Source: cppcc/docs/Three_Bets_arXiv_Draft_0.2.md @ 68f96c8 — curated 2026-08-06; edits land in the source first.

Three Bets on the Future of Software: Compiler Compiler System AI-Assisted Construction

A Position Paper

Draft 0.2 — June 2026

Author: A. F. Urakhchin **Affiliation:** Bet Three LLC (B3) **Contact:** support@b3u.dev

Subject classification (arXiv): cs.SE (primary), cs.AI, cs.PL

The technical substrate referenced in this paper is protected by US Patent 8,464,232 [1]. Its implementation, parsing model, and empirical evaluation are described in a companion technical paper [2]; the present paper takes the substrate as given and addresses its position-level implications. The cross-language source- translation domain treated at the position level in Section 6.1 has, since the present paper's first draft, been given a detailed empirical treatment in a separate companion paper [15].

Abstract

The conversation about artificial intelligence has narrowed to two competing bets about how human-level capability is built. The first, held by the major frontier labs, is that scaling neural networks produces general intelligence as an emergent property. The second, held by a smaller community in the cognitive-science lineage, is that intelligence requires explicit cognitive architecture. Both bets are unresolved, and both engage centrally with whether sufficiently capable AI systems can be produced. This paper argues that a third bet sits beneath both, addresses a question neither engages with directly, and is independently worth making: software construction is fundamentally the transformation of semantic representations into one another, and the substrate that supports those transformations determines what AI assistance can do. The current substrate for AI-assisted construction — source code in text files, semantic structures in developers' heads, prose documentation that no toolchain can verify — places a ceiling on what AI assistance can achieve no matter how capable the underlying language models become. We

describe a substrate that addresses this gap: a self-defining specification language, a compiler-compiler that produces parsers and serializers in four target languages, a canonical binary form with round-trip closure as structural-correctness oracle, and first-class isomorphic mappings between representations. The implementation backing for this architectural model is established in [2]; the present paper articulates the position-level implications, summarizes empirical results on construction of approximately twenty-six sibling repositories over twelve weeks of focused work, describes the *Adaptive Programming* methodology that emerges when AI assistance operates at the specification layer, and considers two application domains — cross-language source translation and ontology-based knowledge extraction — where the substrate reframes problems current tooling addresses poorly. The third bet's position is intentionally narrow: not a path to general intelligence, not a theory of cognition, but a class of substrate that makes AI-assisted specification-layer construction tractable in ways code-layer assistance alone cannot reach.

---

1. Introduction: Three Bets

The current conversation about artificial intelligence has narrowed, more than is generally acknowledged, to two competing bets about how human-level capability gets built.

The first bet — held by the major labs and most of the venture capital flowing into AI — is that scaling neural networks produces general intelligence as an emergent property. Larger transformers, more training data, better feedback mechanisms, and the architectural questions take care of themselves. The empirical evidence is real: today's frontier models do things that surprised the field five years ago, and the scaling curves have not yet visibly saturated. Whether further scaling resolves the characteristic limitations of next-token prediction — hallucination, weak multi-step reasoning, opacity — or whether they require architectural changes is the open question this bet engages with.

The second bet — held by a smaller community working in the lineage of cognitive science and symbolic AI — is that intelligence requires explicit architecture. Knowledge representation that can be inspected and modified. Reasoning mechanisms that compose. Memory systems that persist. Integration across multiple AI paradigms. OpenCog Hyperon [3] is the most ambitious current instantiation of this second bet, with the Atomspace metagraph as integrative hub, MeTTa as the pattern- rewriting language, and PRIMUS as the cognitive architecture above both. Cognitive architectures have produced theoretical frameworks of considerable depth but, after decades of research, have not yet demonstrated capabilities competitive with what scaled neural networks deliver today. Whether the cognitive- synergy hypothesis at the center of this bet — that combining multiple AI paradigms produces emergent capabilities none has alone — is empirically supported remains, at the time of writing, an open question.

Reasonable people disagree about which bet pays off, when, or whether either will. The disagreement is not about which side has better arguments — both sides have serious arguments. The disagreement is about which class of unresolved problem is more tractable.

A third question, addressed neither by scaling nor by cognitive architecture, may be more immediately consequential than either of those bets.

That question is about the substrate of software construction itself.

Most software, including most AI software, gets built through a workflow that has barely changed in three decades. Humans author code in text editors. Language tools provide syntactic assistance. Version control tracks revisions. The semantic structures that connect specifications to implementations to data models to APIs to test cases to documentation — these live primarily in the developers' heads and in scattered prose documentation that the toolchain cannot mechanically verify. When AI assistance arrived, it slotted into this workflow at the code-generation end. Autocomplete, then chat, then agentic execution against codebases [4, 5]. Each layer made human effort more efficient. None of these tools changed the underlying substrate.

