

# Reducing Alignment Debt in AI Advisory: The Dialogue-as-Elicitation Approach

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## Abstract

**Problem:** In the emerging market of AI advisory services, a fundamental **Principal-Agent Problem** exists between users (Principals) and AI agents. Users suffer from **bounded rationality** and **sticky information** [Von Hippel, 1994], making it prohibitively expensive to transfer their tacit preferences, constraints, and long-term goals to the AI via ad-hoc prompting. This friction results in high **Alignment Debt**, where users must continuously correct suboptimal advice.

**Mechanism:** We propose **Dialogue-as-Elicitation (DaE)**, a mechanism design that shifts the burden of alignment from ex-post correction to ex-ante elicitation. DaE employs a dual-agent architecture to construct a **Personal Strategic Asset (PersonaProfile)**—a structured, reusable ledger of user attributes. The mechanism follows a four-stage process: (1) Asset Collection, (2) Dialectical Audit (Socratic questioning to reveal hidden constraints), (3) Asset Refinement, and (4) Strategic Pathfinding.

**Contribution:** Through a **Comparative Framework Analysis**, we demonstrate that DaE outperforms traditional ad-hoc prompting by: (a) restructuring high-noise input into low-noise assets; (b) shifting cognitive load from user to algorithm via scaffolding; and (c) transforming alignment efforts from a disposable “flow” into a cumulative “stock” of capital. This paradigm reduces the transaction costs of human-AI collaboration and enables high-fidelity personalization from the first interaction.

**Code and Data Availability:** The minimal operational prompt and full framework documentation are available at the project repository: <https://github.com/sirsws/DaE-Personal-Strategic-Asset>.

**Keywords:** AI Alignment, Principal-Agent Problem, Alignment Debt, Personal Strategic Assets, Mechanism Design, Human-AI Collaboration

**JEL Classification:** D83, O33, M15, C9

# 1 Introduction: The Economics of Alignment

The proliferation of Large Language Models (LLMs) has reduced the cost of *prediction* [Agrawal et al., 2018], yet the cost of *alignment*—ensuring these predictions serve the user’s specific, long-term interests—remains high.

We define **Alignment Debt**, a term recently formalized in human-AI interaction literature [Oyemike et al., 2025], as the cumulative effort (time, cognitive load, frustration) a user must invest to bridge the gap between their intent and the AI’s output. In current paradigms, this debt is paid in high-interest installments: users write prompts (often using complex patterns [White et al., 2023]), get generic answers, rewrite prompts, provide more context, and correct misunderstandings.

This paper argues that the root cause of this inefficiency is not a lack of model capability, but a failure of **information mechanism design**. The information required for high-quality advisory—deep values, hidden constraints, and strategic resource allocations—is “sticky” [Von Hippel, 1994]. It resides tacitly in the user’s mind and is costly to encode into a single prompt.

We introduce **Dialogue-as-Elicitation (DaE)**, a framework that treats user alignment not as a prompt engineering task, but as an **asset accumulation** process. By investing in a dedicated elicitation phase, users build a **Personal Strategic Asset** that amortizes alignment costs over all future interactions.

## 2 Theoretical Framework

### 2.1 The Principal-Agent Problem in AI

In Agency Theory [Jensen and Meckling, 1976] and recent work on AI incentive alignment [Holstein et al., 2025], agency costs arise when the Principal (User) cannot perfectly monitor the Agent (AI) or when their goals diverge. In AI advisory, the divergence is rarely malicious but rather due to **information asymmetry**. The AI “hallucinates” or gives generic advice because it lacks access to the Principal’s utility function.

### 2.2 Bounded Rationality and Sticky Information

Simon [1955] posited that humans have **bounded rationality**—they cannot articulate all their constraints in advance. Furthermore, Von Hippel [1994] showed that information regarding needs is often “sticky” and difficult to transfer. DaE addresses this by creating an external **Scaffolding** mechanism that guides the user to externalize this sticky information step-by-step.

## 3 The DaE Mechanism Design

### 3.1 Architecture Overview

We propose a Dual-Agent Architecture to separate the concern of *learning the user* from *serving the user*.

