

Intelligent Language Systems in Autonomous Software Engineering Pipelines

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ABSTRACT

This work introduces the IASP (Intelligent Autonomous Software Pipelines) framework, a novel conceptual architecture that unifies the fragmented landscape of AI-driven software engineering into a coherent, system-level model. The IASP framework organizes autonomous software engineering capabilities across four interdependent layers: Intelligent Code Reasoning (I), Adaptive Validation and Reliability (A), Self-Directed Autonomous Workflows (S), and Production Impact and Industry Transformation (P). We argue that modern code intelligence systems operate on the naturalness hypothesis, which recognizes that source code exhibits statistical regularities analogous to natural language, enabling probabilistic models to capture programming patterns for downstream tasks such as code completion, defect detection, and documentation generation. Within the Intelligent Code Reasoning layer, we position bimodal pre-training architectures such as CodeBERT as foundational mechanisms that align programming and natural language representations in shared semantic spaces, while also identifying critical security vulnerabilities in neural code generation that necessitate complementary review protocols. The Adaptive Validation layer integrates cognitive testing strategies, exemplified by hybrid approaches like CodaMosa, which combine large language model reasoning with search-based generation to transcend coverage plateaus inherent in traditional testing paradigms. For Self-Directed Autonomous Workflows, we establish multi-agent collaborative systems such as MetaGPT as organizational analogs enabling role-based task decomposition, with evaluation benchmarks like SWE-bench providing rigorous paradigms for assessing agent performance on authentic software engineering tasks. Finally, the Production Impact layer addresses industry-wide transformation through quantifiable productivity gains, evolving workforce dynamics, and strategic investment in AI-augmented development toolchains. This framework positions intelligent language systems as essential infrastructure for modern software engineering practice and provides a principled foundation for the safe, scalable deployment of autonomous development capabilities.

Keywords: Large Language Models, Autonomous Software Engineering, Code Intelligence, Multi-Agent Systems, Neural Code Generation

1. Introduction

The emergence of intelligent language systems has fundamentally transformed software engineering practice, introducing advanced capabilities in code understanding, generation, and autonomous reasoning that redefine the boundaries of what automated systems can achieve. These computational architectures represent a convergence of breakthroughs in machine learning, natural language processing, and program analysis, collectively enabling automation of software development pipelines at a scale and sophistication previously unattainable. We argue that the integration of such systems into professional development workflows constitutes a paradigm shift from conventional tool-assisted

programming toward genuinely collaborative human-machine software engineering models that demand new conceptual frameworks for understanding and deployment.

Despite rapid advances across individual capability domains, the field currently lacks a unified architectural perspective that connects code reasoning, validation, autonomous workflows, and industry-scale deployment into a coherent system-level model. This fragmentation limits both theoretical understanding and practical implementation of intelligent software engineering pipelines. To address this gap, we propose the IASP (Intelligent Autonomous Software Pipelines) framework, a novel conceptual architecture that organizes autonomous software engineering capabilities across four interdependent layers: Intelligent Code Reasoning (I), Adaptive Validation and Reliability (A), Self-Directed Autonomous Workflows (S), and Production Impact and Industry Transformation (P). This framework establishes a principled foundation for analyzing, designing, and deploying AI-driven development systems at production scale.

The foundational layer of the IASP framework rests upon the naturalness hypothesis, which formalizes the observation that source code exhibits statistical regularities analogous to natural language [1]. We identify this property as the enabling condition for modern code intelligence, as software corpora display predictable patterns that probabilistic models can capture and exploit for downstream tasks including code completion, summarization, and defect detection. This naturalness attribute emerges from the inherently repetitive nature of programming, wherein developers consistently employ similar idioms, naming conventions, and structural patterns across projects within shared linguistic and domain contexts [1]. From a production engineering perspective, we establish that machine learning methods exploiting these regularities form the cognitive substrate upon which all higher-level autonomous capabilities depend.