From inside the workflow, the friction looks like "the AI doesn't know my codebase well enough" or "I need better prompts" or "the context window isn't large enough." These framings locate the problem at the AI-tool interface. The substrate framing locates the problem elsewhere: at the absence of any mechanically verifiable representation of what the software is supposed to do, how its representations relate to one another, what transformations preserve meaning and which do not. The AI cannot help with a structure that doesn't exist; it can only help with the code-level surface that projects from it.

A third bet — the bet this paper articulates — is that software construction is fundamentally the *transformation of semantic representations into one another*, and that the substrate supporting those transformations is what determines what AI assistance can actually do. If true, the bottleneck in AI-assisted construction is not code generation (which contemporary LLMs do increasingly well) but the disciplined maintenance of semantic structures and their relationships (which LLMs do considerably less well, and which traditional toolchains were not designed to support).

This third bet is independent of the first two. It works today on top of current LLMs as the language interface. It would work tomorrow on top of Hyperon-style cognitive architecture if cognitive synergy turns out to be real. The substrate is independent of which AGI bet pays off; it would integrate with whichever does, and remains useful in the meantime. A bet that does not depend on its competitors failing has different epistemic properties than a bet that does.

This paper describes the third bet — what it claims, what has been demonstrated, what it implies — and works through two application domains that illustrate concretely what the substrate makes possible. We summarize the substrate at the architectural level (Section 3); the implementation backing is given in [2].

---

2. Related Work

The third-bet framing sits in a space several research lines partially address but none fully occupies.

Neuro-symbolic AI. The broad program around combining neural and symbolic approaches argues that hybrid architectures can deliver capabilities neither alone reaches [6]. Most of this work focuses on how to integrate symbolic reasoners into neural systems or vice versa, for tasks like reasoning, planning, and verification. The substrate-problem framing is adjacent but distinct: rather than integrating two systems, the substrate provides a representation language in which both can operate over shared semantic structures.

Trustworthy AI agents and formal methods. Recent position work argues that agentic systems require deeper integration with formal methods to be reliable in production [7]. The argument typically locates formal methods at the verification of agent output. The substrate-problem framing relocates them upstream: the substrate provides formal representations the agent operates *against*, so the verification problem becomes structural rather than behavioral.

Model-driven engineering (MDE). A research and industry tradition spanning two decades, MDE has proposed essentially the same move — promoting models to first-class artifacts and generating implementations from them [8]. The major obstacles to MDE adoption have been the tooling burden, the rigidity of generated artifacts, and the gap between modeling languages and programmer working idioms. Recent work has begun to revisit MDE with LLM assistance, with the LLM bridging the modeling-language- to-working-code gap that previously required hand-written transformation rules.

Language workbenches. Systems like JetBrains MPS, Xtext, and Spoofax [9] provide infrastructure for defining domain-specific languages with associated tooling. They share with the substrate described here the conviction that specifications should be first-class artifacts. The architectural emphasis differs: workbenches typically organize themselves around the authoring experience for a specific DSL, while the substrate described here organizes around the cross-representation isomorphism that the substrate problem requires.

AI-assisted programming. Tools including GitHub Copilot [4], Anthropic's Claude Code [5], Cursor, and agentic orchestration frameworks operate primarily at the code-generation surface. They consume the existing substrate (text files, source code, prose documentation) and produce more of the same. Their contribution is the AI assistance itself, not a change in the substrate. The substrate-problem framing argues that this arrangement places a ceiling on what such tools can do for specification-layer work.

Compiler-compilers and round-trip engineering. The intermediate representations produced by parser generators in the YACC, Bison, and ANTLR lineage [10, 11], and the round-trip property that emitted artifacts should be reproducible from their source models, are foundational lines of work. The companion technical paper [2] situates the specific substrate described here against this lineage in detail. The present paper takes the substrate's compiler-construction details as given and addresses its position-level implications.

The third-bet framing therefore sits in a space these prior lines partially address but none fully occupies. Its specific contribution is the combination — substrate that holds semantic representations as first-class artifacts, AI assistance operating at the specification layer rather than the code-generation surface, and an empirical methodology that uses round-trip oracles to validate AI-produced specifications at high throughput.

---

3. The Substrate

This section describes the substrate at the architectural level. Implementation specifics are given in the companion technical paper [2]; the present paper summarizes what readers of the third bet's position-level argument need to know.

The substrate consists of five cooperating artifacts.

A self-defining specification language. Structured representations are expressed in a language defined by its own productions. A single file describes the grammar of the language using the language's own syntax, so the language bottoms out in itself. Any specification written in the language is immediately consumable by the entire toolchain. There is no separate metaschema, no out-of-band declaration mechanism; the system is self-defining in a strict sense. The implementation details and the specific source-language conventions are given in [2, §6].

