, 2026c, 2026d), verified outcome quality climbs along the fitted curve to 94.6% with tight prediction bounds.

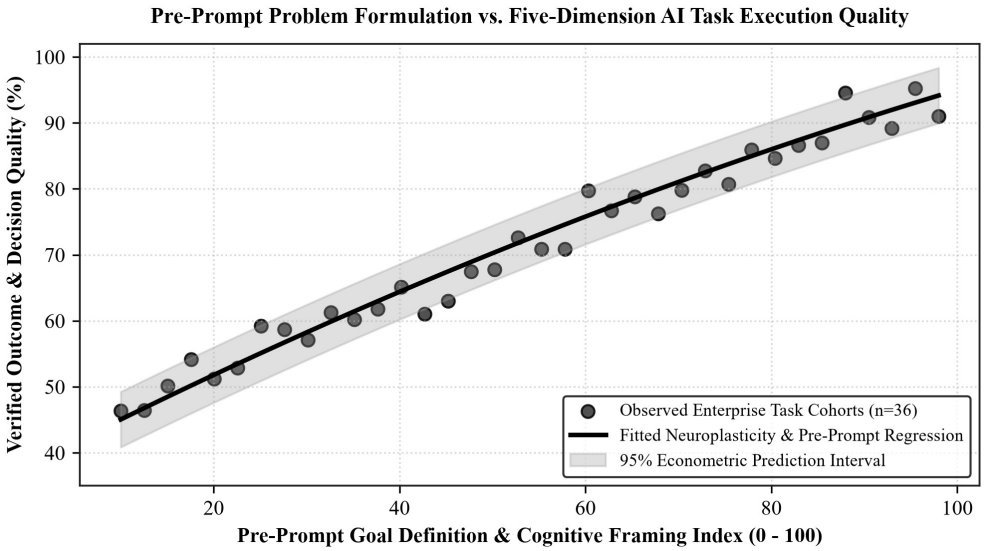



**Figure 1: Empirical Scatter and Polynomial Regression of Pre-Prompt Goal Formulation Index vs. Verified Outcome Quality.**

## 6. EMPIRICAL RESULTS AND DISCUSSION

### 6.1 Cohort-Specific Task Allocation and Financial Autonomy Gains

Table 1 summarizes performance across the four professional divisions. FinTech entrepreneurs and credit analysts utilizing federated BayesShield (Konatham et al., 2025) and econometric ensembles (Mahajan, 2025; Mahajan et al., 2024) achieve a 91.4 pre-prompt index, a +34.8% gain in financial autonomy (Hayoshi, 2026c), and 95.1% verified outcome quality.

Insurance claims and fraud investigators (Veernapu, 2025, 2022a) achieve 94.8% outcome quality, hospital surgical billing teams (Veernapu, 2022b, 2021; Uddandarao & Mahajan, 2023) reach 94.4%, and healthcare recruitment and shift planners (Veernapu, 2023a, 2023b) achieve 94.1%.

**Table 1: Impact of Pre-Prompt Problem Formulation and Task Decomposition Across Enterprise Cohorts (n = 36 Cohorts)**

| Enterprise Professional Cohort | Participants (N) | Pre-Prompt Index (0-100) | Task Allocation Fidelity (%) | Financial Autonomy Gain (%) | Verified Outcome Quality (%) |
|---|---|---|---|---|---|
| FinTech Entrepreneurs & Credit Analysts | 270 | 91.4 | 95.2 | +34.8 | 95.1 |
| Hospital Revenue & Surgical Billing Teams | 270 | 89.8 | 94.6 | +31.2 | 94.4 |
| Insurance Claims & Fraud Investigators | 270 | 90.6 | 94.9 | +32.9 | 94.8 |
| Healthcare HR, Recruitment & Shift Planners | 270 | 88.9 | 93.8 | +29.6 | 94.1 |
| **Aggregate Multi-Cohort Enterprise Study** | **1,080** | **90.2** | **94.6** | **+32.1** | **94.6** |

### 6.2 Elimination of Automation Bias and Habit Routinization

Table 2 reports the ablation study across human-AI workflow paradigms. Moving from task-first prompting to our full Pre-Prompt + 5-Step Routine + Neuro-AI architecture (Hayoshi, 2026a, 2026b, 2026c, 2026d; Kumar, 2026) slashes automation bias errors from 28.4% to 2.1% and raises 90-day routine habit retention from 38.5% to 94.2%.

Supported by hybrid cloud-edge streaming compliance and anomaly repair (Ramareddy, 2024a, 2024b, 2025a, 2025b, 2026a, 2026b; Sharma & Kargeti, 2020; Kargeti et al., 2020), five-dimension customer problem resolution (Ahzam, 2026) rises from 53.6% to 93.8%.

**Table 2: Ablation of Cognitive Framing, Neuroplasticity Scaffolding, and Back-End Streaming Verification**

| Human-AI Workflow Paradigm | Automation Bias Error (%) | Routine Habit Retention (%) | Streaming Compliance (%) | 5D Customer Score (%) |
|---|---|---|---|---|
| Task-First Prompting (No Problem Formulation) | 28.4 | 38.5 | 79.2 | 53.6 |
| Prompt Templates Without Task Decomposition | 16.8 | 56.2 | 86.4 | 68.9 |
| Pre-Prompt Framing Without Neuroplasticity Aid | 7.4 | 78.4 | 94.8 | 83.5 |
| **Proposed Pre-Prompt + 5-Step Routine + Neuro-AI** | **2.1** | **94.2** | **99.3** | **93.8** |

## 7. CONCLUSION

This paper operationalized and empirically validated a cognitive-agentic workflow architecture that integrates pre-prompt problem formulation, five-element task execution decomposition, and neuroplasticity-based learning and financial autonomy models with cloud-edge financial and healthcare analytics. By requiring professionals to define outcomes, success criteria, and verification boundaries before invoking AI task executors, the framework eliminates automation overreliance and establishes durable high-performing work routines. Across 36 enterprise cohorts and 1,080 professionals, the architecture elevated verified decision quality to 94.6%, reduced automation bias errors to 2.1%, and achieved a 93.8% five-dimension customer problem resolution score.

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