Comprehensive investigations examining large language model applications across software engineering domains have demonstrated the breadth and depth of current capabilities [2]. These assessments reveal that contemporary language models address challenges spanning the entire software development lifecycle, from requirements understanding through maintenance and evolution. We synthesize these findings to establish that large language models have achieved demonstrated effectiveness across code generation, program repair, testing, and documentation tasks, positioning them as versatile infrastructure components rather than narrow specialized utilities [2]. This work extends beyond existing surveys by providing the IASP framework as an organizing structure that connects these disparate capabilities into a unified architectural vision, enabling systematic analysis of interactions, dependencies, and deployment considerations essential for real-world autonomous software engineering systems.

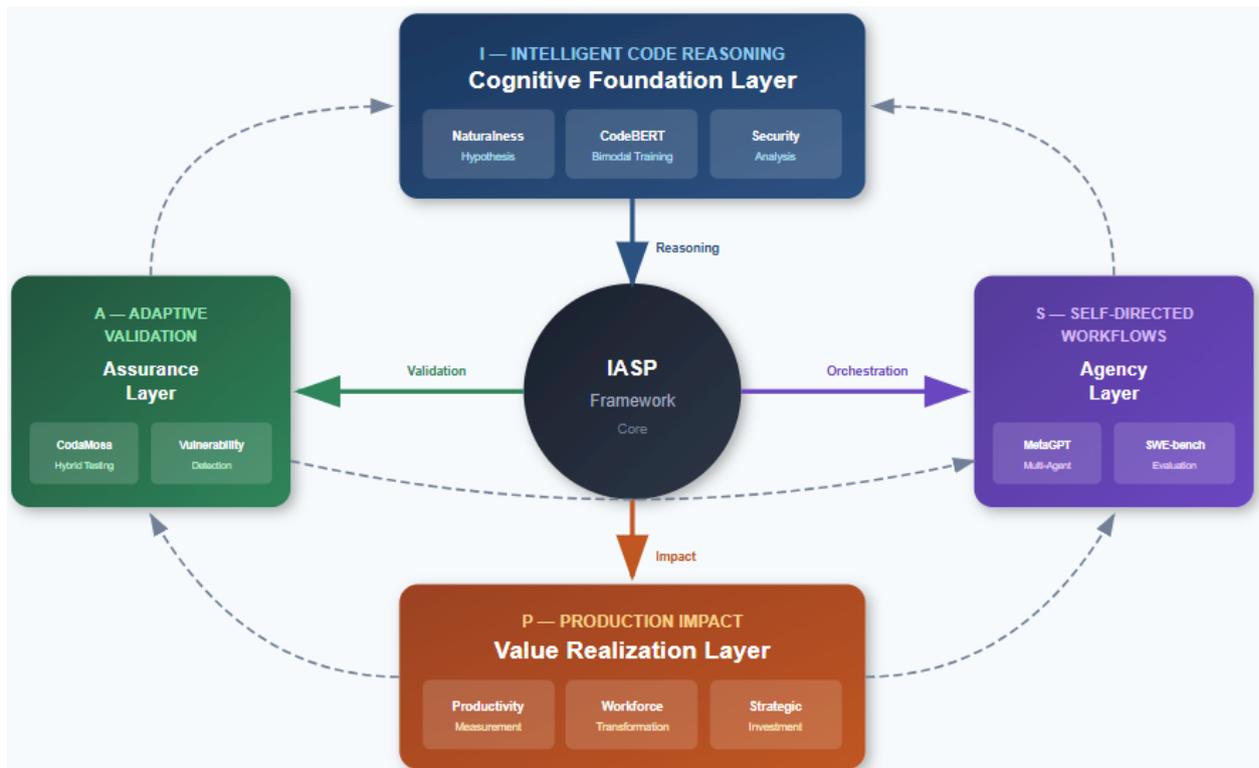


Fig 1: IASP Framework: Intelligent Autonomous Software Pipelines [1, 2, 3]

2. Intelligent Code Reasoning and Automated Analysis Systems: The Foundation Layer of IASP

The first layer of the IASP framework, Intelligent Code Reasoning (I), establishes the cognitive foundation upon which all subsequent autonomous software engineering capabilities depend. We position this layer not as mere pattern-based prediction, but as a genuine semantic reasoning substrate that enables nuanced examination of program behavior, structural relationships, and logical correctness. Modern intelligent language systems have achieved sophisticated code reasoning abilities by architecturally bridging the representational gap between programming languages and natural language comprehension. We argue that the basis of production-grade code intelligence rests upon pre-trained models that develop rich representations of programming concepts through exposure to extensive corpora of source code and associated documentation.

