RESEARCH REPORT

AI-Assisted Software Development

A Longitudinal Single-Subject Case Study

Abstract

Building with AI changes everything: strategy, skill, process, and output. This longitudinal case study tracks that transformation across a full year of production work and every stage of the development lifecycle. The findings attempt to frame what productivity means when humans and agents build together — and give practitioners the tools to measure it.

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Study Period: February 2025 – February 2026
Report Date: February 18, 2026
Version: 4.0
Corpus: 7.3M lines of code | 22,975 files | 5,775+ AI conversations | 425+ commits

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Executive Summary

Software Development is changing. Not only because AI generates code faster; but because the relationship between human and machine is evolving into something more collaborative, more structured, and more powerful than either side produces alone.

This study documents that evolution as it happened. Over the course of a year, one builder worked with three AI coding agents across a substantial portfolio of projects — shipping to real users, solving real problems, and accumulating a dataset that was never designed to be research. Conversations, commits, governance artifacts, and prompts accrued as a natural byproduct of building. The result is a longitudinal record of development behavior at a scale and depth that purpose-built studies rarely achieve. No observer effect. No experimental prompting. Just a year of real work — and what it reveals.

AI is a thinking partner first, a code generator second. Nearly half of all AI interactions were pre-implementation work; namely: discovery, definition, and design. Builders who treat AI as an execution engine miss most of its value.

Governance is the primary productivity lever. The strongest correlation in the dataset is not between AI model capability and output quality. It is between the maturity of the builder's governance framework and the health of their outcomes. Without structure, velocity produces technical debt faster than value.

The human learning curve is real, measurable, and stageable. Builders pass through distinct maturity stages: each with characteristic behaviors, artifacts, and failure modes. Progress is punctuated, not gradual, and triggered by specific forcing functions visible in the data.

Rebuilds can be a strategy, not a failure. The portfolio reveals a recurring pattern: prototype, deploy, learn, rebuild. In AI-assisted development, construction speed changes the economics of this cycle fundamentally. The knowledge carried forward is the asset — not the code.

The practitioner gap is systematic. Every established development practice was designed for human teams. When AI joins as a collaborator, each phase develops characteristic failure modes that traditional practices cannot prevent as they are rooted in asymmetries of knowledge, velocity, and failure modes that compound across the lifecycle.

These findings converge on a framework for human-AI collaboration that emerged from the data itself; not designed in advance but extracted from the patterns that were already working.

Introduction

AI coding assistants moved from experimental novelties to production tools in under two years. The research literature has not kept pace. Most studies capture snapshot performance metrics — how fast, how accurate, how often. What remains unstudied is the longitudinal question: how does a developer or process change over time?

Research Motivation

The study originated not from a research design but from a corpus that already existed. The principal investigator's portfolio of 34+ projects, accumulated over 12 months of production work, constituted a naturally occurring dataset of unusual depth — 5,775+ AI interactions, 425 commits, and 57 governance rules, none of it collected for research purposes. The research question came after the data: what do these patterns reveal about how human-AI collaboration actually works?

Three questions motivated this research:

- Is the human learning curve in AI-assisted development measurable?
- Is AI really a reliable code generator, or is there hidden value yet to be found? And
- Can we find patterns that will not only help learn but improve software development?

Research Questions

The core study questions started with the following four categories of inquiry. These were further expanded with the data analyses into 16 dimensions as described later in Appendix B:

- **Human Adaptation and Learning:**
    - How does prompting sophistication evolve?
    - What are the measurable learning stages?
    - How does learning occur?
- **Agent Performance and Reliability:**
    - How do correction rates change over time?
    - What domains produce the most errors?
    - How does session duration affect quality?
- **Productivity and Output:**

    - What is the actual code generation efficiency?
    - How do agents and migration impact velocity?
    - What is the build-to-overhead ratio?
- **Behavioral and Environmental Factors:**
    - What work patterns correlate with development quality?
    - How does the design-implementation distribution look?
    - What role do governance artifacts play?

Methodology

This is a **single-subject longitudinal mixed-methods** case study combining quantitative content analysis with qualitative thematic coding. The design is retrospective for

- Agent A (Cursor IDE, February–October 2025)
- Agent B (Windsurf/Cascade, September–October 2025), and
- Agent C (Claude Code CLI, November 2025–February 2026).

Data Collection

All data was collected through forensic extraction of organically accumulated artifacts. This is a key methodological strength: every data point reflects authentic production behavior with no observer effect. The data sources include:

Source	Volume	Period
ChatGPT Conversations (Codex Export)	875 conversations (141 MB)	Dec 2022 – Feb 2026
Cursor IDE Prompts	23 prompt files + 21 composer files	Apr – Sep 2025
Claude Code Sessions	12 MB session data + project settings	Nov 2025 – Feb 2026
Git Repositories	425 commits across 10 repositories	Apr 2025 – Jan 2026
Governance Artifacts	57 rules across 19 files	Oct 2025 – Feb 2026
Project Documentation	34+ project directories	Feb 2025 – Feb 2026

Analytical Methods

Quantitative Content Analysis: Every commit was categorized (build/fix/docs/refactor) and every prompt was classified by type (directive/descriptive/specification/collaborative/meta), quality score (0–10), specificity (0–1), and technical depth (0–5). Error pastes (n=211) were filtered from the prompt analysis to avoid skewing quality metrics. See appendix C for definitions.

Temporal Pattern Analysis: Commits were clustered into sessions using a 2-hour window, yielding 224 development sessions. Monthly aggregations capture trends across the full study period. Burst days (3+ commits), gaps (7+ days between commits), and hourly/day-of-week distributions were computed.

Conversation Phase Classification: All 875 ChatGPT conversations were classified into six phases: discovery (exploring problems and possibilities), definition (specifying requirements), design (architectural decisions), implementation (code writing), learning (skill acquisition), and other. This classification enables the design-to-implementation ratio analysis.

Governance Artifact Analysis: All governance rules were extracted verbatim (57 rules from 19 files) and classified as prohibition, mandate, guidance, or critical. Design decisions (90 identified) and scar tissue instances (rules traceable to specific failures) were cataloged.

Validity and Limitations

Strengths: The 12-month observation period captures long-term behavioral change. Triangulation across 6+ data source types provides convergent validity. Multi-agent comparison (three AI tools) controls for agent-specific effects.

Limitations: Single-subject design limits generalizability; findings are hypothesis-generating rather than hypothesis-confirming. Early-month data (February–May 2025) is sparse, with some repositories having minimal commit history. The retrospective analysis of Cursor IDE data relies on exported prompts rather than full interaction logs. Some project repositories were inaccessible for analysis and hence excluded.

A Note on Methodology

This study emerged from a builder operating an AI-assisted development practice across a real portfolio — building products, shipping to production, iterating under genuine constraints. The data was not collected for research purposes; it was generated as a natural byproduct of

building. Commit logs, conversation histories, governance artifacts, and prompt archives existed because the builder was working. The research came later: the realization that ten months of continuous AI-assisted development had produced a dataset of unusual depth and completeness, and that the patterns within it were worth formalizing.

The methodology is autoethnographic: the principal investigator is the subject. The data is comprehensive, but the perspective is singular. These are real limitations. They are also features. The most enduring contributions to software engineering practice — from Agile to DevOps to site reliability engineering — came from practitioners systematizing what worked. The 7D Framework follows that tradition: methodology extracted from practice, not imposed on it. The question is whether the patterns identified here resonate with what other practitioners are experiencing. If they do, the research agenda in Appendix B provides a path to validation at scale.

The Portfolio

The portfolio that forms this study's dataset is not a curated selection of showcase projects. It is the working record of a builder moving through problems, pivots, and compounding ambition. Some projects became production systems; proved a concept and were deliberately set aside; or failed fast and taught valuable lessons. Together they constitute the necessary raw material.

Corpus Summary

Metric	Value
Application Source Code	~270,000 lines across ~2,500 files
Documentation	~255,000 lines (near 1:1 doc-to-code ratio)
Framework / Dependencies	~6.8 million lines (node_modules, venv, Maven, CDK)
Total AI Interactions	5,775+ (4,737 Cursor IDE + 875 ChatGPT + 163 Claude)
Human Prompts Analyzed	7,978 (after filtering 211 error pastes)
Git Commits	425 across 10 tracked repositories
Projects	34+ across 5 ecosystems
AI Agents Used	3 (Cursor IDE, Windsurf/Cascade, Claude Code CLI)
Governance Artifacts	57 rules across 19 files
Study Period	12 months (February 2025 – February 2026)

Development Strategy

Before examining the marquee projects, it is important to understand a deliberate development strategy that characterized the first half of the study period: the builder consistently broke problems into small, independent modules and built them separately before attempting integrated systems. This pattern is visible across the entire portfolio.

Between April and September 2025, the builder produced a stream of focused, single-purpose projects: a reusable navigation component (April), a Python web scraping framework (June), a state-specific insurance statute scraper (June) that could be extended/adapted to another state, a site inventory Chrome extension (August), a landing page for a service (August), and a document processing system (September–October). None of these were large. Each solved one problem, proved one concept, and could stand alone.

This was not accidental. The builder was simultaneously working on a larger multi-tenant platform and insurance rating system—both complex, multi-component applications. The small modules served as controlled experiments informing design and architectural decisions for the larger projects. The Chrome extension explored website crawling techniques that would later influence how tenants were onboarded and initialized. The nav-control-component tested XML-driven UI patterns that appeared in later admin interfaces controlling access, visibility and entitlements. Each small project reduced the risk surface of the larger ones.

