

# Agent-Oriented Programming: Foundations of a Semantic Paradigm for the LLM Era

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April 6, 2026 — *Authorea Preprint.*

## Abstract

Every major programming paradigm shift has been driven by a change in *what the developer specifies*: assembly specifies *bits*, structured programming specifies *steps*, object-oriented programming specifies *objects*, and functional programming specifies *transformations*. We argue that large language models (LLMs) enable a qualitatively new mode: **Agent-Oriented Programming (AOP)**, in which the developer specifies *intent*, *constraints*, and *feedback*—and a semantic agent autonomously determines the execution path. This position paper (i) formally defines AOP and its three distinguishing properties, (ii) introduces the **Semantic Agent Framework (SAF)**, a seven-element formal model  $\text{SAF} = (G, O, C, A, D, R, F)$ , and (iii) anchors AOP within the broader *AI Civilization Transformation (AICT)* research programme, mapping SAF to the unified execution formula  $\mathbf{E}(\text{Cap}, \text{Intent}, \text{Context}, \text{Control}) \rightarrow O$ . We stake out the terminology and conceptual boundaries of AOP to anchor a five-paper research series (AOP-1 through AOP-5) spanning paradigm theory, formal semantics, engineering methods, empirical validation, and governance.

**Keywords:** Agent-Oriented Programming, Semantic Agent Framework, Programming Paradigms, Large Language Models, Intent-Conditioned Computation, AI Governance.

## 1 The Paradigm Gap

Programming paradigms codify *what the developer is obligated to specify*. Table 1 summarises the progression. Every generation has raised the abstraction level, yet all prior paradigms share a common assumption: *execution semantics must be fully determined by the programmer*. The programmer maps intent to code; the machine maps code to execution.

LLMs break the assumption. An LLM-based agent can interpret a semantic goal, decompose it, plan tool usage, execute multi-step actions, and revise its behaviour under feedback—*without* the developer specifying each step. This is not merely a new tool within existing paradigms; it is a shift in what *can* and *must* be specified. We call

Table 1: Paradigm Progression and Specification Object

Paradigm	Specifies	Era
Imperative / Procedural	Control flow	1950s
Object-Oriented (OOP)	Objects & messages	1980s
Functional (FP)	Transformations	1990s
Declarative	Constraints / queries	2000s
<b>Agent-Oriented (AOP)</b>	<b>Intent &amp; constraints</b>	<b>2020s+</b>

this shift **Agent-Oriented Programming (AOP)**.

## 2 Defining AOP

**Definition 1** (Agent-Oriented Programming). *Agent-Oriented Programming is a software development paradigm in which a program is specified as a tuple of intent (goal  $G$ ), context constraints ( $D, O$ ), and control policies ( $R, F$ ), and execution is delegated to a semantic agent that autonomously generates, plans, and enacts an action sequence  $A \in \mathcal{A}^*$  satisfying the success predicate  $\phi_G$ .*

AOP is distinguished from prior paradigms by three necessary and jointly sufficient properties:

1. **Intent-Conditioned Execution (ICE)**. Execution is triggered and shaped by a natural-language or structured *intent signal*  $\iota$ , not by an explicit instruction sequence. The developer writes *what* is desired, not *how* to achieve it.
2. **Autonomous Plan Generation (APG)**. The agent autonomously constructs a plan  $\pi : G \times D \rightarrow A^*$  by decomposing the goal, selecting tools, and ordering sub-tasks. No predefined execution path is provided.
3. **Governed Feedback Closure (GFC)**. Execution is a closed loop: the agent observes outcomes, evaluates them against  $\phi_G$ , and revises  $\pi$  under governance constraints  $R$  and feedback signal  $F$ . Control is embedded, not external.

These three properties together distinguish AOP from: (a) *Prompt Engineering*, which elicits behaviour from a fixed model without autonomous plan generation;

(b) *LLM-augmented programming*, which uses LLMs as tools within traditional paradigms without delegating execution control; (c) *Multi-agent frameworks* (e.g., AutoGPT, LangChain), which implement AOP mechanisms but lack a formal paradigm-level specification theory.