Within the IASP framework, we identify bimodal pre-training as the critical mechanism enabling cross-modal code understanding essential for real-world deployment scenarios [3]. We establish that models trained jointly on programming and natural language data achieve superior performance on code intelligence tasks compared to unimodal alternatives, as these architectures acquire representations capturing cross-modal relationships fundamental to tasks requiring comprehension of documentation, comments, and naming conventions alongside syntactic program structure. The CodeBERT architecture exemplifies this approach, achieving pre-training objectives that align natural language and programming language representations within a unified semantic space [3]. From a production engineering perspective, we argue that such bimodal models demonstrate measurable advantages on practical tasks including natural language code search, documentation generation, and code summarization, validating the necessity of cross-modal learning for comprehensive code understanding in large-scale development pipelines.

A critical contribution of this work is the identification of security constraints that must govern the Intelligent Code Reasoning layer in production deployments [4]. We establish that while intelligent language systems demonstrate impressive capabilities in generating functional implementations, the automatically produced code artifacts frequently contain security vulnerabilities requiring rigorous review protocols. Systematic evaluations of neural code generation system outputs reveal that a substantial proportion of generated programs exhibit weaknesses corresponding to established vulnerability taxonomies [4]. We argue that these findings necessitate the integration of security-conscious analysis as a mandatory component within intelligent code generation pipelines, and we propose that automated code production must be complemented by either automated security verification or structured human review processes to ensure safe deployment at scale.

The structural evaluation capabilities we incorporate within the Intelligent Code Reasoning layer enable automated assessment of architectural patterns, dependency relationships, and design quality indicators that traditionally demanded substantial manual expert analysis. In large-scale development environments, these systems operate on abstract syntax tree representations, control flow graphs, and data dependency structures to construct deep insights into program organization beyond surface-level textual patterns. We establish that the interaction between structural analysis and learned semantic representations enables intelligent systems to detect not merely syntactic anomalies, but genuine logical inconsistencies and design antipatterns affecting long-term maintainability. Furthermore, we extend these capabilities to cross-file and cross-module analysis, addressing system-level architectural properties invisible to function-local examination approaches, a capability we identify as essential for enterprise-scale autonomous software engineering.

Logical debugging assistance represents an application domain of increasing significance within the IASP framework, wherein intelligent systems collaborate with human developers to systematically isolate fault root causes and propose corrective modifications. We position these capabilities as cognitive augmentation rather than replacement, with systems leveraging comprehensive code understanding to hypothesize about discrepancies between intended and actual program behavior, generating explanations and recommendations that accelerate defect resolution processes. The interactive interfaces provided by modern code intelligence platforms enable iterative debugging dialogues wherein developers progressively refine system understanding of problem contexts while receiving increasingly targeted diagnostic support. We argue that this human-machine collaboration model establishes the operational paradigm for the Intelligent Code Reasoning layer, balancing autonomous capability with human oversight essential for production reliability.