A compiler-compiler. Given a specification in the language above, a compiler produces implementation artifacts: parser and serializer code, accessor APIs, and binary-format encoders, in multiple target languages from a single source. The compiler is itself bootstrapped through the specification language — the meta-grammar defines the language the compiler reads, and the compiler compiles the meta-grammar to produce its own parser. A mechanical self-consistency property follows: any grammar's parser must round-trip the grammar's source back to itself, and the meta-grammar's parser must round-trip the meta-grammar's source. The bootstrap loop and its empirical demonstration are the subject of [2, §6, §8].

A canonical binary form. A standardized binary serialization of any specification-conformant content that round-trips byte- identically with its textual source. The binary form is consumed by multiple language runtimes — C++, Python, JavaScript, Rust — through a unified API. The same binary file is readable by all four; any wire crossing between substrate-aware components can carry structured content any other substrate-aware component can decode. The binary form's layout and the multi-language emission are detailed in [2, §5, §7].

Round-trip closure as the structural-correctness oracle. A transformation `F` from textual form `X` to binary form `Y`, paired with its inverse `G` from `Y` back to `X'`, is structurally correct on input `X` if `X' = X` under whatever equality relation applies. The oracle does not require the test author to know what the output should be in absolute terms; it requires only that the pair of transformations be consistent. This property makes round-trip testing applicable to validation of generated artifacts at the rate the AI can produce them, rather than at the rate a human reviewer can verify them. The oracle's mechanical character is what gives Adaptive Programming (Section 4) the throughput characteristics it exhibits. The oracle's empirical demonstration on the meta-grammar and on multiple target-language grammars is reported in [2, §8].

Isomorphic mappings between representations. The same conceptual structure may live as a grammar, an SQL schema, an object-oriented API, a wire protocol, a documentation fragment, and a test harness. The substrate makes these mappings first- class: each mapping is itself a specification, declared and tracked, with its own conformance criteria. When a representation changes, the mappings indicate which dependent representations need updating. The cross-representation consistency that traditional codebases maintain through prose convention and discipline becomes mechanically tractable.

These five pieces together constitute the substrate. None individually is revolutionary. The combination — specifically the combination's relationship to AI-assisted construction at the specification layer — is what the substrate problem requires.

The crucial property is what AI assistance can do *against* the substrate. An LLM operating against the specification language has a small, uniform target with mechanical conformance criteria, where an LLM operating against arbitrary source code has a large, non-uniform target with no mechanical conformance criteria. An LLM proposing a new specification can have its proposal validated in milliseconds by the compiler-compiler, where an LLM proposing new code requires test-suite execution at best and human review at worst. An LLM proposing an isomorphic mapping between two specifications has a verifiable target — the mapping is itself a specification, with its own conformance criteria — where an LLM proposing implicit cross-representation consistency has no target at all.

The substrate changes what AI assistance is for. Rather than producing artifacts the human must review, the AI produces specifications the substrate validates. The human's role shifts from artifact review to specification supervision: deciding what the system should do, refining the specifications that express what it should do, and accepting the substrate-validated implementations the specifications imply.

---

4. The Adaptive Programming Methodology

A workflow discipline arises when the substrate of Section 3 is exercised on real construction work. We call this discipline *Adaptive Programming* and describe its outline here. It is not a programming language, a tool, or a methodology in the heavyweight sense. It is a regularity that emerges when AI assistance operates at the specification layer.

The cycle is the following. A verbal specification — written prose, possibly conversational with the AI assistant — describes what some piece of the system should do. The AI assistant proposes a refined specification in the substrate's specification language. The proposal is reviewed by a human. Once accepted, the substrate's compiler-compiler produces the implementation artifacts the specification implies in whatever target languages are required. Round-trip oracles validate the artifacts structurally. Test cases — themselves often generated from the specification — exercise the behavior. Failures surface as inconsistencies between specifications or as gaps in the specifications' coverage of the intended behavior. The cycle repeats.

What is notable about the cycle is what does *not* happen. The human does not write the parsing code, the serialization code, the accessor APIs, the binary encoders, the test harness scaffolding, or the cross-language equivalents of any of these. The substrate produces them. The human does not review the produced code in detail; the round-trip oracle and the substrate's structural guarantees provide the assurance the review would otherwise provide. The human reviews the *specification*, which is small enough to actually review, mechanically validated against the substrate's conformance criteria, and consequently a much higher-leverage object of human attention than the artifacts it implies.

The AI assistant's role is the bridge. The verbal specification the human provides is, by construction, informal. The substrate's specification language is formal. The AI's job is to propose the formalization. When the AI proposes well, the human's verification is shallow (does this match what I meant?). When the AI proposes poorly, the human refines the verbal specification or directly edits the proposed formal specification, and the cycle continues. The round-trip oracle ensures that bad formal specifications cannot silently produce bad artifacts: if the substrate accepts the specification, it produces conformant artifacts.