Period	Type	Purpose	Fed Into
Apr 2025	React component	XML-driven multi-pane navigation	Admin UI patterns
Jun 2025	Python library	Reusable web scraping framework	State configurable insurance scraper
Jun 2025	Data utility	State statute collection + MCP compliance agent	Compliance data pipeline
Jun–Sep 2025	Platform (Python + React)	Modular insurance rating engine	Standalone (multi-jurisdiction)
Aug–Sep 2025	Chrome extension	Website content discovery + crawling	Tenant onboarding and initialization concepts
Aug 2025	Landing page	AI service marketing site	Agent widget deployment pattern
Sep–Oct 2025	Document processor	Document splitting, content extraction, bundling, and structuring	Insurance document workflow
Oct 2025	Infrastructure (Java/CDK)	Multi-tenant workspace foundation	Platform-level tenant isolation

The shift away from this build-small-first strategy coincided with the transition to AI-heavy development in late October. As the developer gained confidence in AI-assisted construction speed, the economics changed: it became faster to build integrated systems directly (with AI generating boilerplate and scaffolding) than to assemble them from pre-built modules. But the small-module phase was not wasted. The architectural intuitions developed during those months—about separation of concerns, about API contracts, about keeping components focused—became the governing principles that would later direct, manage and constrain AI agents. The 300-line file size limit in ClauseLib, the service layer decomposition in flagship-v3, and the separated admin console all trace their lineage to the habits formed during the build-small-first period.

Path to Enterprise System

The most significant pattern in the portfolio is the three-generation evolution of the ChatPlatform, where each generation was a deliberate rebuild that incorporated critical lessons from its predecessor. It is the story of a tinker project becoming a marquee enterprise-grade application.

Generation 1: (June–August 2025)

ChatPlatform-v1 began as a lightweight widget prototype—a tinker project to explore whether multi-tenant AI chat agents were feasible. The key technical bet was asymmetric encryption for secure agent identification and a dual-mode architecture separating Operations and Inventory APIs. These architectural choices—multi-tenancy and separated API concerns—would survive through every subsequent generation. ChatPlatform-v1 was archived after proving the concept, but its DNA lived on.

Generation 2: (July–November 2025)

ChatPlatform-v2 was the first attempt to build a production system on ChatPlatform-v1's foundation. It expanded dramatically: an admin console, a serverless backend, template-based tenant provisioning, and real-time analytics. It went through two production releases. But the architecture grew organically—handlers became monolithic, the admin console was tightly coupled to the backend, and the codebase accumulated the kind of structural debt that comes from building fast without governance. The 6 surviving commits belie what was months of active development; the commit discipline itself was part of the problem.

After the October release, development stalled from the recognition that the architecture had reached its limits. The monolithic handler had grown to over 1,500 lines. Adding features meant

touching everything. This is the classic "successful prototype trap": the code works, but it cannot evolve.

Generation 3: (November 2025–January 2026)

The third generation was a clean slate rebuild. The first three commits tell the story: "initialized project," then "Migrate the template server code and admin from Generation 2. The builder deliberately started fresh but immediately pulled forward the proven components—not copying the codebase but reimplementing the concepts with a service-oriented architecture. The 1,500-line monolithic handler was decomposed into four focused Lambda handlers backed by a set of three service layer helpers.

Launched on Dec 9, the system had matured into a genuine enterprise application with well-separated concerns: the operations agent, API endpoints, and backend services lived in one application, while the admin console had been architecturally separated with well-defined interface contracts—JSON schema validation for configuration, standardized HTTP response builders, and clear API boundaries. The admin console used React 19 with TypeScript, Vite, and Tailwind, communicating with the backend exclusively through documented API contracts rather than shared state.

The third generation system accumulated 187 commits over 58 days—a 15x increase in commit velocity compared to Gen 2. This explosion in throughput was not just AI speed; it reflected the compounding effect of governance documents (ARCH.md, CURRENT_STATE.md, evolution of a system and framework) that made each AI session productive from the first prompt.

Generation	Period	Commits	Architecture	What It Proved
Gen 1	Jun–Aug 2025	12	Dual-mode widget prototype	Multi-tenancy + encryption feasibility
Gen 2	Jul–Nov 2025	6 (2 prod releases)	Monolithic handler + coupled admin	Production viability; hit architectural ceiling
Gen 3	Nov 2025–Jan 2026	187	Service layer + separated admin	Enterprise-grade with governance framework

The Prototype→Production→Gap→Rebuild cycle is not a failure pattern — it is a deliberate strategy. In AI-assisted development, rebuilds cost days, not months. The real asset is the knowledge accumulated across generations, not the code.

Prototype Trajectory

Not all projects need three generations. A purpose-built application deployed rapidly to production as "Launch" followed a different path: One and Done. With 70 commits over October

through December 2025, it went from a concept to a fully deployed AWS stack—Cognito authentication, API Gateway, Lambda functions, DynamoDB, S3, CloudFront CDN, and Route53 DNS—in a matter of weeks.

The architecture was deliberately self-contained: a Vite/React frontend, a Lambda-backed progress API, and AWS CDK infrastructure-as-code, all in one monorepo. There was no need for multi-tenant isolation, no service layer decomposition, no governance framework beyond basic project documentation. The scope was clear, the requirements were fixed, and the deployment was final. This is the AI-assisted equivalent of a well-executed sprint: high velocity, tight scope, and no iteration beyond the initial build.

Parallel Domains

Running parallel to the Enterprise lineage was a second ecosystem: a set of insurance-domain projects that illustrate the build-small-first strategy most clearly. The state web-scraper (June 2025) was a focused Python utility built as an MCP server with a compliance agent—its sole purpose was to collect one state insurance statutes and make them queryable. That data pipeline fed directly into a larger compliance project (June–September 2025), a modular insurance rating platform supporting multiple lines of business and jurisdictions, starting with one line of insurance in one state. This project was architecturally modular: a Python rule engine, a React admin console, and a separate React client, designed so that each jurisdiction and product line could be plugged in independently consuming common services.

In November 2025 a two-day experiment from this ecosystem would have outsized influence on the study's findings. Built as a Composable Clause Library for Insurance, ClauseLib was a serverless service with just 6 commits—but it was the project where the 300-line file size governance limit was first formalized and held at 0% violations. The documentation-as-governance patterns tested in ClauseLib (keeping files small, writing prescriptive component specs before coding) transferred directly to the third generation enterprise platform bootstrap that began two weeks later. In this sense, ClauseLib was a proof-of-concept not for insurance technology but for a new and evolving development methodology.

Development Strategies

Taken together, the portfolio reveals three distinct strategies for how projects mature in AI-assisted development, each appropriate to different conditions:

Strategy	Example Projects	When It Works
Build-Small-First	webscraper, Inventory, nav-control, documentation, servicing	Unknown domain, high uncertainty, need to prove feasibility before committing
Generational Rebuild	ChatPlatform-v1 → ChatPlatform → Flagship-v3	Platform ambitions where architecture must evolve with understanding
Sprint-to-Deploy	LaunchSite → Deploy	Clear scope, fixed requirements, bounded complexity

The builder's trajectory across the study period moved from predominantly Build-Small-First (April–September) to a mix of Generational Rebuild and Sprint-to-Deploy (October–January). This was not a rejection of the modular approach—it was a graduation from it. The habits of small-component thinking became internalized governance principles: the 300-line file limit, the service layer decomposition, the separated admin console with API contracts. What started as a strategy for managing uncertainty became the architectural instincts that made AI-assisted platform development productive.

Repository Profiles

Project	Stack	Commits	Period	Role in Study
flagship-v3	Node/TS + Lambda	187	Nov–Jan	Flagship platform: 3-phase evolution, richest data source
LaunchSite	Vite/React + CDK	70	Oct–Dec	Sprint-to-deploy: concept to [production URL]
ChatPlatform-v1	Node/TS + AWS	12	Jun–Aug	ChatPlatform Gen 1: proved multi-tenant feasibility
ClauseLib	Node/TS	6	Nov	Governance experiment: 300-line limit, 0% violations
ChatPlatform	JS/React + Lambda	6	Jul–Nov	ChatPlatform Gen 2: hit architectural ceiling, triggered rebuild
Engage	Node/TS	5	Nov	Next-gen lead engagement platform
RateCalc	Python + React	—	Jun–Sep	Modular insurance rating engine (multi-jurisdiction)
StateScraper	Python (MCP)	—	Jun	Data pipeline: FL statute collection for RateCalc
InfraCore	Java/CDK	—	Oct	Multi-tenant infrastructure foundation
Inventory	JS (Chrome Ext)	—	Aug–Sep	Site crawling POC: informed tenant onboarding

Project	Stack	Commits	Period	Role in Study
DocProcessor	React + Node	—	Sep–Oct	Document processor: splitting, extraction, bundling

Several additional projects ([template-a], [MethodologyPlatform], [product]-ux-study, [prototype-b], project-templates, 7D-Framework, Assistant) are template scaffolds, research prototypes, or documentation that informed the methodology but did not produce application code analyzed in this study.

Builder Evolution

The central finding of this study is that **human learning drives collaboration quality gains**. Over 10 months and 7,978 analyzed prompts, the builder underwent a measurable transformation in how they communicate with, govern, and leverage AI coding agents. This chapter documents that transformation through three lenses: prompt maturity, learning stages, and governance evolution.

Prompt Maturity

The most granular view of human evolution comes from prompt analysis. After filtering 211 error pastes (stack traces and error code dumps that would artificially inflate word counts), 7,978 human prompts were analyzed for quality, specificity, type distribution, and linguistic sophistication.