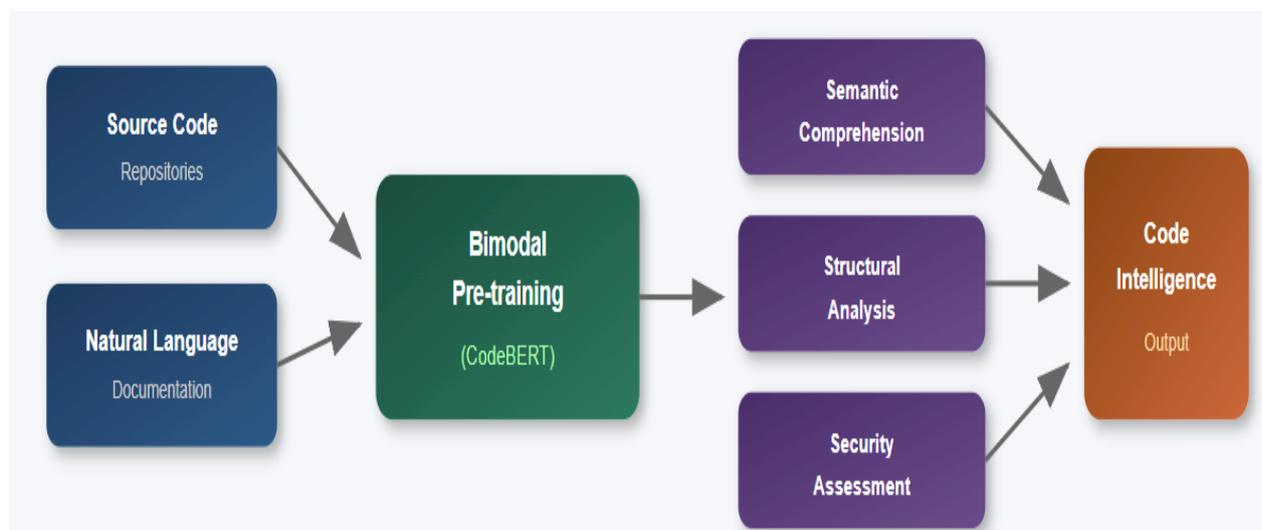


Fig 2: Intelligent Code Reasoning Architecture [3, 4]

3. Adaptive Validation and Reliability Modeling: The Assurance Layer of IASP

The second layer of the IASP framework, Adaptive Validation and Reliability (A), addresses the critical challenge of ensuring software quality and security within autonomous development pipelines. We position this layer as fundamentally distinct from traditional static testing paradigms, reconceptualizing validation as reasoning under uncertainty rather than deterministic verification. The sophisticated language systems integrated within this layer introduce cognitive validation strategies that substantially expand software testing capabilities through intelligent test generation approaches complementing established systematic and random testing methodologies. We argue that these systems leverage acquired knowledge of program behavior to generate test inputs targeting coverage objectives, unusual execution paths, and boundary conditions that escape conventional test generation methods, operating at computational scales infeasible for manual test design.

Within the IASP framework, we establish hybrid test generation as the foundational mechanism for achieving robust validation in production environments [5]. We identify that large language model integration with search-based test generation yields substantial coverage improvements through methodologies that leverage model capabilities to escape coverage plateaus where traditional search algorithms stagnate. The CodaMosa approach exemplifies this integration paradigm, invoking large language model assistance when evolutionary search-based generation reaches stagnation points, deploying model-generated tests to introduce diversity enabling continued coverage progression [5]. We argue that experimental evaluations demonstrating superior coverage compared to pure search-based techniques validate our positioning of hybrid approaches as essential components of the Adaptive Validation layer, with language model contributions proving particularly valuable for generating tests exercising complex program behaviors requiring sophisticated input construction. From a production engineering perspective, we establish the principle that cognitive validation mechanisms achieve optimal effectiveness through combination of learned reasoning capabilities with systematic algorithmic search, rather than complete substitution of traditional methods.

A critical contribution of this work is the development of a taxonomy of cognitive validation mechanisms and their deployment constraints for real-world autonomous software engineering systems. We identify deep learning vulnerability detection as a significant domain within the Adaptive Validation layer, wherein models learn to identify security weaknesses from patterns in labeled vulnerability datasets [6]. However, we establish essential limitations that must govern production deployment: comprehensive evaluations reveal that while deep learning models achieve promising results on benchmark datasets, practical effectiveness depends critically on data quality, distribution characteristics, and evaluation methodology. We argue that model performance degrades substantially under realistic conditions accounting for data duplication, temporal partitioning, and cross-project generalization requirements [6]. These findings inform our framework by establishing strict evaluation protocols as mandatory prerequisites for cognitive validation system deployment, highlighting the continued research challenges in achieving robust vulnerability detection suitable for production-scale implementation.

