AI-DRIVEN ENTERPRISE PROCESS AUTOMATION: EVALUATING AUTOMATION ARCHITECTURES FOR KNOWLEDGE-INTENSIVE PROCESSES

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Abstract:

Digital transformation in Knowledge-intensive Processes is shifting toward Agentic **Business Process Management** to overcome challenges posed by unstructured data complexity. This **research-in-progress** evaluates the structural tension between operational efficiency and compliance in Knowledge-intensive Processes automation by examining Generative AI extraction, database architectures, and performance trade-offs between Python and Low-Code/No-Code platforms under AI governance frameworks. Using Design Science Research, this study proposes a five-pillar conceptual framework and establishes a qualitative baseline through domain expert interviews. **Initial findings reveal structural fragmentation as core barriers, driving a 20 to 40% waste premium.** This paper provides the architectural foundation and experimental protocol for future quantitative benchmarking.

1 Introduction

Digital transformation in modern organizations is increasingly driven by advances in **Generative AI (GenAI)** and AI-driven enterprise automation, enabling firms to automate complex information processing and decision-making tasks. While AI tools have become commonplace, with 88% of organizations reporting regular AI use in at least one business function, the transition from experimental pilots to enterprise-level scale remains a significant challenge [15]. Notably, 62% of organizations are now experimenting with or scaling **AI agents**, systems capable of planning and executing multi-step workflows, with the most rapid adoption occurring in IT and knowledge management sectors [15]. This rapid adoption places new emphasis on AI governance, knowledge management, and scalable enterprise automation architectures capable of integrating GenAI technologies into operational processes, as unmanaged scaling often leads to architectural fragmentation and increased technical debt. The friction between scalable automation and operational integrity becomes a critical bottleneck when processes rely on highly specialized knowledge.

This challenge is particularly evident when dealing with complex regulatory environments; recent research suggests that pattern-based parsing remains essential for constructing reliable knowledge graphs from unstructured legal texts, such as traffic or industry regulations [21]. Within enterprise information systems, these developments are closely related to the evolution of **Business Process Management** (BPM). Traditional BPM systems are hindered by rigidity, as they are primarily designed for predefined and standardized flows; consequently, they are often less convenient for knowledge-intensive decision-making tasks [13]. Such rigid models frequently induce an **Expert Frustration Gap**, where deterministic workflows fail to capture the

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collaborative and evolving nature of **Knowledge-Intensive Processes (**KiP), thereby hindering optimal expert performance [3, 13].

From a management perspective, this rigidity represents a significant loss in organizational productivity and agility. These limitations become particularly critical in **KiP**, where execution relies on expert intuition, contextual variables, and evolving data structures [3, 8, 13]. Unlike standardized processes which follow a linear, deterministic logic (e.g., *if A then B*), KiP are defined by their non-repeatability, high dependence on unstructured data, and goal-driven nature. A primary obstacle in KiP automation is the prevalence of unstructured enterprise workflows that require high-integrity information extraction [19, 23]. Addressing this requires multi-stage pipelines that integrate advanced text recognition with LLM-based reasoning to provide decision support in professional environments [18]. Consequently, the success of such digital transformations depends on the synergy between robust knowledge management, AI governance, and flexible automation architectures [8]. To reconcile these requirements, recent research proposes **Agentic BPM:** Agentic BPM is a paradigm where autonomous AI agents act as primary participants in process reasoning and execution, leveraging the Sense-Think-Act lifecycle to address the non-deterministic nature of KiP [7, 22, 26]. Unlike traditional BPM, which relies on predefined, deterministic workflows, Agentic BPM enables adaptive, context aware automation through reasoning and tool-use.

Such architectures transcend standardized scripts by enabling autonomous reasoning, promising enhanced agility in KiP. However, selecting appropriate automation architecture remains a critical design decision. Current design faces a **paradigm tension**: **Low-Code/No-Code** (LCNC) platforms offer rapid development but often lack the integration flexibility of custom Python-based pipelines [1]. Furthermore, LCNC-driven democratization introduces risks regarding **Shadow AI** and auditability, complicating the governance of autonomous agents [1, 2].

Despite these strategic trade-offs, no study systematically benchmarks these architectures under governance constraints in KiP environments. [7, 9]. Without systematic evidence regarding performance, maintainability, and governance [13], organizational leaders lack a validated framework to ensure both operational efficiency and regulatory compliance [18]. Consequently, this research investigates how these architectural choices influence the implementation of AI-driven automation. By examining the interplay between GenAI, LCNC orchestration, and Python pipelines, this study proposes a preliminary scalable and trustworthy model.