The trend lines tell a clear story. Quality scores rose from 0.48 in Q1 2024 to 0.96 by Q4 2025—a doubling that represents the shift from bare commands ("fix this") to structured specifications with context, constraints, and acceptance criteria. Average word count grew from 36 words per prompt to 94 words, a 2.6x increase that reflects increasingly detailed communication.

Specificity scores climbed from 0.31 to 0.68, indicating that prompts increasingly referenced specific files, functions, and architectural components rather than vague descriptions. Most strikingly, the percentage of prompts including explicit constraints rose from 5.2% to 17.0%—the developer was not just describing what they wanted but defining the boundaries of acceptable output.

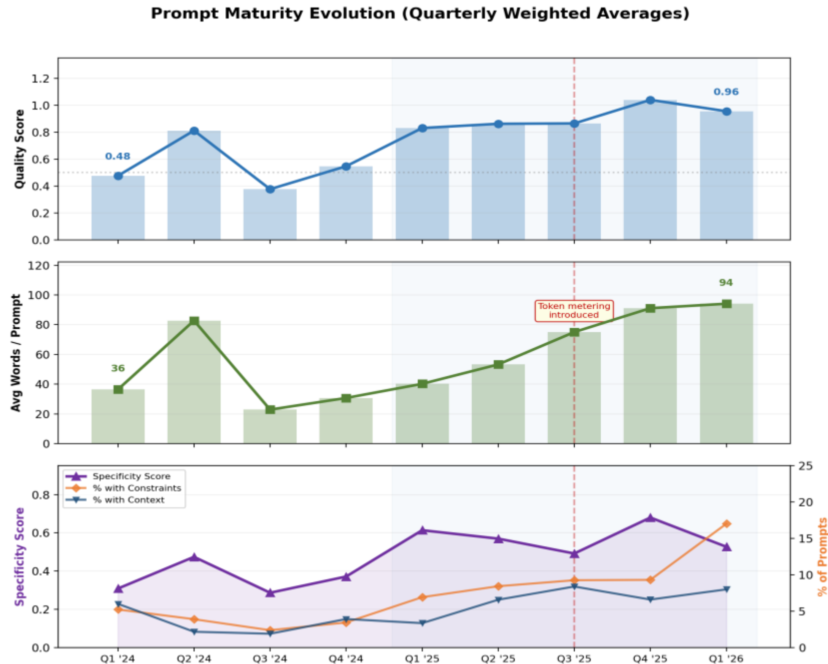


Figure 2. Prompt quality score, average word count, and specificity evolution shown as quarterly weighted averages from Q1 2024 to Q1 2026, with token metering introduction marked.

The type distribution shifted in parallel. Early interactions were overwhelmingly directive ("do this," "fix that"), comprising over 54% of prompts. By 2026, directive prompts declined to approximately 40% while two new categories dominated: specification-type prompts that provided explicit constraints and acceptance criteria, and collaborative prompts that treated the AI as a thinking partner rather than a command executor. The developer stopped giving orders and started writing briefs.

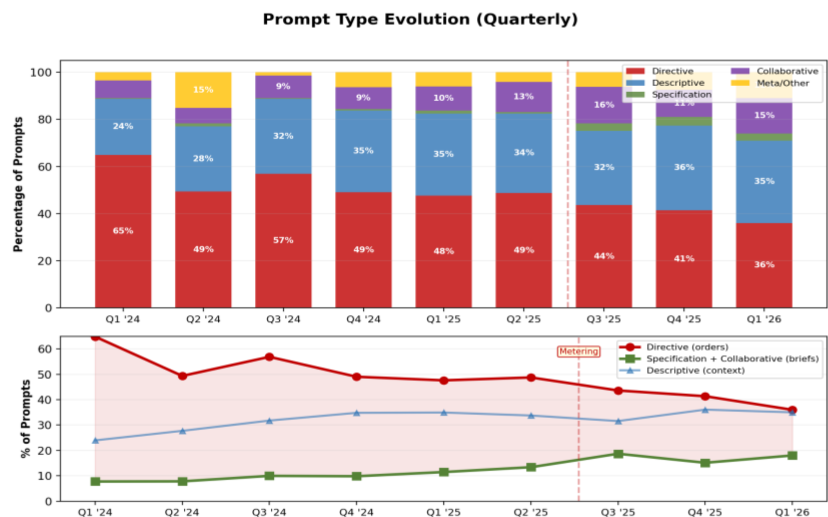


Figure 3. Quarterly prompt type distribution (top) and the key trend line showing directive prompts declining while specification and collaborative prompts rise (bottom).

The linguistic evidence reinforces this trajectory. The developer’s technical vocabulary grew from 61 unique terms in the first month to 1,135 by the most recent—an 18x expansion that reflects the development of a shared language between human and AI. Terms like "service layer," "tenant isolation," "context budget," and "session packaging" became standard lexicon, appearing in both governance documents and daily prompts. Vocabulary density (advanced terms per interaction) tripled from 8–12 terms to 42–49 terms per workspace, and conventional commit message adoption went from 0% to 86%. The developer didn’t just learn to write better prompts; they internalized a technical communication style that made every interaction with AI more productive.

Learning Trajectory

The longitudinal data reveals five distinct stages of builder maturity, each identifiable by its governance posture, velocity characteristics, and relationship to the AI agent.

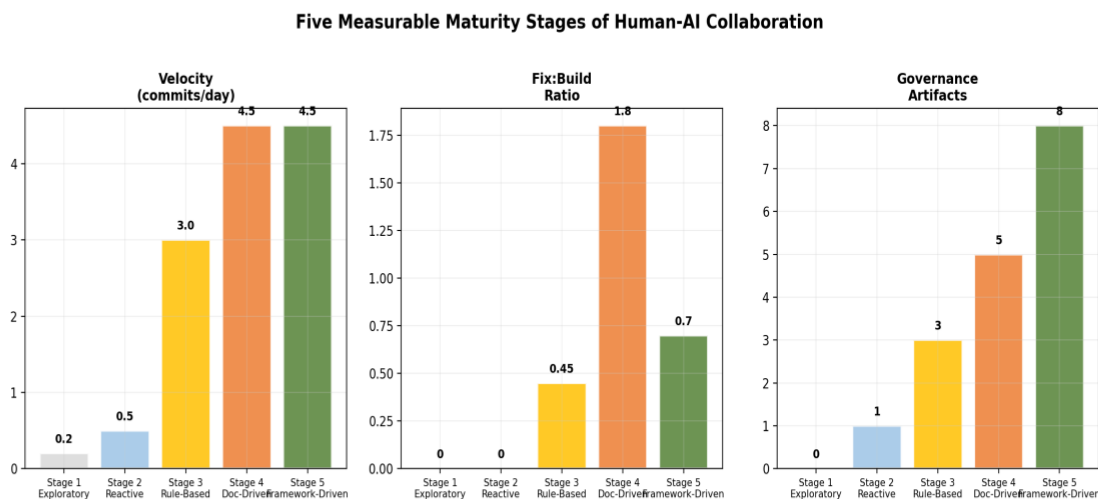


Figure 4. Three key metrics across the five identified maturity stages of human-AI collaboration.

The **Exploratory stage (February–June 2025)** had no governance artifacts. Technology choices were scattered—CRA, Bootstrap, raw HTML, Python—and projects were small, independent, and frequently abandoned after proving a single concept. This was the build-small-first period described in Chapter 4, and the builder’s AI interactions reflected it: 0.2 commits per day, short conversations, and a tool-user mentality where the AI was treated like a more capable Stack Overflow.

The **Reactive stage (July–October 2025)** began when things started breaking. The first .cursorrules files appeared as direct responses to specific failures: "NEVER touch production tenants" after a production data incident, "ALWAYS run Braintrust evals before merge" after a regression, "ALWAYS gate lead delivery" after a billing problem. Every rule was scar tissue—

institutional memory encoded as constraints. The language was prohibitionist ("never," "always," "must"), and the builder's focus narrowed from scattered experimentation to two verticals: the ChatPlatform and insurance systems.

The **Rule-Based stage (November 2025)** marked the shift from reactive to proactive. ClauseLib codified the 300-line file maximum and interface-first development requirements—rules derived from architectural principles rather than past incidents. CLAUDE.md created the first AI-specific context optimization file, designed not for the human to read but for the agent to consume. Multiple projects launched simultaneously, and the builder demonstrated the ability to maintain architectural consistency across parallel workstreams.

The **Documentation-Driven stage (December 2025)** was the study's crucible. ARCHITECTURE.md was locked on December 19 as a prescriptive document—the first time the builder committed to a fixed architectural vision before building. The results were paradoxical: December produced the highest commit volume in the study (325 commits, 76% of all activity) but also the worst fix-to-build ratio (1.8:1). The builder was shipping fast but spending nearly two correction commits for every feature. The documentation helped but could not, by itself, prevent the AI agent from introducing errors at high velocity.

The **Framework-Driven stage (January–February 2026)** resolved the paradox. A comprehensive governance framework (later formalized as a methodology; see Section 10) organized the complete development lifecycle. .agent files provided 60+ lines of preemptive engineering guidelines per project. The results were immediate: session duration dropped 58% (from 94.3 to 39.3 hours), the fix-to-build ratio fell to 0.7:1, and velocity sustained at 4.5 commits per day—but now with quality. The same builder, evolving AI models, the same codebase. While AI capabilities also improved during this period, the dominant variable that changed was the governance framework.