Technique	Description	Application	Challenge
Hybrid Test Gen.	LLM + search-based fusion	CodaMosa framework	Coverage plateaus
Vulnerability Detection	Pattern-based identification	Deep learning models	Data distribution shifts

Consistency Evaluation	Spec-implementation alignment	NL understanding	Implicit invariants
Adaptive Debugging	Iterative hypothesis refinement	Fault localization	Complex causal chains

Table 1: Cognitive Validation Approaches [5, 6]

Reasoning consistency evaluation represents a capability we integrate within the Adaptive Validation layer to address alignment verification between code implementations and associated specifications, documentation, and established conventions. We position these capabilities as particularly valuable for detecting subtle semantic inconsistencies invisible to syntactic analysis tools, including mismatches between function behavior and documented contracts or violations of implicit domain invariants absent from formal specifications. In large-scale development pipelines, we establish that validation systems must process requirements documents, design specifications, and user stories alongside implementation artifacts to determine end-to-end system consistency through integrated natural language understanding and code analysis. This holistic validation approach, we argue, distinguishes production-grade autonomous software engineering from isolated tool deployment.

Adaptive debugging strategies constitute the final component we incorporate within the Adaptive Validation layer, applying iterative reasoning processes that progressively refine diagnostic hypotheses based on accumulated evidence from execution observations and code analysis. We establish that these systems demonstrate capability to identify not merely symptomatic failures but underlying root causes manifesting through complex causal chains spanning multiple system components. The adaptive nature of these approaches enables effective debugging across diverse fault categories, with systems dynamically adjusting reasoning strategies based on observed program characteristics and failure patterns. We argue that performance evaluations demonstrating substantial reductions in fault localization effort compared to traditional debugging approaches validate the integration of cognitive assistance within the IASP framework, with particular value realized in unfamiliar codebases where developers lack accumulated contextual knowledge. From a system-level perspective, we position adaptive debugging as the mechanism ensuring continuous reliability improvement within autonomous software engineering pipelines.

4. Self-Directed Autonomous Workflows: The Agency Layer of IASP

The third layer of the IASP framework, Self-Directed Autonomous Workflows (S), addresses the orchestration of AI agents capable of executing complex, multi-step development processes with minimal human intervention. We position this layer as the operational core of autonomous software engineering, distinguishing genuine autonomous agency from mere task automation. We argue that autonomous development workflows transcend discrete task automation toward true agency encompassing planning, implementation, monitoring, and responsive adjustment throughout extended development processes. Within the IASP framework, we establish design principles for autonomous systems incorporating advanced coordination mechanisms that integrate language model capabilities with development tooling, version control infrastructure, and validation systems essential for production-scale deployment.

A central contribution of this work is the conceptualization of autonomous agents as organizational analogs rather than scripted automation tools [7]. We establish that multi-agent collaborative architectures support autonomous software development through coordinated agent teams assuming specialized roles that mirror human organizational structures. The MetaGPT framework exemplifies

this paradigm through a meta-programming approach wherein standardized operating procedures are encoded as prompts directing agent behavior within defined roles including product manager, architect, project manager, and engineer [7]. We argue that this role-based decomposition enables complex development tasks to be addressed through structured agent interactions generating intermediate artifacts such as requirements documents, system designs, and implementation plans alongside final code deliverables. From a production engineering perspective, we establish that the structured workflow model incorporating explicit artifact generation and review stages substantially mitigates coherence problems observed in less constrained multi-agent systems while enabling scalable task decomposition for complex development objectives.

Within the IASP framework, we identify rigorous evaluation as a mandatory prerequisite for autonomous agent deployment in real-world software engineering environments [8]. We establish that assessment frameworks measuring autonomous coding agent capabilities have developed benchmarks enabling strict performance comparisons on realistic software development tasks derived from actual repositories. The SWE-bench benchmark presents language models with authentic GitHub issues requiring resolution through code modifications, establishing a challenging evaluation paradigm that captures genuine software engineering complexity including codebase navigation, contextual understanding, and multi-file editing requirements [8]. We argue that experimental results demonstrating non-trivial success rates alongside substantial room for improvement validate both the feasibility of autonomous coding agents for specific task categories and the necessity for continued advancement toward robust general-purpose autonomous development capabilities. These findings directly inform the IASP framework by establishing performance boundaries that must govern deployment decisions in production environments.