2 State of the Art

2.1 Agentic BPM Foundations

Recent BPM research focuses on the convergence of **GenAI** and traditional automation, birthing the **Agentic BPM** paradigm. This approach extends classical infrastructures with adaptive reasoning via the Sense-Think-Act lifecycle, allowing agents to perceive context and dynamically execute actions [7, 22]. Practical implementations demonstrate that **large language models** (LLMs) effectively handle task-specific requirements, such as summarization and segmentation, when supported by adequate contextual frameworks [18].

However, realizing business value is moderated by organizational maturity. Zebec and Štemberger [26] identify five progressive levels of AI capability, emphasizing that higher maturity requires a transition from Agents for **BPM** (task support) to BPM for Agents (coordination of autonomous systems) [22]. Identifying these stages is critical in KiP, which necessitates specialized metrics to track maturity and performance effectively [24].

2.2 Reliability and Integrity Challenges in GenAI Modeling

Despite the potential for autonomy, **GenAI-driven** modeling faces significant reliability hurdles. Empirical evaluations using the 3C framework (Clarity, Correctness, Completeness) reveal that while AI-generated models appear intuitive, they frequently suffer from structural rule violations and inconsistent logic [6]. Specifically, LLMs are prone to "hallucinating" invalid relationships when generating structured formats like XML, necessitating robust validation frameworks to ensure transparency [6, 12]. From a management perspective, the non-deterministic nature of GenAI introduces risks to process integrity, often creating a 'black-box effect' where autonomous decisions lack human oversight. This is particularly critical as underlying GenAI models often suffer from unintended semantic and sentiment biases during information processing [10], which can compromise the integrity of governance frameworks [7, 22]. To mitigate these gaps, research advocates Meta-Framing, a governance technique defining the maximal permissive boundaries within which an agent operates [7].

2.3 Architectural Paradigms: LCNC vs. Pro-Code Governance

Supporting AI-driven enterprise automation requires robust infrastructure to handle unstructured data. Recent studies highlight the efficacy of hybrid architectures that combine Optical Character Recognition (OCR) with LLMs to optimize the trade-off between accuracy and inference latency [19, 23]. Organizations are increasingly adopting LCNC platforms to democratize automation and support agile development [2, 9]. However, a significant paradigm tension exists regarding long-term maintainability. Abahussain and Al-Ammary [1] note that while LCNC accelerates initial deployment, it can "backfire" as systems grow in complexity, leading to high hidden costs, vendor lock-in, and the accumulation of Security Debt. Furthermore, in high-volume industrial tasks, LCNC pipelines often exhibit brittleness compared to custom Python stacks. For "copy-heavy" tasks like identity extraction, LCNC systems often waste computational budget by decoding tokens one-by-one, whereas custom **Python/OCR architectures** can process the same data in constant time with higher reliability [23]. When applied to complex KiP scenarios, the "black-box" nature of LCNC orchestration layers can further complicate system debugging, auditability, and the enforcement of legal and ethical guardrails [1, 22].

3 Research Methodology

3.1 Approach

This study follows a **design-oriented research approach**, positioning the article as the initial phase of a broader PhD research project aimed at developing and evaluating a scalable and governance-compliant framework for GenAI-driven automation in KiP.

The research is grounded in the **Design Science Research (DSR)** paradigm, which focuses on the creation and evaluation of innovative artifacts to solve complex organizational problems [11, 16]. In contrast to purely explanatory research, DSR emphasizes artifact construction, iterative refinement, and practical relevance, making it particularly suitable for addressing the socio-technical challenges of AI-driven enterprise automation. Following the six-step DSRM process [16], Problem Identification is addressed in Chapter 1, while Solution Objectives are defined via the five-pillar framework (Section 4.1). The Design and Development of the GenAI and database artifacts are detailed in Sections 4.2 and 4.3, with the initial Demonstration of the architecture's utility provided in Chapter 5. Finally, the Evaluation and Communication phases, involving full-scale technical benchmarking and governance validation, are established as the trajectory for future research within the broader PhD project. Within this context, the present article represents a design-oriented foundation study, rather than a fully completed evaluation cycle. Its primary objective is to develop a conceptual framework for structuring GenAI-driven KiP automation, define a corresponding experimental design, and provide initial empirical grounding. Accordingly, the study follows a sequential mixed-methods approach [5], where qualitative exploration precedes artifact design, and later phases (beyond this paper) will include **quantitative validation and benchmarking**.