> *The December crisis is the study's most important data point. It proves that AI-assisted velocity without governance produces technical debt faster than value. The transition from Stage 4 to Stage 5—from "document what you want" to "constrain how it gets built"—is the single highest-leverage behavioral change a developer can make when working with AI agents.*

Conversation Evolution

One of the clearest measurable signals of human maturation is the change in conversation length over the study period. The data reveals a four-phase evolution in how the builder structured AI interactions:

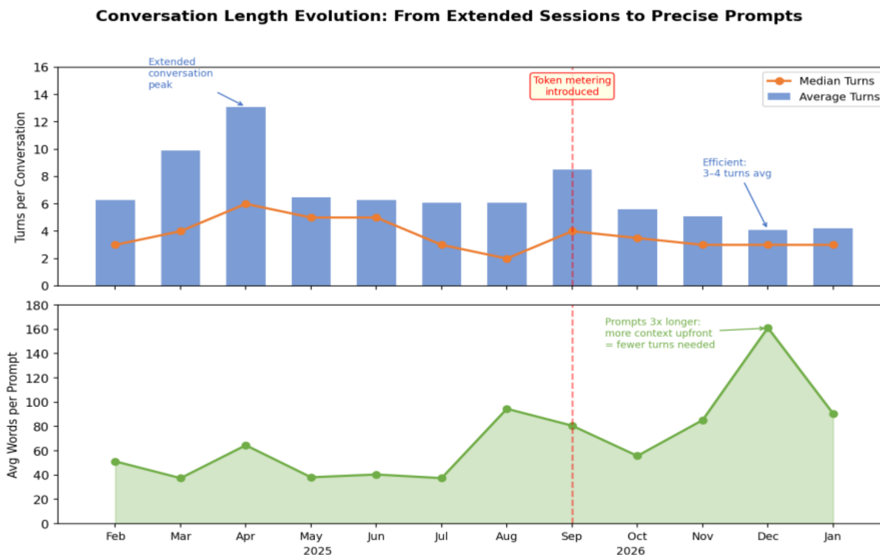


Figure 5. Turns per conversation (top) and average words per prompt (bottom) across the study period, showing the inverse relationship: as prompts grew longer and more specific, conversations grew shorter.

In the earliest months (February–March 2025), conversations averaged 6–10 turns—the builder was learning to communicate with AI through iterative back-and-forth, using short prompts (37–51 words average) and relying on multiple rounds of clarification. April 2025 marked the peak of extended conversations at 13.1 average turns per conversation, with some sessions stretching to 129 turns. This was the "marathon session" phase: the builder would start with a vague directive and iterate through dozens of correction cycles.

The May–August period shows a gradual reduction to 6 turns average, reflecting growing skill at front-loading context. But the most dramatic inflection point came in September 2025, when token metering was introduced to the AI platforms. Suddenly, every turn had a cost. This external constraint—fundamentally an economic one—accelerated a behavioral shift that was already underway: prompts jumped from ~40 words to 80+ words average, context inclusion doubled from 5–6% to 12.6%, and the builder began structuring prompts as complete specifications rather than conversational starters.

By December 2025 through January 2026, the transformation was complete. Conversations averaged just 3.8–4.2 turns with a median of 3, while average prompt word count peaked at 161 words—a 4x increase from the May–July baseline. The builder had learned to pack architectural context, constraints, acceptance criteria, and file references into a single prompt, receiving correct output in one or two exchanges rather than iterating through ten. In January, 19.2% of prompts included explicit constraints, compared to under 5% a year earlier.

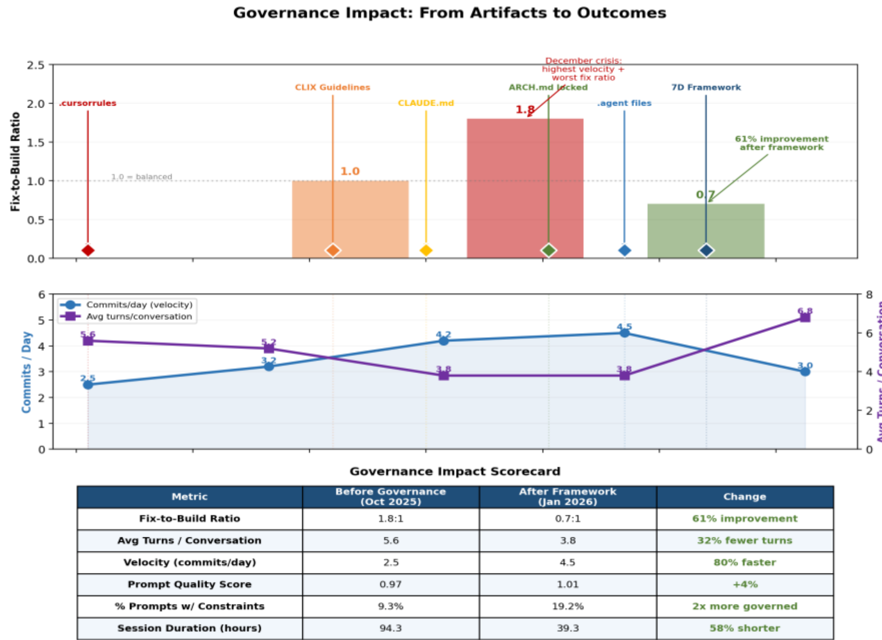
Phase	Period	Avg Turns	Avg Words/Prompt	Driver of Change
Exploratory Back-and-Forth	Feb–Apr 2025	6–13	37–65	Learning to communicate with AI
Stabilizing	May–Aug 2025	6	38–95	Growing skill at front-loading context
Metering Inflection	Sep 2025	8.5	81	Token limits make every turn count
Precision Prompting	Oct 2025–Jan 2026	3.8–5.6	56–161	Governance + metering = specification-grade prompts

Key Insight: The introduction of token metering in September 2025 acted as a forcing function for prompt quality. Like a word limit on an essay, the constraint did not diminish output quality—it improved it. The builder stopped treating AI conversations as iterative dialogues and started treating them as engineering specifications. Fewer turns with better prompts produced faster, more accurate results. The economic constraint aligned with the governance trajectory that was already in motion.

AI-Native Governance

The maturity stages described above are visible in the builder's behavior. But they are also encoded in artifacts—57 rules across 19 governance files that evolved from human-readable constraints to AI-native specifications. The most important shift was not in what the rules said but in who they were written for.

The early .cursorrules files (October 2025) were written for the builder to remember: prohibitions phrased in human language, triggered by specific past failures. ClauseLib Guidelines (November 2025) were the transitional form: still human-readable but structured enough that an AI agent could parse and follow them. The real breakthrough came with CLAUDE.md (December 2025) and the .agent files (January 2026), which were explicitly designed for AI consumption—optimized for token efficiency, structured as hierarchical context documents, and including "red flag" patterns that instructed the agent to stop and ask before proceeding. The governance was no longer about the agent; it was for the agent.



Metric	Before Governance (Oct 2025)	After Framework (Jan 2026)	Change
Fix-to-Build Ratio	1.8:1	0.7:1	61% improvement
Avg Turns / Conversation	5.6	3.8	32% fewer turns
Velocity (commits/day)	2.5	4.5	80% faster
Prompt Quality Score	0.97	1.01	+4%
% Prompts w/ Constraints	9.3%	19.2%	2x more governed
Session Duration (hours)	94.3	39.3	58% shorter

Figure 6. Governance impact showing artifact creation timeline mapped to fix-to-build ratio (top), velocity and conversation efficiency (middle), and before/after scorecard (bottom).

The culmination was a comprehensive governance methodology file (January 2026), which formalized the full development lifecycle and instructed AI agents on how to navigate each phase. This is governance at the methodology level: not "don’t touch production data" but "here is how you think about a development session from start to finish." The specifics of this formalized methodology are described in Section 10. The difference between these two levels of governance is the difference between Stage 2 and Stage 5, and it is the single largest contributor to the productivity gains documented in this study.

AI Agent Collaboration

The last section examined the builder's evolution through the lens of inputs — prompts, governance artifacts, and learning stages — this chapter turns to outputs. Commit patterns, fix-to-build ratios, error domain distributions, and velocity progressions to look for empirical evidence that the behavioral changes produced measurable difference in development outcomes. The data spans 425+ commits across 10 tracked repositories.

Commit Activity Patterns

The commit activity timeline reveals the study's central narrative arc. Activity builds gradually from April through October 2025, then surges dramatically in November–December. December 2025 alone accounts for 76% of all recorded commit activity. The composition of these commits tells the deeper story: the December surge is dominated by fix commits (red), indicating that high velocity without adequate governance generates enormous correction overhead.