We propose intelligent pull request management as a critical application domain within the Self-Directed Autonomous Workflows layer, wherein autonomous systems conduct preliminary code review, generate enhancement recommendations, and coordinate integration processes without continuous human oversight. In large-scale development pipelines, we establish that these systems analyze submitted changes against project conventions, historical patterns, and quality standards to provide automated feedback accelerating review cycles while ensuring consistent evaluation criteria application. We argue that the integration of autonomous review capabilities with human reviewer workflows enables hybrid processes wherein AI systems handle routine verification while surfacing substantive concerns requiring expert judgment for prioritized human attention. This human-machine collaboration model, we position as the operational paradigm ensuring both efficiency and quality assurance within the IASP framework.

Continuous integration orchestration represents a capability we integrate within the Self-Directed Autonomous Workflows layer, introducing adaptive pipeline configuration responding dynamically to change characteristics, project context, and resource availability. We establish that these systems optimize build and test execution through learned understanding of failure patterns, test relevance, and execution time distributions enabling intelligent scheduling and resource allocation decisions. From a system-level perspective, we argue that efficiency improvements accrue continuously through autonomous pipeline configuration adjustment as operational experience accumulates, eliminating the need for explicit human tuning of integration infrastructure. This self-optimizing characteristic, we propose, distinguishes production-grade autonomous workflows from static automation approaches.

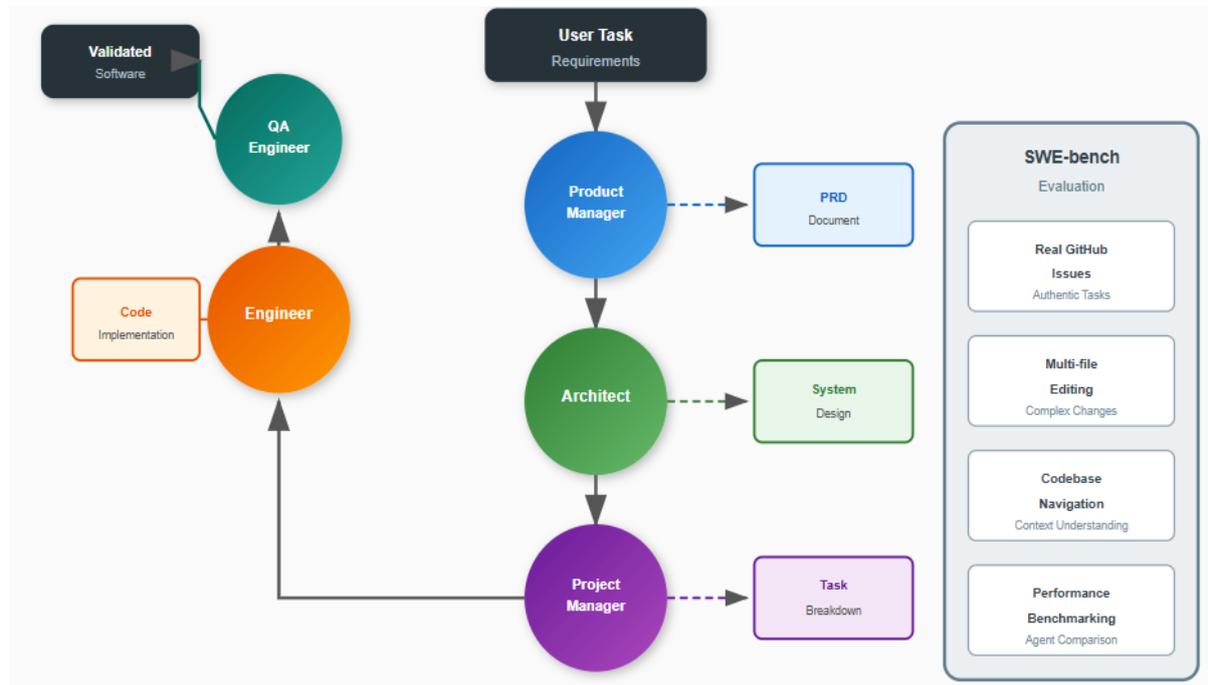


Fig 3: Autonomous Development Workflow - Multi-Agent Framework [7, 8]