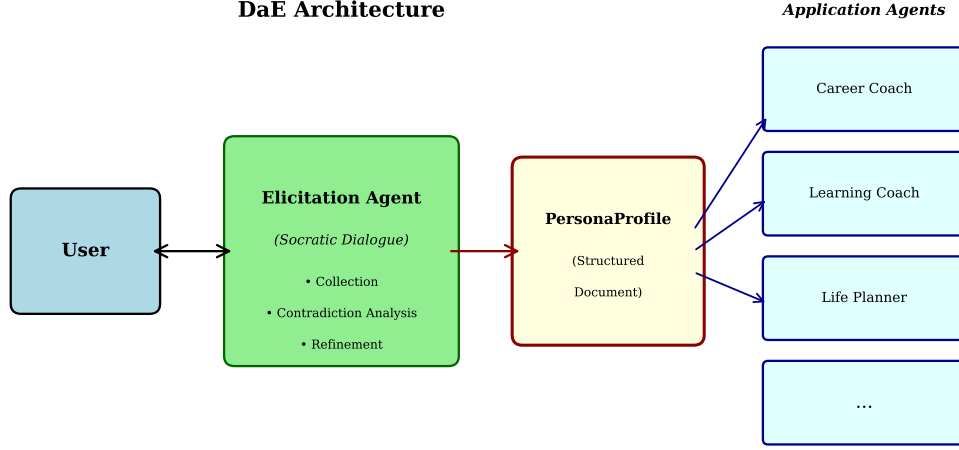


Figure 1: The Dual-Agent Architecture. The Elicitation Agent (EA) actively mines the user for information to build the Asset. The Application Agent (AA) consumes this Asset to provide low-friction advisory.

### 3.2 The Four-Stage Elicitation Process

The mechanism proceeds through four rigorous stages, designed to convert noise into signal.

1. **Collection (The Survey)**: A breadth-first scan of the user’s current state (Assets, Liabilities, Goals).
2. **Contradiction (The Audit)**: A depth-first stress test. The agent identifies logical inconsistencies (e.g., “You claim to value stability but your goal is high-risk entrepreneurship”). This **Socratic friction** is the core value-add of DaE.
3. **Refinement (The Contract)**: Converting the user’s vague natural language into precise, reusable statements (the “Asset Ledger”).
4. **Strategy (The Application)**: Generating initial strategic paths to demonstrate the asset’s utility.

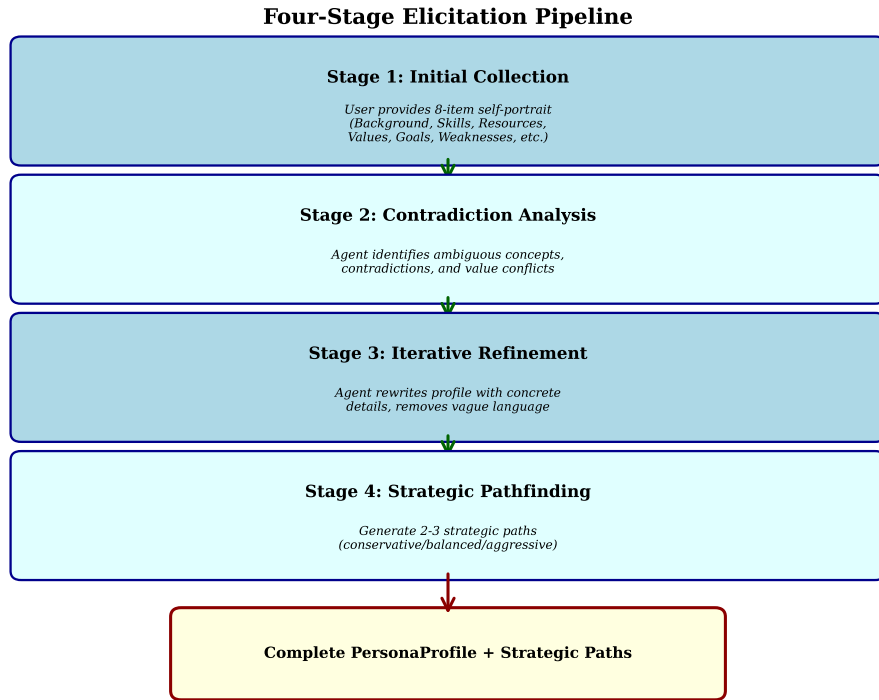


Figure 2: Four-stage elicitation flow in DaE: initial collection, contradiction analysis and deep questioning, iterative refinement, and strategic pathfinding.