Adaptive Programming is what AI-assisted software construction looks like when the substrate problem is solved. The labor is specification, not code. The verification is structural, not behavioral-by-proxy. The cycle runs at the rate the AI can produce specifications rather than at the rate a human can review artifacts. Construction throughput rises substantially — not because the work is easier in some absolute sense, but because the throughput model is different.

---

5. What Has Been Demonstrated

The substrate's claims would be aspirational if they had not been exercised on real construction work. The empirical record matters precisely because the third-bet thesis is empirical: either substrate-grounded AI-assisted software construction works or it doesn't. Theorizing about it is cheap; building things with it is the test.

The work to date forms a project family of approximately twenty- six sibling repositories under a single development tree, totalling roughly eighty thousand lines of code across multiple languages, produced over approximately twelve weeks of focused work using Adaptive

Programming as described in Section 4. The substrate itself was foundation work prior to this twelve-week record; the demonstration tracks above the substrate took the twelve weeks.

Substrate self-validation. The substrate has been internally validated to the level a substrate of its kind requires: every grammar processed by the compiler-compiler produces a parser that round-trips the grammar's own source; every binary representation produced by any of the substrate's language runtimes is consumable by every other runtime through the unified API; the meta-grammar self-round-trips. These are not properties an inconsistent system could have. The technical paper [2, §8] documents the self-test sequences in detail.

JSON parsing benchmark. The technical paper [2, §9] reports empirical comparison against nlohmann/json and simdjson on three standard JSON benchmark corpora. The headline findings: the canonical-binary form loads within approximately 2× of simdjson parse time on every input, and a grammar-aware walk implementation outperforms simdjson's DOM walk by approximately 5× on every input. The detailed methodology and results are reserved for the technical paper; the present paper notes only that the empirical results place the substrate-grounded artifact in the same performance band as the dominant existing baselines.

Cross-language translation worked example. The substrate's application to cross-language source translation (Section 6.1) has, since the present paper's first draft, been exercised on a non-trivial worked example: the canonical RealWorld / Conduit backend specification, originally implemented in Python with FastAPI, was mechanically lifted to a ten-family DSL representation and re-emitted as a TypeScript service. The resulting service passes 293 of 293 assertions of the canonical RealWorld Postman conformance collection — exceeding the upstream Python baseline of 280 assertions. The methodological pattern that drove the work — explicit `LOCK` invariants declared at every slice opening, hand-authored golden artefacts validated by byte-equal diff before any implementation iteration — landed forty-two of the arc's forty-six slices on zero implementation iteration. The detailed treatment is the subject of [15]; the present paper notes only that one of the two worked domains of Section 6 has, between Draft 0.1 and Draft 0.2, moved from architectural sketch to behavioural conformance against a canonical oracle.

Two AI-framework demonstration tracks. On top of the substrate, two demonstration tracks were built against contemporary AI-agent frameworks. The first substitutes canonical-binary wire formats for the JSON serialization that LangGraph uses internally for tools, memory, telemetry, agent-to- agent messaging, and LLM calls. The second does the same against the Claude Agent SDK's published extension points. Both tracks consume their host framework without modifying it; both produce demonstration agents whose every wire crossing carries canonical-binary content, where every artifact is independently decodable through the substrate's API in external consumers.

Economic observation. An economic observation from this work is that adding the substrate to a second AI framework cost approximately 40% of what adding it to the first cost, with the difference being inheritance from the substrate's accumulation. The substitution-library claim becomes empirical: the marginal cost of supporting an additional framework decreases as the substrate accumulates.

Throughput observation. A methodological observation is more striking. Each demonstration milestone — eight for the first framework, five for the second — required between three days and two weeks of focused work. The original effort estimates, written before any milestone executed using conventional single- engineer scoping, suggested twelve to twenty-seven weeks per framework. Realized effort came in roughly four to nine times under conventional estimates. The explanation is not that the work was easier than expected; it is that the throughput model is different. Verbal specifications drive AI-assisted construction, round-trip oracles validate the results, and the human-AI loop runs at a rate conventional estimation does not account for.

Distributed-system measurement. A separate measurement track explored the substrate's behavior in distributed-system contexts. A consumer in one language reading binary content emitted by a producer in another language operates without the foreign- function-interface boundary that dominates text-format pipelines. Per-atom costs in Rust came in roughly four to twelve times faster than equivalent operations in Python, because the substrate eliminates the FFI boundary that dominates Python's atom-insertion cost. Memory footprint dropped by roughly an order of magnitude. The substrate enables deployment topologies that text-format pipelines cannot reach at acceptable cost.

These measurements support a narrower and sharper version of the third-bet thesis. The substrate does not make general software construction trivial. It makes specific classes of work substantially more tractable, particularly: cross-language wire formats requiring byte-stable structured representation; multi- framework substitution work where the substrate amortizes across framework instances; distributed-system topologies favoring binary transport; and AI-assisted construction where round-trip oracles validate generated artifacts structurally rather than behaviorally.