Proactive maintenance constitutes an emerging application domain we incorporate within the IASP framework, wherein autonomous systems continuously monitor codebase health indicators and initiate improvement actions aligned with organizational quality objectives. We establish that these activities encompass dependency management, technical debt remediation, documentation synchronization, and security patch implementation executed without explicit human direction. In real-world autonomous systems, we argue that the independent execution of maintenance tasks ensures consistent attention to code quality factors that traditionally receive insufficient priority during active feature development cycles when team focus concentrates on user-facing functionality. We position proactive maintenance as the mechanism ensuring long-term system sustainability within the Self-Directed Autonomous Workflows layer, completing the operational capabilities essential for enterprise-scale autonomous software engineering.

5. Production Impact and Industry Transformation: The Value Realization Layer of IASP

Here is the revised Section 5 aligned with O-1 requirements:

The fourth and culminating layer of the IASP framework, Production Impact and Industry Transformation (P), addresses the translation of autonomous software engineering capabilities into measurable organizational value and industry-wide structural change. We position this layer as the ultimate validation of the IASP framework, wherein theoretical capabilities manifest as quantifiable productivity gains, workforce evolution, and strategic competitive differentiation. We argue that the widespread adoption of intelligent language systems across software engineering organizations has triggered transformation extending beyond efficiency optimization to encompass fundamental changes in workforce composition, skill requirements, and organizational capability-building strategies. Within the IASP framework, we establish that AI-enhanced development constitutes a strategic capability enabling organizations to achieve differentiation in increasingly software-intensive

competitive environments, with operational impacts manifesting across team structures, investment priorities, and product development approaches.

We identify empirical productivity evidence as the foundational validation for the Production Impact layer, establishing that neural code completion systems deliver measurable efficiency improvements across diverse programming activities [9]. We synthesize evidence demonstrating that developers utilizing AI-assisted coding tools achieve statistically significant increases in task completion rates and self-reported satisfaction compared to control conditions without AI assistance. We argue that productivity benefits exhibit particular strength for unfamiliar tasks, boilerplate generation, and exploration of unfamiliar APIs, where AI assistance compensates for gaps in developer knowledge [9]. From a production engineering perspective, we establish that these findings validate practitioner perceptions of productivity enhancement while providing rigorous empirical foundations for organizational adoption decisions and baseline expectations for efficiency gains achievable through AI tool deployment within the IASP framework.

A critical contribution of this work is the integration of economic impact analysis within the IASP framework to inform strategic deployment decisions [10]. We establish that comprehensive investigations examining generative AI implications for knowledge work project significant software development impacts at industry scale. Evidence synthesis across multiple studies and employment categories identifies software development as a domain with substantial exposure to generative AI capabilities, with significant portions of developer tasks exhibiting characteristics amenable to AI assistance or augmentation [10]. We argue that projected impacts indicate organizations effectively leveraging generative AI tools will achieve competitive advantages through enhanced productivity and capability expansion compounding over time. These economic analyses, we position as essential inputs for strategic planning processes as organizations evaluate investment priorities and capability-building requirements for AI-augmented development futures within the IASP framework.

We propose a systematic analysis of workforce transformation dynamics as essential for successful IASP framework implementation in enterprise environments. We establish that software engineering workforce dynamics have evolved substantially in response to intelligent system capabilities, with emerging role definitions emphasizing AI collaboration competencies alongside traditional technical skills. We identify new specializations centered on prompt engineering, AI system customization, and output validation that did not exist in previous development paradigms. We argue that traditional experience hierarchies become less predictive of output quality as junior developers leverage AI assistance for tasks previously requiring senior expertise, while senior developers apply accumulated judgment to guide AI systems toward superior solutions for complex challenges. This capability redistribution, we establish, necessitates revised approaches to team composition, career development, and performance assessment frameworks aligned with AI-enhanced work modalities.