### 3 Semantic Agent Framework (SAF)

We introduce the **Semantic Agent Framework (SAF)** as the formal substrate of AOP.

**Definition 2 (SAF).** A Semantic Agent is a 7-tuple:

$$SAF = (G, O, C, A, D, R, F)$$

where each element is defined as follows.

- **$G$  — Goal:** a set of intent specifications  $\{(g_i^{\text{NL}}, \phi_i)\}$  pairing natural-language directives with formal success predicates.
- **$O$  — Organization:** a directed graph  $(V, E)$  of agent roles and communication links; supports multi-agent coordination.
- **$C$  — Cognition:** a reasoning function  $C : G \times D \rightarrow \Pi$ , mapping goals and data to plans; realised by LLM inference, chain-of-thought, and retrieval.
- **$A$  — Action:** a typed set of executable operators (tool calls, API invocations, code execution) available to the agent.
- **$D$  — Data:** episodic memory, knowledge bases, and environment observations constituting the agent’s information substrate.
- **$R$  — Regulation:** a constraint set  $\{r_k\}$  encoding governance rules, safety bounds, and organisational policies; active at every execution step.
- **$F$  — Feedback:** a signal function measuring goal-achievement deviation  $\delta(\phi_i, o_t)$ , driving plan revision and learning.

#### 3.1 Mapping to the AICT Execution Formula

SAF is grounded in the unified *AI Civilization Transformation* (AICT) execution formula [7]:

$$E(\text{Cap}, \text{Intent}, \text{Context}, \text{Control}) \longrightarrow O$$

The element-level correspondence is locked as follows (Table 2):

This mapping is **canonical and locked**: all subsequent AOP-series papers (AOP-1 through AOP-5) must preserve these symbol-to-concept assignments. Any deviation must be explicitly justified.

Table 2: SAF  $\leftrightarrow$  AICT Formula Canonical Mapping

AICT Term	SAF Elements	Semantics
Cap (Capability)	$A + C$	Execution power + reasoning
Intent	$G$	Goal specification space
Context	$D + O$	Information + organisation
Control	$R + F$	Governance + feedback loop
$O$ (Output)	$\phi_G$ satisfied	Goal predicate achieved

#### 3.2 Key Theorem (Preview)

**Proposition 1** (Knowledge–Control Separability,  $K \neq C$ ). *In an AOP system, the knowledge encoded in the agent’s cognition module  $C$  is formally separable from the control policy encoded in  $R$  and  $F$ . Specifically,  $\exists$  executions  $e_1, e_2$  such that  $C(e_1) = C(e_2)$  but  $R(e_1) \neq R(e_2)$ , demonstrating that knowledge and control are orthogonal design axes.*

The full proof and computational implications appear in AOP-2 [9].

*Intuition.* A translation agent with fixed multilingual competence ( $C$  identical) produces formal legal prose under  $R_1$  and colloquial output under  $R_2$ —same knowledge, different governance. Changing register requires updating  $R$  alone, not  $C$  or  $G$ ; this is  $K \neq C$  in operation, and the direct motivation for decomposing  $\mathcal{P} = \mathcal{P}_G \cup \mathcal{P}_D \cup \mathcal{P}_R$ .

#### 3.3 Engineering Concept Grounding

A natural completeness test for SAF is whether it subsumes the six engineering concepts commonly used to describe LLM-based systems: *LLM*, *Prompt*, *Context*, *Skill*, *Harness*, and *Agent*. Table 3 shows the grounding.