What the substrate does not do is solve hard AGI problems. It does not propose a path to general intelligence. It does not claim that the mechanical verification it provides is in any sense a model of cognition. The third bet is narrower and, for that reason, empirically grounded rather than aspirational.

---

6. Two Worked Domains

To make concrete what the substrate enables in domains beyond its own construction, this section considers two application areas where the problem shape changes when the substrate is present. Both domains share an underlying structure: a human-readable representation and a structured target representation, with the informal bridge between them as the load-bearing engineering work. The substrate's contribution in both is to make the bridge a first-class specification the toolchain can validate.

6.1 Cross-language source translation

A persistent practical question is how to convert software written in one general-purpose language — say, Python — into equivalent software in another, such as JavaScript or TypeScript. Arbitrary source-to-source translation is intractable because the two languages live in different runtime-semantic worlds with significant non-isomorphism in their type systems, exception models, standard libraries, and reflection capabilities.

The substrate reframes the problem. A large fraction of code that practitioners actually want to translate is code *organized around a data model*: schema validation, serialization, transformation, aggregation, business-rule dispatch. The data model is the load- bearing artifact; the source language is one rendering of operations on that model. The substrate's specification language expresses the data model; its compiler-compiler emits parser, serializer, and accessor APIs in multiple target languages from a single specification.

For code already organized this way, no translation is required: both renderings exist simultaneously and the substrate keeps them consistent. For code not yet organized this way, the path is to lift the implicit data model to an explicit specification, with AI assistance proposing the lift and round-trip oracles verifying that the original code's behavior on representative inputs matches the substrate-emitted code's behavior on the same inputs. The AI's job becomes data-model recovery — a more tractable target than direct source-to-source translation, because the substrate's specification language is small and uniform.

The honest scoping is that this approach works for the data- model-shaped fraction of real codebases, not for the script- shaped fraction. A script orchestrating shell commands or resting on language-specific runtime features is not what the substrate is for. But the data-model-shaped fraction is large in practice: schema-driven web APIs, validation libraries, structured serialization, business-rule engines, configuration systems, ontology processing. For this fraction, translation becomes a specification lift followed by substrate compilation.

The Python-to-JavaScript instance is not architecturally special. The same approach applies to Java-to-Go, C++-to-Rust, TypeScript- to-Python, or any other pair where the source code is operating against structured data and the target language has a comparable runtime model. The substrate's contribution is that the specification layer is shared across all targets, and lifting work done for one source-target pair amortizes across the entire matrix.

The cross-language translation approach has, since the present paper's first draft, been exercised on a worked example reaching behavioural conformance against the canonical RealWorld backend specification [15]. A Python FastAPI implementation of the specification was decomposed into a ten-family DSL representation, re-emitted as a TypeScript service, and validated against the canonical RealWorld Postman conformance collection — 293 of 293 assertions passing. The detailed treatment, including the ten-family taxonomy, the three-loop pipeline architecture, the forty-six-slice execution arc, and the five named failure modes documented during the arc, is [15]. The empirical result is consistent with the substrate-grounded reframe described above: the data-model lift is the load-bearing engineering work and the target-language rendering follows mechanically.

6.2 Knowledge representation and extraction

A parallel domain is formal ontologies in families such as OWL2 [12], and the automation of extracting axioms from raw data against those ontologies. Implementing OWL2 in the substrate is a tractable exercise; every target grammar is. What current practice does not address well is the *maintenance* of the ontology as new data arrives.

The substrate's contribution is best stated by a metaphor practitioners offered in conversation: it is the difference between looking *at* a three-dimensional model from inside three dimensions and looking at it from a fourth dimension. The fourth dimension is where decisions about the model itself become tractable, because both the model and the data the model represents are simultaneously visible.

The substrate operates from that fourth dimension. The specification language can express the ontology, the data-to- ontology mapping, and the ontology's own schema as first-class artifacts. All three are inspectable by the toolchain. All three can be reasoned about by AI assistance with a formal target to verify against. The ontology is not just a thing the extraction pipeline produces; it is a specification the pipeline runs against, the pipeline's behavior is itself a specification, and inconsistencies surface as structural conflicts rather than as silent quality degradation.

This enables three tiers of extraction work that current pipelines collapse into one undifferentiated activity.

Tier 1 — extraction of axioms consistent with the current ontology. An AI processes raw data, proposes triples or higher- arity assertions, and the substrate validates that each proposal is well-formed against the current ontology schema. Valid proposals are added; ill-formed proposals are rejected. This is the case current pipelines handle reasonably well; the substrate's contribution is making validation mechanical rather than statistical.