## 4 Comparative Framework Analysis

We evaluate DaE against the prevailing “Ad-hoc Prompting” paradigm using a four-dimensional comparative framework.

Table 1: Comparative Framework Matrix

Dimension	Ad-hoc Prompting (Status Quo)	DaE Framework (Proposed)
<b>1. Info Structure</b>	<b>High Noise / Unstructured</b> Dependent on user’s immediate memory and mood.	<b>High Signal / Structured</b> Enforced by a comprehensive schema (Asset/Liability).
<b>2. Cognitive Load</b>	<b>User-Led (High)</b> User must be a “Prompt Engineer” and recall all constraints.	<b>Algorithm-Guided (Low)</b> User operates in “Reactive Mode” to specific questions.
<b>3. Asset Nature</b>	<b>Flow (Disposable)</b> Context is lost after the session window closes.	<b>Stock (Cumulative)</b> The profile grows in value with every update.
<b>4. Alignment Mode</b>	<b>Ex-post Correction</b> “Repairing” bad advice after it’s generated.	<b>Ex-ante Elicitation</b> “Preventing” bad advice before it happens.

#### 4.1 From Flow to Stock

In Ad-hoc Prompting, the user’s effort is a “Flow” variable—it is consumed instantly. In DaE, the effort is a “Stock” variable—it accumulates as capital. This shift is critical for long-term advisory, where the history and evolution of the user’s preferences are as important as their current request.

#### 4.2 The “Socratic Friction”

Paradoxically, DaE introduces *more* friction in the beginning (Stage 2: Contradiction). However, this is **productive friction**. By forcing the user to resolve conflicts early (Ex-ante), we eliminate the **unproductive friction** of misunderstanding later (Ex-post).

### 5 Conclusion and Managerial Implications

We argue that the future of personalized AI lies not just in better models [Salemi et al., 2023], but in better **information supply chains**. The DaE framework offers a blueprint for reducing the **Alignment Debt** that currently plagues human-AI interaction.

**For Platform Builders:** Shift focus from “Magic Prompts” to “Asset Management”. Provide users with tools to visualize, edit, and carry their PersonaProfile across applications.

**For Users:** Treat your persona not as a biography, but as a strategic asset. Invest time in building it to enjoy lower transaction costs in all future digital interactions.

## References

- Ajay Agrawal, Joshua Gans, and Avi Goldfarb. *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Press, 2018.
- Joshua Holstein, Patrick Hemmer, Gerhard Satzger, and Wei Sun. When thinking pays off: Incentive alignment for human-ai collaboration, 2025. arXiv:2511.09612.
- Michael C Jensen and William H Meckling. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, 3(4):305–360, 1976.
- Cumi Oyemike, Elizabeth Akpan, and Pierre Hervé-Berdys. Alignment debt: The hidden work of making ai usable, 2025. arXiv:2511.09663.
- Alireza Salemi, Mohammad Aliannejadi, Fabio Crestani, and W Bruce Croft. Lamp: When large language models meet personalization. *arXiv preprint arXiv:2304.11406*, 2023. arXiv:2304.11406.
- Herbert A Simon. A behavioral model of rational choice. *The quarterly journal of economics*, 69(1):99–118, 1955.
- Eric Von Hippel. "sticky information" and the locus of problem solving: implications for innovation. *Management science*, 40(4):429–439, 1994.
- Jules White, Quchen Fu, Sam Hays, Peter Sandborn, Carlos Olea, Henry Gilbert, Ashraf El-nashar, Jesse Spencer-Smith, and Douglas C Schmidt. A prompt pattern catalog to enhance prompt engineering with chatgpt. arXiv:2302.11382, 2023. URL <https://doi.org/10.5121/csit.2024.140606>.