Table 3: Engineering Concepts Grounded in SAF

Concept	SAF	Grounding note
LLM	$C$	Realises $C : G \times D \rightarrow \Pi$ ; substrate of reasoning, not the agent.
Context	$D$	Episodic history, retrieved documents, environment observations.
Skill	$A$	Typed executable operators: tool calls, APIs, code execution.
Harness	$R$	Runtime constraint set: safety guardrails, evaluation bounds, policy enforcement.
Agent	SAF tuple	A fully instantiated $(G, O, C, A, D, R, F)$ ; $O$ composes multiple agents.
Prompt	$G \cup D \cup R$	<b>Not atomic.</b> Conflates intent ( $G$ ), knowledge ( $D$ ), and governance ( $R$ ).
Debug	$F, R$	Audit deviation $\delta(\phi_G, o_t)$ in $F$ and constraint violations in $R$ —not stack traces.

The critical insight is that **Prompt is not a first-class SAF element**. Treating it as monolithic conflates knowledge (what is true,  $D$ ) with control (what is permitted,  $R$ )—the exact conflation the  $K \neq C$  theorem diagnoses. When a prompt-level failure occurs, engineers cannot determine whether the fault lies in goal specification ( $G$ ), knowledge ( $D$ ), or governance constraints ( $R$ ). SAF’s decomposition makes each layer independently auditable and replaceable.

## 4 Research Agenda

This position paper anchors a five-paper series summarised in Table 4.

Table 4: AOP Series Research Agenda

Paper	Focus	Core contribution / Target
AOP-1	Paradigm Declaration	Stored-program $\rightarrow$ intent-conditioned shift. <i>Minds &amp; Machines</i>
AOP-2	Formal Semantics	SAF state-space; IAS; $K \neq C$ proof. <i>IEEE Intelligent Systems</i>
AOP-3	Engineering Methods	CEF; Prompt-as-Policy. <i>ACM TOSEM</i>
AOP-4	Empirical Validation	AOP vs. OOP/FP on HumanEval/SWE-bench; accuracy cliff $\theta$ . <i>ESA</i>
AOP-5	Governance	$R$ as hard constraint layer; Zero-Trust Execution. <i>Ethics &amp; IT</i>

## 5 Relation to Existing Work

Shoham’s AOP [1] addressed BDI-agent programming for hand-crafted agents specifying *mental states*; our AOP specifies *intent and constraints* delegated to foundation-model agents with emergent cognition. The two frameworks share vocabulary but differ in computational substrate. Contemporary frameworks (ReAct [2], LangChain, AutoGPT, LangGraph) implement AOP *mechanisms* but lack a paradigm-level formal theory. SAF is not another framework; it is a *paradigm specification language* within which such frameworks are instances.

## 6 Scope and Terminology Lock

**Scope.** AOP applies to systems in which an LLM or equivalent foundation model serves as the primary cognitive engine ( $C$ ); it does *not* cover rule-based or symbolic agents without a semantic reasoning substrate.

**Prohibited substitutions.** The following substitutions are **prohibited** in all AOP-series papers:

Canonical Term	Never substitute with
Intent-Conditioned Execution	“prompt-based”, “instruction-following”
Autonomous Plan Generation	“pipeline”, “workflow”, “chain”
Governed Feedback Closure	“RLHF loop”, “eval loop”
Semantic Agent Framework	“agent architecture”, “agent system”
$K \neq C$ Separability	“decoupling”, “modularisation”

**Open questions.** Key open problems include: (i) formal verification of stochastic cognition  $C$ ; (ii) convergence guarantees for the AOP feedback loop under adversarial inputs; (iii) compositional governance: how multiple  $R$

constraint sets combine without conflict in multi-agent  $O$  configurations.

## 7 Conclusion

We have argued that LLM-based agents constitute a genuine paradigm shift in software development, characterised by the three properties ICE, APG, and GFC. We have formally defined AOP (Def. 1), introduced the Semantic Agent Framework  $\text{SAF} = (G, O, C, A, D, R, F)$  (Def. 2), established its canonical mapping to the AICT execution formula, and previewed the  $K \neq C$  separability theorem. This position paper serves as the terminological and conceptual anchor for a five-paper research series. We invite community feedback on the definitional boundaries and the open problems listed above.

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