Tier 2 — extraction that the current ontology cannot accept as- is. The AI produces a proposed triple; the substrate flags it as conflicting with an existing axiom or as referring to a class or property the ontology has not declared. Current pipelines lose information here: they either drop the conflicting extraction, force-fit it into an inappropriate slot, or surface it to a human as an unstructured error. The substrate treats the conflict as a structured object. A triage step — itself AI-assisted — determines whether the extracted triple is wrong (the AI misread), the existing axiom is wrong (a previous extraction was incorrect and got accepted), or the ontology is incomplete (the data is asserting something genuine the ontology has not yet articulated). The triage produces a decision; the decision is a structured edit to one of the three specifications (extraction mapping, axiom database, ontology schema); the substrate validates the edit; the system moves on.

Tier 3 — ontology evolution. When the data persistently asserts what the ontology cannot accommodate, the appropriate response is to grow the ontology. The substrate makes this tractable because the ontology's structure is itself a specification, expressed in the same language as everything else. An AI can propose a refactoring; the substrate can validate that the refactored ontology accepts the previously conflicting extractions, that it remains consistent with the extractions that were already accepted, and that the new schema continues to round-trip cleanly through the toolchain. The refactoring becomes a checked edit rather than an unstructured restructuring.

The "fourth dimension" framing is not metaphorical in the loose sense. The substrate operates one specification layer above the ontology and the extraction mapping. From that layer, both are visible, inspectable, editable, and their consistency is mechanically checkable. That layer does not exist in current ontology toolchains; the substrate makes the connection a first- class artifact and gives the system a place to stand when the connection needs to change.

6.3 What the domains share

The two domains have been presented separately, but the underlying move is the same.

In code translation, the bridge between source and target language that current tools cannot maintain becomes maintainable when the bridge is recast as a data-model specification and the substrate handles the rendering into each target. The AI's contribution shifts from generating target-language source to recovering the data model the source code is operating against.

In knowledge extraction, the bridge between raw data and OWL2 axioms that current pipelines cannot maintain becomes maintainable when the bridge is recast as a set of cooperating specifications (extraction mapping, ontology schema, axiom database) and the substrate gives the system a place to inspect and edit all three. The AI's contribution shifts from end-to-end pipeline construction to AI-assisted evolution of specifications the substrate validates.

The common move is: identify the implicit semantic structure that the current workflow treats as background, lift it to an explicit specification the substrate can hold, and let the substrate carry the consistency burden the human or the AI was carrying badly.

---

7. The Hyperon Connection

The work most directly relevant to the broader AI conversation is the substrate's integration with the Hyperon ecosystem [3]. This deserves specific treatment because it illustrates the third bet's relationship to the cognitive-architecture bet in concrete terms.

Hyperon's bet is that cognition is the dynamics of a self- modifying metagraph (the Atomspace) under pattern-rewriting (MeTTa) governed by a cognitive architecture (PRIMUS). MeTTa is the language in which programs are written and in which the Atomspace's content is expressed; programs are themselves graph structures other programs can rewrite. The architecture is, by current standards, ambitious and pre-alpha.

MeTTa has a grammar. The grammar is small — S-expression syntax with permissive symbol naming, a few prefix conventions for variables and space references, and one comment syntax.

The substrate treated MeTTa as a target language: a specification in the substrate's language describing MeTTa's surface syntax was authored, the compiler-compiler produced the parser-serializer pair, and the round-trip oracle was exercised against existing MeTTa test corpora. The result is a four-runtime read path for MeTTa source — binary representations of MeTTa programs, consumable in C++, Python, JavaScript, and Rust through the same API any other substrate-built parser uses.

This produced an observation that matters for the broader AI conversation: a Rust consumer reading MeTTa-as-binary and populating a Rust atomspace operates without the FFI cost that dominates the equivalent Python path. The per-atom cost goes from the thousand-nanosecond range (Python crossing the language boundary to insert atoms) to the hundred-nanosecond range (Rust native operation). Memory footprint drops by an order of magnitude. The deployment topology where one producer feeds many cluster nodes — the natural shape for any Atomspace-based system at scale — benefits substantially.

The point of this observation is not the magnitude of any particular speedup. It is that the substrate's value to Hyperon does not depend on Hyperon's AGI bet paying off. Whether or not cognitive synergy turns out to be real, whether or not PRIMUS produces human-level intelligence, the Atomspace as a distributed metagraph needs a wire format for moving structured content between producer and consumer nodes. The substrate provides one, with round-trip closure as the oracle and four runtime consumers natively supported. The substrate is useful at the engineering layer whether or not Hyperon's broader claims mature.

If Hyperon does mature — if cognitive synergy turns out to deliver the capabilities its proponents argue for — the substrate is positioned to integrate as the foundation layer beneath it. The Atomspace's content, the MeTTa programs that rewrite it, the wire formats that move metagraph fragments between cluster nodes: all have natural representations in the substrate's specification language with corresponding binary forms. The integration path is engineering work, not architectural rethinking.