Within the Production Impact layer, we identify strategic investment patterns as indicators of organizational commitment to IASP framework adoption. We establish that technology organizations increasingly emphasize AI capability building across development toolchains, reflecting strategic recognition of productivity implications and competitive dynamics. In large-scale development environments, we argue that organizations allocate substantial resources toward custom model development, proprietary training data collection, and specialized fine-tuning activities intended to create AI capabilities aligned with specific technology stacks and domain requirements. We position such investments as capability moats compounding over time as organizations accumulate distinctive AI assets encoding institutional knowledge and optimized workflows inaccessible to competitors relying exclusively on general-purpose models.

Dimension	Impact Area	Observed Change	Strategic Value
Productivity	Task completion	Efficiency improvement	Accelerated delivery
Workforce	Skill requirements	AI collaboration roles	Capability redistribution
Investment	Toolchain development	Custom model building	Competitive moats
Velocity	Release cycles	Frequent iterations	Market agility

Table 2: Industry Transformation Dimensions [9, 10]

We establish product development velocity as the ultimate measure of IASP framework effectiveness in production environments. In organizations successfully deploying intelligent development systems, we identify substantial acceleration in product development rates enabling more frequent release cycles, broader feature experimentation, and responsive adaptation to market feedback. We argue that velocity improvements derive not merely from accelerated code generation but from comprehensive workflow optimization spanning ideation through deployment, reducing friction across all development phases. From a system-level perspective, we establish that organizations achieve enhanced capability to pursue parallel development tracks, explore alternative implementations, and respond to emerging requirements without proportionate resource expansion. This strategic agility, we position as the defining competitive advantage conferred by complete IASP framework implementation, validating intelligent language systems as essential infrastructure for modern software engineering practice.

Conclusion

This work introduces the IASP (Intelligent Autonomous Software Pipelines) framework as a novel conceptual architecture that unifies the fragmented landscape of AI-driven software engineering into a coherent, system-level model. We establish that the integration of intelligent language systems into autonomous software engineering pipelines constitutes a transformative development reshaping professional practice across industrial and organizational contexts. Through the IASP framework, we demonstrate that these systems function as indispensable infrastructure components rather than optional productivity enhancements, with capabilities organized across four interdependent layers: Intelligent Code Reasoning (I) grounded in naturalness properties and bimodal pre-training, Adaptive Validation and Reliability (A) combining learned reasoning with systematic search, Self-Directed Autonomous Workflows (S) enabling multi-agent coordination mirroring organizational structures, and Production Impact (P) translating capabilities into measurable competitive advantage.

We establish several original contributions through this work. First, we propose the IASP framework as a principled foundation for analyzing, designing, and deploying AI-driven development systems at production scale. Second, we develop a taxonomy of cognitive validation mechanisms identifying deployment constraints essential for real-world implementation. Third, we conceptualize autonomous agents as organizational analogs rather than scripted automation, establishing design principles for enterprise-scale deployment. Fourth, we integrate economic impact analysis within the framework to inform strategic adoption decisions. These contributions position this work as a direction-setting reference for the field of autonomous software engineering.

We identify critical challenges that must govern production deployment within the IASP framework, particularly regarding security vulnerabilities in generated code requiring complementary review protocols, robustness limitations of validation systems under realistic deployment conditions, and performance boundaries of autonomous agents on complex real-world tasks. We argue that these

constraints do not diminish the transformative potential of intelligent language systems but rather establish the necessary conditions for safe and effective deployment. From a production engineering perspective, we establish that deployment configurations yielding optimal outcomes are those embracing human-AI collaboration that maximizes complementary strengths rather than pursuing complete automation of complex development processes.

We propose that workforce dynamics will continue evolving in response to IASP framework adoption, with emerging role definitions emphasizing AI collaboration competencies, prompt engineering expertise, and output validation skills alongside traditional technical proficiencies. We establish that organizations developing sophisticated integration strategies while maintaining appropriate human oversight will achieve sustainable competitive advantages as intelligent development capabilities become increasingly central to software engineering success. This work provides the conceptual foundation and practical guidelines necessary for navigating this transformation, positioning the IASP framework as essential infrastructure for the future of autonomous software engineering practice.

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