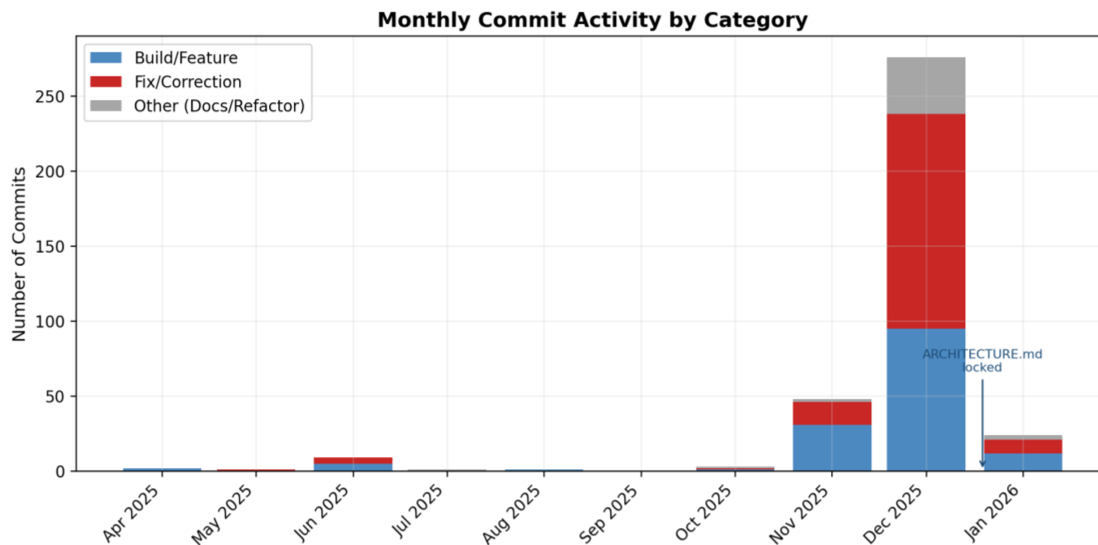


Figure 7. Monthly commit activity by category, showing the December 2025 peak and subsequent stabilization.

January tells a different story: fewer commits, more net features, a healthier build-to-fix ratio. The governance infrastructure built in December was now paying compound interest.

Fix-to-build Ratio

The most concrete evidence of change was the fix-to-build ratio. This tracks the number of correction commits per feature commit. In flagship-v3's four phases, this metric tells a clear story of governance impact:

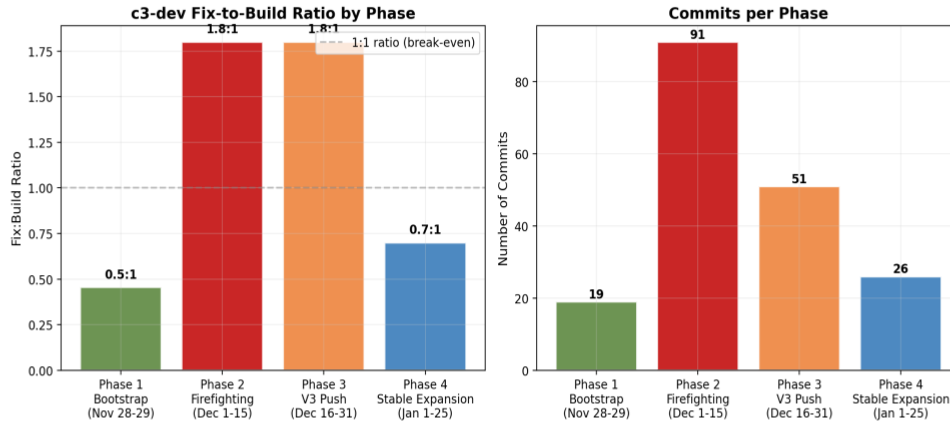


Figure 8. flagship-v3 fix-to-build ratio across four development phases, showing 61% improvement from Phase 2 to Phase 4.

Phase 1 (Bootstrap, November 28–29): 19 commits at a 1:2.2 fix-to-build ratio. Building outpaces fixing due to greenfield advantage—no existing code to break.

Phase 2 (Firefighting, December 1–15): 91 commits at a 1.8:1 ratio. Production deployment triggers CORS, IAM, and endpoint crises. December 8–9 alone produced 46 commits in 2 days, overwhelmingly fixes. Only 1.3 features were delivered per coding day despite 9.1 commits/day velocity.

Phase 3 (V3 Push, December 16–31): 51 commits at a 1.8:1 ratio. ARCHITECTURE.md was locked on December 19. The ratio has not yet improved because the architectural knowledge has not yet propagated through the codebase. The V3.0 production rollout on December 24 and the service layer refactor on December 29 (+3,177/−539 lines) lay the foundation.

Phase 4 (Stable Expansion, January 1–25): 26 commits at a 0.7:1 ratio. For the first time, building exceeds fixing. 1.9 features per coding day versus 1.3 in Phase 2. The governance infrastructure created in Phases 2–3 pays compound dividends.

> *The Phase 2 → Phase 4 improvement from 1.8:1 to 0.7:1 (a 61% reduction in fixes relative to features) is the most concrete evidence in the corpus that documentation-driven governance directly improves development outcomes.*

Fix Commits by Domain

Analysis of 173 fix commits reveals which requirement domains generate the most correction overhead. UI/UX issues dominate at 37%, followed by API/Integration at 25%, Config/Environment at 17%, and Logic/Flow at 15%. Security and Data/State issues are comparatively rare.

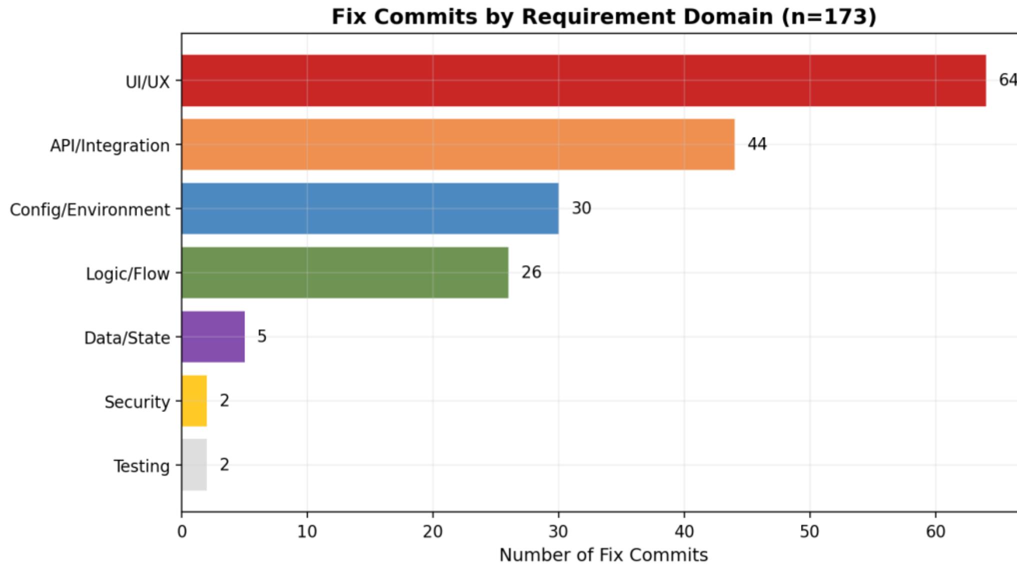


Figure 9. Distribution of 173 fix commits across requirement domains.

This distribution has practical implications: AI agents are most reliable at core logic but struggle with visual presentation, cross-service integration, and environment configuration—precisely the domains where human oversight provides the highest value.

Velocity Progression

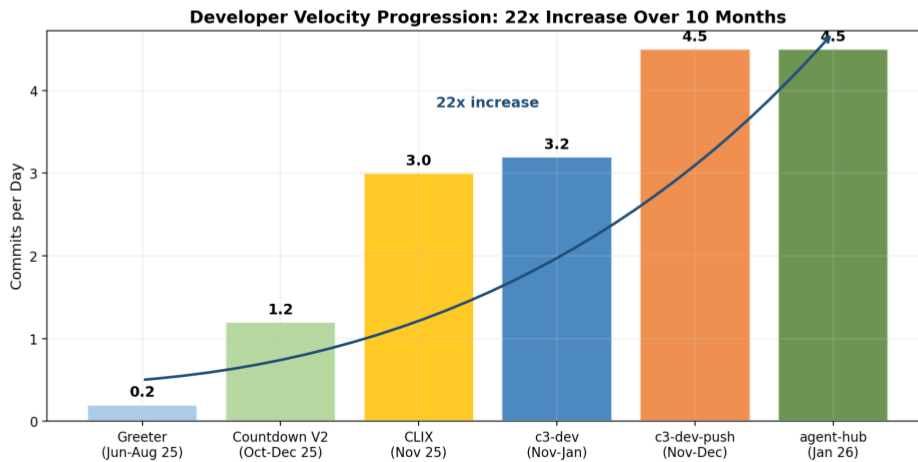


Figure 10. Builder velocity progression from 0.2 to 4.5 commits per day across projects.

From 0.2 commits/day in June 2025 to 4.5 in January 2026 — a 22x increase. AI models improved during this period, but that was a tailwind, not the engine. The velocity gain traces directly to the builder’s ability to structure sessions, front-load context, and eliminate the correction cycles that consumed the early months.

Design versus Implementation

Perhaps the most surprising finding of this study is the distribution of human-AI interactions across development phases, that is the hidden work of AI-driven implementations. The prevailing narrative around AI coding tools emphasizes implementation: AI writes code, the human reviews it. The data tells a fundamentally different story.

Phase Distribution

Classification of all 875 ChatGPT conversations into six phases reveals that **46.6% of all AI interactions were pre-implementation work**: discovery (28.3%), definition (13.7%), and design (4.6%). Implementation accounts for only 23.5% of conversations. Learning (7.3%) and other activities (22.5%) comprise the remainder.