If Hyperon does not mature — if the cognitive-architecture bet turns out to require breakthroughs that do not arrive — the substrate remains useful for what it does: substrate-grounded wire formats, AI-assisted construction of structured-data systems, the substitution-library pattern against whichever frameworks turn out to be load-bearing in whatever paradigm dominates. The substrate is agnostic about which AGI bet wins because it sits beneath the question.

---

8. Limitations and Threats to Validity

A paper that did not name what remains uncertain about its own claims would be doing the wrong job. Several things about the third bet are genuinely open.

Single-practitioner record. The substrate has been exercised on a project family of substantial size, but the family is the product of one practitioner's work over roughly a year. Independent external validation by practitioners not involved in the substrate's development does not yet exist. The patterns and disciplines surfaced by the work may or may not transfer cleanly to other practitioners. The four-to-nine-times throughput multiplier reported in Section 5 was measured against the same practitioner's own prior estimation; whether it holds when other practitioners adopt the methodology is empirical and unmeasured.

Self-measurement threat. The methodology described here was developed and exercised by an author who is also one of the substrate's primary authors. The throughput numbers therefore measure the methodology against a baseline (the same person's prior estimation) that is not independent. Independent estimation by practitioners blind to the substrate's existence would be a sharper test. We have not run that experiment.

Scaling properties. The substrate's scaling properties to substantially larger projects than the demonstrated family are inferable but not measured. The project family is large enough to be a serious test case but not large enough to test limits. What happens at ten times the current scale, with multi- practitioner concurrent development, or across substantially more diverse target domains, is open.

Stage-of-maturity asymmetry across worked domains. The two domains discussed in Section 6 remain at different stages of maturity, though the asymmetry has narrowed between Draft 0.1 and Draft 0.2. The cross-language translation approach has been exercised on the substrate's own multi-language emission — a worked example in which the same data-model specification is emitted as parser/serializer/accessor APIs in three languages with round-trip validation in each — and, since Draft 0.1, on a Python-to-TypeScript translation of the canonical RealWorld backend specification reaching 293 of 293 assertions against the canonical Postman conformance collection [15]. The general lifting tool that would handle arbitrary existing code is no longer purely sketched: the worked example exercises a concrete instance of the lift, with a ten-family DSL taxonomy and a three-loop pipeline architecture both demonstrated end-to-end on a non-trivial benchmark. Whether the taxonomy generalises beyond Conduit-shaped applications remains an empirical open question that [15, §13] lists as a forward-work item. The ontology-extraction approach remains more aspirational: a substrate implementation of OWL2 is straightforward engineering, but the three-tier maintenance loop is described at the architectural level without a built worked example yet. Forward work in both domains is meaningful, with the ontology-extraction domain the larger gap as of Draft 0.2.

Relationship to model capability evolution. The throughput numbers reported here were obtained against the language models available during the construction window. Whether the same methodology delivers the same multipliers as the models improve, plateau, or in some scenarios degrade is empirical. The substrate is, by design, independent of which specific LLM is the language- interface layer; it would integrate with whatever model is current. But the *multiplier* available from the integration is not, as a matter of theory, model-independent.

Substrate availability. The substrate's status under US Patent 8,464,232 [1] means it is not currently available as an open-source artifact. Independent practitioners cannot pick it up and run it; replication is gated by commercial conversation. Whether, when, and under what terms this changes is a strategic question we do not address here. The position the paper takes is the position; the substrate's availability is a separate matter.

---

9. Discussion and Future Work

The third-bet framing implies a sequence of research and engineering directions that current AI-assisted-construction conversation does not centrally address.

Orchestration above the substrate. The first is the construction of orchestration systems that maintain collections of cooperating specifications, propagate edits coherently across isomorphic mappings, and surface inconsistencies as structural conflicts. This is the layer above the substrate the paper has not described in detail; it is the natural next phase of substrate-grounded construction work. We have outlined it in earlier internal work but not built it as an integrated system.

Empirical study with independent practitioners. The second is empirical study of the throughput characteristics of Adaptive Programming when practiced by practitioners other than the substrate's authors. The four-to-nine-times multiplier is internally measured against the same practitioner's prior estimation; external replication would sharpen the claim substantially. Designing such studies is methodologically nontrivial — the comparison group cannot have the substrate while the treatment group does, which makes blinding hard — but the question is worth posing.

Cognitive-architecture integration. The third is the integration of substrate-grounded construction with the broader symbolic-AI conversation. The substrate's relationship to systems like OpenCog Hyperon — graph-structured representations of knowledge, programs that rewrite the representations, cognitive architectures above both — is amenable to the same multi-language wire-format treatment the substrate handles for other binary protocols. The deployment topologies enabled by structured-binary transport between producer and consumer nodes have non-trivial implications for distributed cognitive systems. We have begun this work in a limited form (Section 7); significant forward work remains.