3.2 Methods for Empirical Results

A central methodological contribution of this study is the generation of first empirical results from Phase 1 **(RQ1),** focusing on identifying challenges in automating **Software licenses** which is a **Knowledge-Intensive Process** involving unstructured data and compliance complexity (see Section 5). **Twelve semi-structured** interviews were conducted with high-level experts (Heads of Business Intelligence, General Managers, License Managers) from logistics, automotive, and financial sectors, with **58% having 20+ years** of experience in IT infrastructure and compliance. This high degree of professional expertise ensures the reliability of the thematic findings and the derived waste premium estimates. These results are derived from a qualitative multi-method design, ensuring both theoretical grounding and empirical validity. A **Systematic**

Literature Review (SLR) is conducted to establish a rigorous and auditable foundation on KiP characteristics, data complexity, and automation limitations, following established procedures for evidence-based synthesis [14]. This is complemented by online surveys, which capture broader practitioner perspectives and enable the identification of recurring patterns across heterogeneous process environments [5]. To deepen the analysis, semi-structured interviews with domain experts are used to investigate process variability, unstructured workflows, and governance constraints, which are central challenges in KiP. This method is particularly suitable for capturing context-dependent and tacit knowledge [5].

The data collected is analyzed using **Thematic Analysis** [4], enabling systematic coding and the identification of key bottlenecks such as structural fragmentation, operational burden, and automation constraints, as reported in Section 5. The combination of methods ensures triangulation and robustness. In line with Design Science Research [11, 16], these findings serve as empirical input for artifact design, defining meta requirements for the conceptual framework, and guiding the subsequent research design.

4 Design Science Research and Conceptual Framework

4.1 Establishing Research Questions and Formulating Solution Objectives

Based on the identified research gap, this study investigates how different automation architectures influence the implementation of GenAI-driven enterprise automation in KiP. This chapter presents the conceptual framework (five-pillar model) : Domain, Input, Storage, Execution, and Control (see Figure 1) developed via Design Science Research

Pillar 1: Domain – Knowledge-Intensive Processes

RQ1- What challenges arise when automating KiP such as Software License Management that involve unstructured industrial data and complex compliance rules? RG1- To identify key bottlenecks related to data complexity, process variability, and limitations in autonomous decision-making within KiP environments.