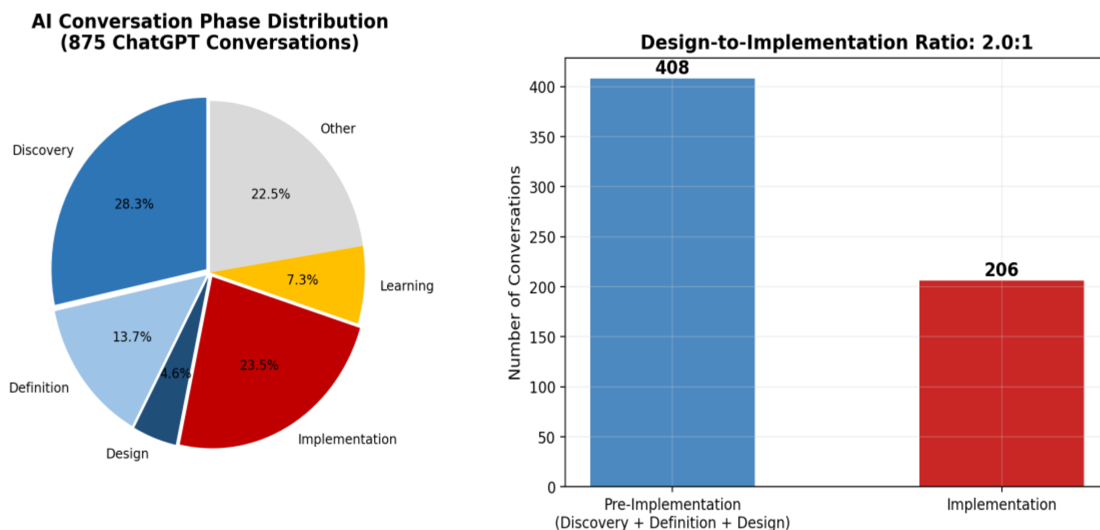


Figure 11. Phase distribution of 875 ChatGPT conversations and design-to-implementation ratio.

This yields a **design-to-implementation ratio of 2.0:1**. For every conversation where the builder asked AI to write code, two conversations occurred where the builder used AI as a thinking partner for problem exploration, requirements specification, or architectural decision-making.

Design Conversations

The 408 design-phase conversations follow characteristic patterns. **Discovery conversations** (n=248) typically begin with open-ended exploration: "I want to analyze this repository for how we can leverage it," or "Can you track the trials on this environment?" These conversations are the longest on average, with 16+ back-and-forth exchanges.

Definition conversations (n=120) translate discovery into requirements: "I need to define a Leadership Dashboard. The goal is to provide a view into utilization/utility/use of the Product Enterprise." These conversations feature the highest average prompt word counts (164 words) and the most structured outputs (numbered requirements, phased roadmaps, metric definitions).

Design conversations (n=40) make architectural decisions: technology selection, component boundaries, data model design. These are the most technically dense and often reference previous conversations or project documentation.

Implications for Vibe Engineering

The 2.0:1 design-to-implementation ratio directly contradicts what has been termed "vibe coding"—the practice of using AI to generate code from minimal prompts without systematic design thinking. The data shows that this builder consistently invested in pre-implementation work, using AI for discovery, definition and design before writing any code.

These findings were adopted into a repeatable methodology (see Section 10), which the builder later formalized as a system for seamless development process. The framework was not invented abstractly; it was extracted from the builder’s own organic behavior as revealed by this analysis. The builder naturally gravitated toward using AI for discovery and definition before implementation, and the formalized framework simply codified this instinct into a repeatable process.

Human vs. AI Design

Analysis of project documentation reveals a consistent pattern across the portfolio. In all seven analyzed projects, the ideation phase showed clear human markers: explicit problem statements, business model definitions, and user persona identification. Requirements were classified as "Explicit-Human" across all projects, with pre-development documentation, API contracts, and data schemas designed before implementation.

The design phase showed the most nuanced human-AI collaboration. While the human made all major architectural decisions (technology choices, component boundaries, security models), the AI contributed to detailed implementation design within the human’s architectural constraints. Projects classified as "Deliberate-Human" design (ClauseLib, LaunchSite Guide V2,

Engage) had the lowest fix-to-build ratios, while "AI-Led" design projects (flagship-v3 early phases) showed higher correction overhead—further evidence that human architectural governance is the primary productivity lever.

Productivity through Governance

The strongest correlation in the dataset is one between governance artifact creation and productivity improvement. This chapter synthesizes the evidence.

Governance–Productivity Correlation

Four temporal correlations establish governance as the primary productivity driver:

1. **ARCHITECTURE.md locked December 19 → fix rates begin declining.** The prescriptive architecture document created a shared contract between human and AI that reduced architectural ambiguity.
2. **ClauseLib Guidelines formalized November 12 → flagship-v3 bootstrap uses the patterns November 28.** Governance knowledge transferred directly from one project to the next.
3. **.agent files created January 2026 → platform-admin-v3 sustains 4.5 commits/day.** The most prescriptive governance produced the highest sustained velocity.
4. **Governance methodology formalized → session duration drops 58%.** The complete methodology reduced the average session duration from 94.3 hours to 39.3 hours while maintaining output quality.

Governance Rules

Verbatim extraction of all 57 governance rules across 19 files reveals the following distribution:

Rule Type	Count	Percentage	Example
Prohibition ("NEVER...")	12	21%	NEVER touch production tenants
Mandate ("ALWAYS...")	18	32%	ALWAYS run evals before merge
Guidance (best practice)	15	26%	Files should be < 300 lines
Critical (gate/checkpoint)	12	21%	Must pass critical eval group before PR merge

The rule distribution tells a story about governance maturity. Early governance is dominated by prohibitions and mandates (reactive rules responding to failures). Later governance shifts toward guidance and critical checkpoints (proactive rules preventing anticipated problems). The ratio of prohibition to guidance rules decreases from approximately 3:1 in October 2025 to 1:1 by January 2026.

Documentation-to-Code Ratio

In flagship-v3, the project with the most complete data, the documentation-to-code ratio is 1.7:1 (76KB of documentation versus 44KB of application source code). This is extraordinary by traditional software engineering standards, where documentation typically represents a small fraction of total project volume.

The data suggests that in AI-assisted development, documentation serves a dual purpose: it communicates architectural intent AND constrains the AI agent’s behavior. Prescriptive documentation is not overhead; it is the primary mechanism through which the human maintains control over AI-generated code. The projects with the highest documentation-to-code ratios (flagship-v3, ClauseLib) also show the healthiest fix-to-build ratios, consistent with the thesis that documentation is the productivity lever.

Institutional Memory as Governance

One of the study’s most original findings is the "scar tissue" phenomenon: governance rules that map directly to specific past failures. In the earliest .cursorrules files, nearly every prohibition can be traced to a concrete incident. "NEVER touch production tenants" followed a production data incident. "Points rollover for free tier (should expire!)" followed a billing logic bug.

This pattern has two implications. First, the governance artifacts serve as institutional memory—a persistent record of lessons learned that survives across sessions and projects. Without these artifacts, the same mistakes would recur because neither the human nor the AI remembers previous session context. Second, the evolution from scar tissue (reactive) to framework (proactive) represents a qualitative leap in how the builder manages institutional knowledge: from encoding individual failures to encoding systematic principles.

Key Findings and Discussion

The evidence presented across the preceding chapters — portfolio evolution, builder maturity, collaboration outputs, design patterns, and governance mechanisms — converges on a set of findings. The data reveals a nuanced story: one of human growth, deliberate methodology, and the emergence of governance as the defining factor in sustainable productivity. The findings below distill the study's core contributions and their practical implications.

Finding 1: The Human Learning Curve Is Real and Measurable

The five maturity stages are visible across multiple independent metrics: velocity (22x increase), fix-to-build ratio (61% improvement), prompt quality (0.0 to 0.81), prompt word count (14x increase), specificity (nearly doubled), and governance artifact count (0 to 57 rules). These metrics triangulate a single conclusion: the builder measurably improved as an AI user. The improvement is not gradual; it follows a punctuated equilibrium pattern with distinct inflection points at stage transitions.

Finding 2: AI Is Used More for Thinking Than for Coding

The 2.0:1 design-to-implementation ratio (Chapter 8) reveals that AI coding tools are misnamed. Nearly half of all AI interactions were discovery, definition, and design work — before any code was written. Builders who treat AI exclusively as a code generator are leaving the majority of its value on the table.

Finding 3: Governance Is the Primary Productivity Lever

The dominant variable is not the AI model — it is the governance around it. AI agents did improve through model updates during the study period, but that improvement was secondary. The larger driver was structured human direction: prescriptive documentation, architectural constraints, file size limits, and session management practices that shaped what the AI built before the first line of code was generated.

Finding 4: Rapid Prototype-Deploy-Rebuild Cycle

The multi-generation ChatPlatform lineage (documented in Chapter 4) demonstrates that rebuilds are a strategy, not a failure. Each generation incorporates lessons from its predecessor: Prototype proved multi-tenancy, Enhancements proved template provisioning, flagship-v3 synthesized both with service layer architecture. The total development cost of all generations was less than what a single extended development cycle would have required,

because AI-assisted construction speed makes rebuilds cheap and knowledge accumulation makes each rebuild better.

Finding 5: Technology Convergence Is a Rational Response

The convergence of 10+ projects on React/TypeScript/Vite/Tailwind/shadcn is not accidental. It represents an optimization for AI-assisted development specifically: consistent tooling reduces agent confusion (no context switching between patterns), enables direct knowledge transfer between projects, and builds governance artifacts that apply across workstreams. The cost of tooling fragmentation compounds in AI-assisted teams — each divergent stack requires separate context-loading, separate governance documents, and separate agent calibration. Convergence is not a constraint; it is infrastructure for the collaboration layer.

Finding 6: Fix Domains Reveal AI Blind Spots

The concentration of fix commits in UI/UX (37%) and API/Integration (25%) domains reveals where AI agents are least reliable. AI excels at core logic and data manipulation but struggles with visual presentation, cross-service integration, and environment configuration. This domain map can guide developers toward investing human oversight where it provides the highest value.