Tooling above the substrate. The fourth, and most central to the paper's position, is the recasting of AI-assisted software construction tooling around the specification layer. Tools that present a development experience in which the human's attention is on specifications the substrate validates, rather than on artifacts the human must review, are buildable today. Such tools do not require breakthroughs in LLM capability; they require taking the specification layer seriously as the surface AI assistance operates against.

The paper closes with an observation that has been implicit throughout. The third-bet framing is independent of which AGI bet — scaling or cognitive architecture — pays off. The substrate is useful on top of current LLMs as the language interface, integrates with cognitive-architecture systems where they mature, and is independent of which broader bet wins. The practical implication is that the substrate problem can be worked on now, with current tools, without waiting for unresolved AGI questions to clarify. The work is concrete; the validation is empirical; the position is empirically grounded rather than aspirational. Substrate-grounded AI-assisted construction is a research direction the field has the means to pursue, and the paper's modest goal is to make the direction visible enough that practitioners reaching for such a substrate independently can recognize that one exists.

References

[1] Urakhchin, A.F. *Compiler Compiler System with Syntax- Controlled Runtime and Binary Application Programming Interfaces.* US Patent 8,464,232. Granted June 11, 2013. https://patents.google.com/patent/US8464232B2/en

[2] Urakhchin, A.F. *Compiler Compiler System with Isomorphic Runtime and Binary Structured Intermediate Representations. Self-hosting bootstrap, multi-language runtime emission, and JSON parser benchmarks.* arXiv preprint, 2026. (Companion technical paper to the present work; provides substrate implementation details, parsing-model formalization, round-trip-oracle methodology, and empirical evaluation against nlohmann/json and simdjson baselines.)

[3] Goertzel, B., Pennachin, C., Geisweiller, N. *Engineering General Intelligence (Volumes 1-2).* Atlantis Press, 2014. (OpenCog and Hyperon foundational work; cited in §7 in the context of the cognitive-architecture bet's relationship to the substrate.)

[4] Chen, M., et al. *Evaluating Large Language Models Trained on Code.* arXiv:2107.03374 [cs.LG], 2021. (Codex / GitHub Copilot foundational evaluation.)

[5] Anthropic. *Claude Code and Claude Agent SDK.* Documentation at https://claude.com/claude-code

[6] Garcez, A.S.d., Lamb, L.C. *Neurosymbolic AI: The 3rd Wave.* arXiv:2305.00813 [cs.AI], 2023.

[7] Anonymous Authors. *Position: Trustworthy AI Agents Require the Integration of Large Language Models and Formal Methods.* OpenReview submission wkisIZbntD, 2024.

[8] OMG. *Model Driven Architecture Specification.* Object Management Group, 2003 and subsequent revisions. (Foundational MDE reference.)

[9] Erdweg, S., van der Storm, T., Völter, M., et al. *The State of the Art in Language Workbenches.* Software Language Engineering (SLE 2013), Springer LNCS. (JetBrains MPS, Xtext, Spoofax.)

[10] Johnson, S.C. *Yacc: Yet Another Compiler-Compiler.* Bell Laboratories Computing Science Technical Report 32, 1975.

[11] Parr, T. *The Definitive ANTLR 4 Reference.* Pragmatic Bookshelf, 2013.

[12] W3C. *OWL 2 Web Ontology Language Document Overview (Second Edition).* W3C Recommendation, 2012.

[13] Brachman, R.J., Levesque, H.J. *Knowledge Representation and Reasoning.* Morgan Kaufmann, 2004. (Foundational KR reference; OWL family lineage.)

[14] Yao, S., et al. *ReAct: Synergizing Reasoning and Acting in Language Models.* International Conference on Learning Representations (ICLR), 2023. (Agentic LLM workflow grounding.)

[15] Urakhchin, A.F. *Compiler Compiler System Translation Pipeline: From Python to TypeScript with Full RealWorld Conformance.* arXiv preprint, 2026. (Companion empirical paper; detailed treatment of the cross-language source translation domain from Section 6.1 of the present paper. Reports a forty-six-slice adaptive-programming arc producing a Python-to-TypeScript translation of the canonical RealWorld backend specification passing 293 of 293 assertions of the canonical Postman conformance collection.)

Manuscript prepared for submission to arXiv (cs.SE primary, cs.AI and cs.PL cross-list). Comments to the author welcomed at the contact address above. The substrate referenced throughout is operated by Bet Three LLC under US Patent 8,464,232; engagement with the reference implementation is through commercial channels. The companion technical paper [2] provides implementation backing for the architectural claims summarized in Section 3. The companion empirical paper [15] provides the detailed worked example for the cross-language source translation domain of Section 6.1.