Learnings Productized

December 2025 produced 325 commits — 76% of the study's total activity — and the worst fix-to-build ratio recorded: 1.8 correction commits for every feature. ARCHITECTURE.md had been locked on December 19 as a prescriptive document, and the builder was shipping faster than at any point in the study. But speed without structure was generating technical debt faster than value. The documentation told the AI agent *what* to build; it did not tell the agent *how to think about building*.

That distinction — between architectural specification and development methodology — became the foundation of everything that followed. But the December crisis was a symptom, not a root cause. The root cause was that every established software development practice — discovery, requirements, design, documentation, development, deployment, and testing — had been designed for human teams and was failing systematically when AI joined as a collaborator.

The Practitioner Problem

The challenges across the study period were not isolated incidents. They formed patterns that recurred across projects, tools, and domains. During the study, the builder documented these patterns across seven practitioner articles published in January 2026, identifying over fifty specific failure modes that traditional development practices could not overcome.

The failures shared a common architecture: three asymmetries that compound across every phase of the development lifecycle.

***Asymmetric knowledge**.* Humans carry tribal knowledge — "we never use that library, it leaks memory under load," "that API documentation is wrong, here's what it actually does." This knowledge transfers through pairing, code review, and hallway conversations. AI does not ask or participate in casual knowledge transfers. It confidently proposes solutions that violate institutional knowledge, selects the library that leaks, refactors the module nobody should touch, and trusts the documentation that everyone else knows is wrong. It does this faster than humans can catch it. The instinct is to blame the AI. The actual problem: knowledge that lived in human heads never made it to where AI could access it.

***Asymmetric velocity**.* Human discovery operates at human speed — stakeholder interviews take hours, domain modeling requires reflection, architecture decisions need debate. AI-assisted development does not wait. The development cycle runs faster than the discovery cycle can feed it. Assumptions get encoded into working code. By the time discovery reveals the assumption was wrong, thirty features depend on it. The cost of ambiguity scales with velocity: faster development means faster propagation of misunderstanding.

***Asymmetric failure modes**.* Humans fail by forgetting, overlooking, and running out of time. AI fails by assuming, fabricating, and confidently proceeding without necessary context. A 90% complete specification gets completed with confident guesses about the remaining 10%. The output looks finished. The assumptions are invisible. The gap between what was specified and what was built does not surface until something breaks in production — or worse, passes tests that validate the AI's interpretation rather than the original intent.

These asymmetries produced cascading failures that the builder catalogued across the development lifecycle:

In *discovery*, traditional upfront processes collapsed because AI-speed development generated needs faster than traditional discovery. The tribal knowledge trap — institutional knowledge

locked in human heads, inaccessible to AI — produced plausible output that passed casual review and broke the chain further down the pipeline. The context overload trap — dumping everything into large context windows — triggered the "lost in the middle" phenomenon where critical instructions got buried and more documentation produced worse decisions.

In *definition*, AI assumed rather than asked (the Assumption Problem). It built what was written, not what was intended (the Literal Interpretation Problem). It worked from specifications that represented decisions from three sprints ago while the team had moved on (the Zombie Requirements Problem). Requirements so obvious that humans never wrote them down — "of course the delete button asks for confirmation" — went unimplemented because unspecified means unbuilt (the Obvious Gap). And misinterpretations that would have affected one feature at human speed became foundations for ten features at AI speed before anyone noticed (the Blast Radius Problem).

In *design*, context integrity failures (modularity collapse, code slop, reuse refusal, Frankenstein patterns), system architecture failures (interface race conditions, schema chaos, infrastructure sprawl, config rigidity), reality gaps (visual-vs-code drift, mock data mirages, happy path bias, security by omission), and process failures (project tracking blindness, dead document traps) became prominent. The common root: design practices assumed human implementers who see the whole codebase, ask about existing patterns, and pause at ambiguity. AI sees what fits in context, creates rather than discovers, and builds through whatever pattern fits the immediate prompt.

In *documentation*, the builder discovered that traditional practices produced failures when the system changed faster than documents could update. The most consequential challenge was the realization that documentation is not overhead — it is the synchronization mechanism between human-speed thinking and AI-speed execution. When documentation works, the sprinters stay coupled despite velocity differences. When it fails, they spiral apart, and the 10x productivity potential collapses to slop.

In *development*, the fundamental challenge was that "build the feature" had become a prompt rather than a process. The chunking challenge (work units that fit AI context while remaining coherent), the verification challenge (distinguishing "runs" from "runs correctly"), and circular validation (AI writing code and tests that reflect identical assumptions, shipping wrong behavior confidently) all pointed to the same gap: no methodology governed the relationship between human intent and AI execution within a development session.

In *deployment*, the pipeline became a swarm — fifty independent micro-releases across services before lunch, each passing tests, collectively overwhelming every operational

assumption built for human-speed releases. Infrastructure sprawled because agents build without an architect's conscience. Rollback became impossible because no one captured the before-state across fifty micro-changes. Security principles that were guidelines rather than guardrails got bypassed under deployment pressure.

In *diagnostics*, the gap between what tests validate and what users need became the study's final recurring failure. Tests pass. The application does not work. The AI writes code based on its interpretation of requirements, then writes tests that verify its interpretation. Both reflect the same assumptions. Neither validates against original intent. Coverage at 94% measures lines executed, not scenarios validated.

The Two-Level Governance

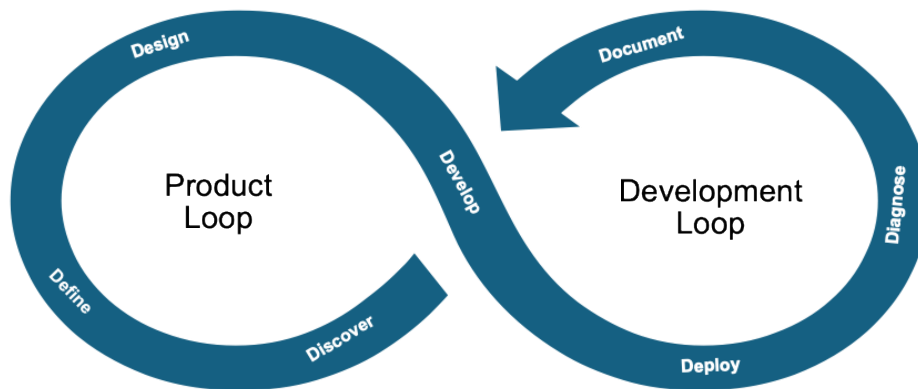
The core insight from documenting these failures was that governance operates at two fundamentally different levels.

The first level is constraint-based: file size limits, prohibited patterns, technology mandates, deployment gates. The .cursorrules files of October 2025 and the Guidelines.md of November 2025 operated at this level. These rules, many of them encoded as scar tissue from specific failures, reduce errors within a defined scope. But they do not compose into a coherent development process. An agent can follow fifty individual rules and still produce a structurally incoherent session — starting implementation before requirements are clear, skipping diagnostic steps, or generating code that satisfies every constraint in isolation but fails as a system.

The second level is methodological: a complete model of how a development session should unfold from first prompt to final commit. This is the level of the 7D Framework.

The Framework

The 7D Framework re-organizes the complete development lifecycle into two complementary cycles bridged by documentation. The Product Cycle — Discover, Define, Design to capture the pre-implementation work. This was needed to overcome the challenges that the conversation analysis revealed accounting for a 2.0:1 design-to-implementation ratio. This cycle directly addresses the assumption problem, the tribal knowledge trap, and the blast radius problem by requiring that intent, constraints, and context be externalized before execution begins.



The Documentation Bridge encompasses the prescriptive artifacts (ARCHITECTURE.md, .agent files, and a 21KB AGENT-GUIDANCE.md specification) that encode governance into persistent, AI-consumable form — the primary productivity lever identified earlier. This bridge addresses the synchronization challenge by creating a shared source of truth that operates at AI speed rather than meeting cadence.

The Technology Cycle — Diagnose, Develop, Deploy — structures implementation, testing, and release within the constraints already established, with a diagnostic emphasis informed by the domain analysis of AI blind spots and the circular validation problem that emerged in testing.

The critical design decision in the framework was its intended audience. Early governance artifacts — the .cursorrules files of October 2025 — were written for the builder to remember: human-readable prohibitions triggered by past failures. The Guidelines.md of November were transitional: structured enough for an agent to parse, but still human-centric. CLAUDE.md in December shifted the audience entirely to the AI agent, optimized for token efficiency and hierarchical context loading. The AGENT-GUIDANCE.md file completed this evolution: a 21KB specification that does not merely list rules but instructs the agent on how to navigate each phase of the development lifecycle. It includes red-flag patterns that tell the agent to stop and ask before proceeding, phase-transition criteria, and preemptive engineering guidelines spanning 60+ lines per project. The governance is no longer *about* the agent; it is *for* the agent.

Results

When deployed in January 2026, the results were immediate and unambiguous. Average session duration dropped 58%, from 94.3 to 39.3 hours. The fix-to-build ratio fell to 0.7:1 — the healthiest in the study. Velocity sustained at 4.5 commits per day, but now with quality: for the first time, building consistently exceeded fixing. The same builder, evolving AI models, the same codebase. The dominant variable that changed was the governance methodology.

The 7D Framework represents the transition from Stage 2's reactive scar tissue to Stage 5's comprehensive governance — from encoding individual failures to encoding systematic principles. It demonstrates that the practitioner challenges documented across discovery, definition, design, documentation, development, deployment, and diagnostics are not inevitable costs of AI-assisted development. They are symptoms of applying human-team practices to human-AI collaboration. The framework is not a theoretical construct applied to the data; it is the data — fifty-plus failure modes, three asymmetries, and ten months of practitioner experience — compressed into a reusable methodology.

Conclusions

A detailed log of a year of real work turned out to produce something valuable: a longitudinal record of what human-AI collaboration looks like when the stakes are real and the feedback is unforgiving.

The six findings in this study are not independent observations — they are a system. Human learning enables better prompting. Better prompting produces more reliable outputs. More reliable outputs reward governance investment. Governance investment enables faster iteration. Faster iteration surfaces the failure modes that become the next layer of governance. The cycle compounds. What looks like a 22x velocity increase is the visible output of that compounding; the mechanism is the maturity progression documented in Chapter 5.

What makes this study unusual is not the metrics — it is the mechanism. The scar tissue phenomenon documents something no snapshot study can capture: how individual failures become institutional memory, how institutional memory becomes governance, and how governance compounds into sustained productivity. That process takes time. It leaves traces. And it only becomes visible longitudinally.

The framework that emerged from these findings is documented in the pages that follow. It was not designed in advance — it was extracted from patterns that were already working, formalized, and validated against the corpus that produced it. Whether it transfers to other builders, teams, and contexts is the next question worth answering.

Ten months ago, the builder in this study typed "fix this" into an AI coding tool and waited to see what happened. Ten months later, that same builder deploys a 21KB methodology specification that instructs AI agents on how to navigate a complete development lifecycle — from discovery

through deployment — within explicit constraints, phase-transition criteria, and diagnostic checkpoints.

Better systems and better tools are coming — faster models, deeper reasoning, richer collaboration interfaces. The methodology will evolve with them. The builders and teams who invest in developing their human-AI collaboration practice — who treat working with AI as seriously as the tools themselves — will compound their advantage with every generation of improvement.

This study is an invitation to that work. The data is here. The patterns are documented. The research agenda is defined. What comes next gets built by practitioners — comparing notes, refining methods, and pushing the frontier of what human-AI teams can accomplish together.

Appendix A: Complete Project Inventory

Project	Stack	Commits	Period	Maturity	Ecosystem
flagship-v3	Node/TS + Lambda	187	Nov–Jan	Production	ChatPlatform
flagship-deploy	Node/TS	138	Nov–Dec	Deploy Track	ChatPlatform
platform-admin	React/TS + Vite	121	Jan 2026	Production	ChatPlatform
LaunchSite V2	Vite/React	70	Oct–Dec	Production	Marketing
ChatPlatform-v1	Node/TS + AWS	12	Jun–Aug	Archived	ChatPlatform
ClauseLib	Node/TS	6	Nov	Framework	Insurance
Engage	Node/TS	5	Nov	Early	ChatPlatform
ChatPlatform	JS/React	4	Jul–Nov	Archived	ChatPlatform
InfraCore	Java/CDK	—	2025	Infrastructure	Infrastructure
7D-Framework	Markdown	—	Jan 2026	Methodology	Methodology
RateCalc	Python	—	2025	Active	Insurance
StateScraper	Python	—	2025	Active	Insurance
+ 20 more	Various	Various	2025–26	Mixed	Various

Appendix B: Research Questions Summary (51 Total)

The complete set of 51 research questions spans 15 dimensions organized into three priority tiers. The table below summarizes the dimensional structure and data uniqueness of each tier; the full enumerated questions are maintained in the companion research agenda document.

Priority	Dimensions	Questions	Data Uniqueness
Tier 1: Novel	Scar Tissue, Generational Evolution, Gap Phenomenon, Rebuild Pattern, Pattern Propagation	8	No other dataset
Tier 2: Distinctive	Learning Stages, 40/60 Ratio, Agent Migration, Trust Dynamics, Domain Transfer	15	Rare longitudinal
Tier 3: Confirming	Human Adaptation, Agent Performance, Productivity, Behavioral Factors, Token Economics, Quality	28	Extends literature

Appendix C: Measurement Framework

Metric	Definition	Observed Trend
Prompt Quality Score	Composite of context, constraints, acceptance criteria, examples (0–10). Normalized to 0–1 in reporting. See Rubric C.1 below.	0.0 → 0.81
Prompt Specificity	Ratio of concrete, resolvable references to total descriptive content (0–1). See Rubric C.2 below.	0.34 → 0.67
Technical Depth	Level of technical sophistication in prompt content (0–5). See Rubric C.3 below.	Not tracked as trend
Fix-to-Build Ratio	Fix commits / feature commits per phase	1.8:1 → 0.7:1
Velocity	Commits per active development day	0.2 → 4.5
Design-to-Implementation Ratio	Design-phase / implementation-phase conversations	2.0:1
Documentation-to-Code Ratio	Documentation KB / source KB	1.7:1 (flagship-v3)
Conventional Commit %	Feat:/Fix:/Docs: format adoption	0% → 86%
Vocabulary Density	Unique advanced terms per workspace	8–12 → 42–49
Session Duration	Average hours per development session	94.3 → 39.3
Governance Rules	Total rules across all governance files	0 → 57

Note: Prompt Quality Scores are reported as normalized values (raw composite score ÷ 10) throughout this report. A reported value of 0.81 corresponds to a raw score of 8.1 out of 10.

Rubric C.1: Prompt Quality Score (0–10)

Composite score across four equally weighted sub-dimensions (each scored 0–2.5 points). The raw total (0–10) is normalized to 0–1 for reporting.

Scoring Sub-dimensions

Sub-dimension	0 points	1.25 points	2.5 points
Context Provision	No project context, file references, or architectural framing. Prompt assumes the agent remembers prior state.	Partial context: names a file or component but omits project structure, dependencies, or current state.	Full architectural context: identifies project, relevant files, current state, and how the request fits into the broader system.
Constraints	No constraints specified. Agent has unlimited degrees of freedom.	Implicit or partial constraints (e.g., “keep it simple”) without enforceable boundaries.	Explicit, measurable constraints: file size limits, technology restrictions, prohibited patterns, scope boundaries (e.g., “do not modify files outside /services, max 300 lines per file”).
Acceptance Criteria	No definition of done. Success is evaluated retroactively through trial and error.	Vague success criteria (e.g., “it should work” or “make it look good”).	Testable acceptance criteria: expected behavior, edge cases, output format, or verification steps (e.g., “the endpoint should return 200 with a JSON payload matching this schema”).

Examples / References	No examples, code snippets, or reference patterns provided.	Partial reference: mentions an analogous pattern or points to a file without quoting relevant structure.	Includes concrete examples: code snippets, API signatures, schema excerpts, or explicit “follow the pattern in X” references.

Score Interpretation

Range (normalized)	Label	Typical Behavior	Study Period
0.0–0.2	Bare command	“fix this”, “make a nav bar”, “add authentication”	Feb–Apr 2025
0.2–0.4	Descriptive	States desired outcome with some context but no constraints or criteria	May–Jul 2025
0.4–0.6	Structured	Includes context and partial constraints; beginning to front-load information	Aug–Oct 2025
0.6–0.8	Specification	Full context, explicit constraints, acceptance criteria; resembles a mini-requirements document	Nov 2025–Jan 2026
0.8–1.0	Engineering-grade	All four sub-dimensions maximized; prompt functions as a standalone work order requiring minimal clarification	Jan–Feb 2026

Rubric C.2: Prompt Specificity (0–1)

Continuous score measuring the ratio of concrete, resolvable references to total descriptive content in the prompt.

Range	Label	Characteristics	Example
0.0–0.2	Vague	No file names, function names, line numbers, error codes, or component identifiers.	“the login page is broken”
0.2–0.4	Low	Names a general area but not specific files or functions.	“there’s a bug in the authentication flow”
0.4–0.6	Moderate	References specific files or components by name; may include one or two concrete identifiers.	“the handleAuth function in auth-service.ts is returning null”
0.6–0.8	High	Multiple concrete references: file paths, function names, error codes, line numbers, or API endpoints.	“in /services/auth-service.ts, handleAuth() at line 47 throws TypeError when req.session is undefined”
0.8–1.0	Fully grounded	Every relevant entity is named: files, functions, dependencies, error messages, expected vs. actual behavior, and specific test cases.	“update validateTenant() in /services/tenant-service.ts (line 112–134) to check for expired tokens before calling DynamoDB”

Rubric C.3: Technical Depth (0–5)

Ordinal scale measuring the level of technical sophistication demonstrated in the prompt. Each level subsumes the characteristics of the levels below it.

Score	Label	Characteristics	Example
0	Non-technical	Plain language with no technical terminology. Could be stated by a non-developer.	“make the page look nicer”
1	Basic technical	Uses common technical terms without architectural understanding.	“add a button that calls the API”
2	Component-aware	References specific technologies, frameworks, or architectural layers correctly.	“add a React component that fetches from the /tenants REST endpoint”
3	Architecture-aware	Demonstrates understanding of system architecture: service boundaries, data flow, state management.	“create a Lambda handler in the services layer that validates tenant config against the DynamoDB schema before provisioning”
4	Pattern-aware	References design patterns, architectural principles, or cross-cutting concerns.	“refactor the monolithic handler into separate service-layer modules following the existing decomposition pattern”
5	System-aware	Addresses multi-system interactions, deployment implications, performance, security boundaries, or production operations.	“implement the webhook receiver with idempotent processing, dead-letter queue for failed events, and CloudWatch alarms on error rate”