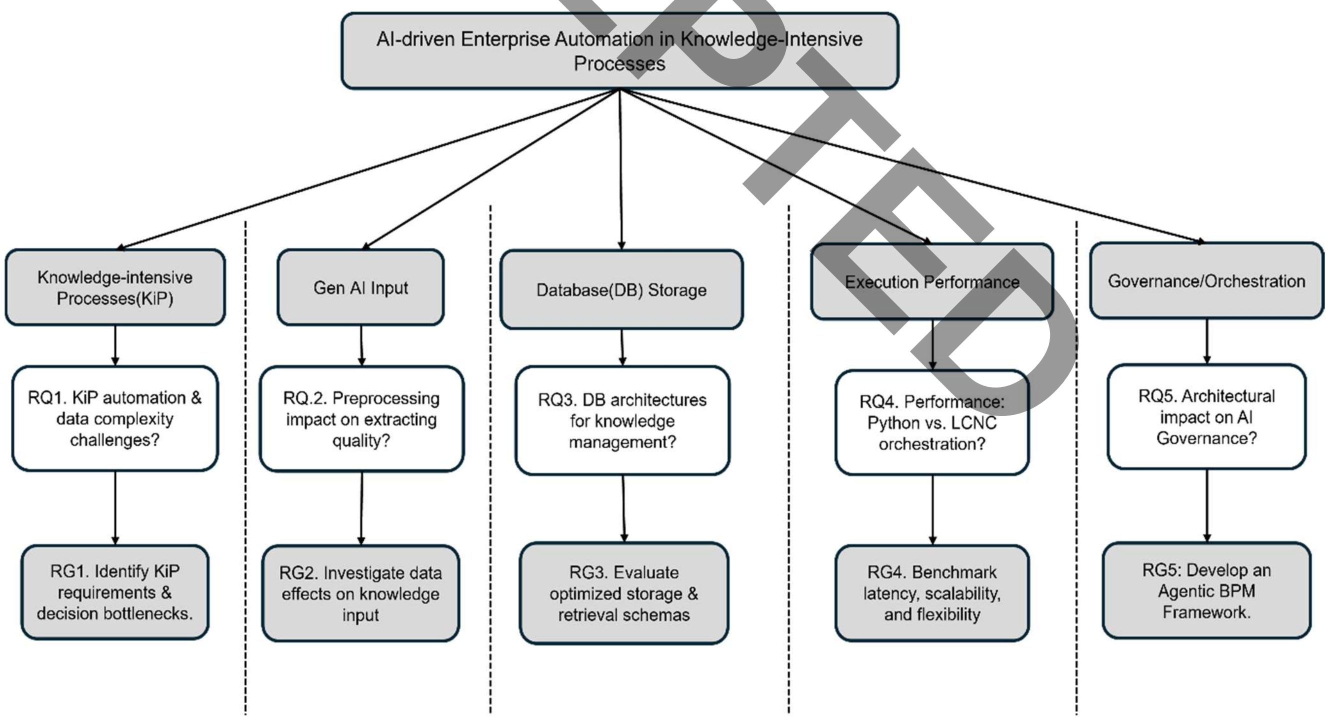

Figure 1-Research areas, questions, and goals

Pillar 2: Input – GenAI-Based Information Extraction

RQ2- How do preprocessing strategies and LLM configurations affect the accuracy and reliability of GenAI-based information extraction? **RG2-** To analyze the impact of data preparation pipelines on the quality and consistency of structured outputs generated from unstructured industrial data.

Pillar 3: Storage – Knowledge Management Architectures

RQ3- Which database architecture is most suitable for managing structured knowledge generated through GenAI extraction? **RG3-** To evaluate and design data storage solutions (e.g. relational vs. vector-based) that support efficient retrieval, scalability, and long-term knowledge management.

Pillar 4: Execution – Automation Architecture Performance

RQ4- How do Python-based automation pipelines compare to Low-Code/No-Code (LCNC) platforms in terms of performance, scalability, and flexibility? **RG4-** To benchmark both approaches using-controlled experiments, focusing on latency, throughput, and system adaptability in KiP scenarios.

Pillar 5: Control – Governance and Decision Framework

RQ5- How do automation architectures influence AI governance, auditability, and compliance in enterprise environments? **RG5-** To develop a decision framework that balances operational efficiency with governance requirements for Agentic BPM systems.

4.2 Design of Conceptual Framework for GenAI-driven KiP Automation

This study results in a structured conceptual framework (see Figure 1) that organizes GenAI-driven enterprise automation into five interrelated pillars: Domain, Input, Storage, Execution, and Control. These pillars provide the architectural requirements necessary to address the technical and governance gaps identified in Section 1 and Section 2.

Based on the defined research questions and objectives, the study develops a multi-phase research design aligned with the Design Science Research Methodology (DSRM) (see Figure 2). The research process begins with a KiP domain analysis, combining a Systematic Literature Review (SLR), surveys, and semi-structured interviews to identify meta-requirements, the results are detailed in section 5. These insights inform the design and development of GenAI extraction pipelines and database architectures, following an iterative generate/test cycle. Subsequently, a controlled experimental setup is established to benchmark Python-based automation pipelines against LCNC orchestration platforms. The evaluation follows the Goal-Question-Metric (GQM) framework, enabling the collection of objective and quantifiable performance data, including latency and throughput. Finally, the results are integrated into a governance and decision framework, developed using the Analytic Hierarchy Process (AHP), which supports the evaluation of trade-offs between operational efficiency and compliance requirements. This structured research design ensures a systematic transition from qualitative insights to quantitative evaluation and decision support.

4.3 Development of Research Roadmap

Following the methodology established in Section 3.1, this study applies the six-step nominal process [16] to move from problem identification to the communication of a validated decision framework for Agentic BPM. The literature review serves as the theoretical foundation and runs parallel to all phases to ensure the research remains state-of-the-art.

Phase 1: KiP Domain Analysis (RQ1)- To identify the requirements for Agentic BPM in KiP settings, this study utilizes a Systematic Literature Review (SLR) to provide a trustworthy, rigorous, and auditable foundation [14]. This is complemented by online surveys and semi-structured qualitative interviews to capture the multiple realities of process participants [4, 5]. The collected data is synthesized using Thematic Analysis [4] to establish the meta-requirements for the subsequent design phase.

Phase 2 and 3: GenAI and Database Artifact Design (RQ2 and RQ3)- The development of the GenAI extraction engine and database architecture follows the Generate/Test Cycle of DSRM [11]. These represent purposeful IT artifacts designed to address the problem of unstructured data integrity in KiP [16]. Prototyping is used as the primary instantiation method, allowing for iterative refinement of preprocessing pipelines, LLM configurations, and database schemas based on technical feedback.

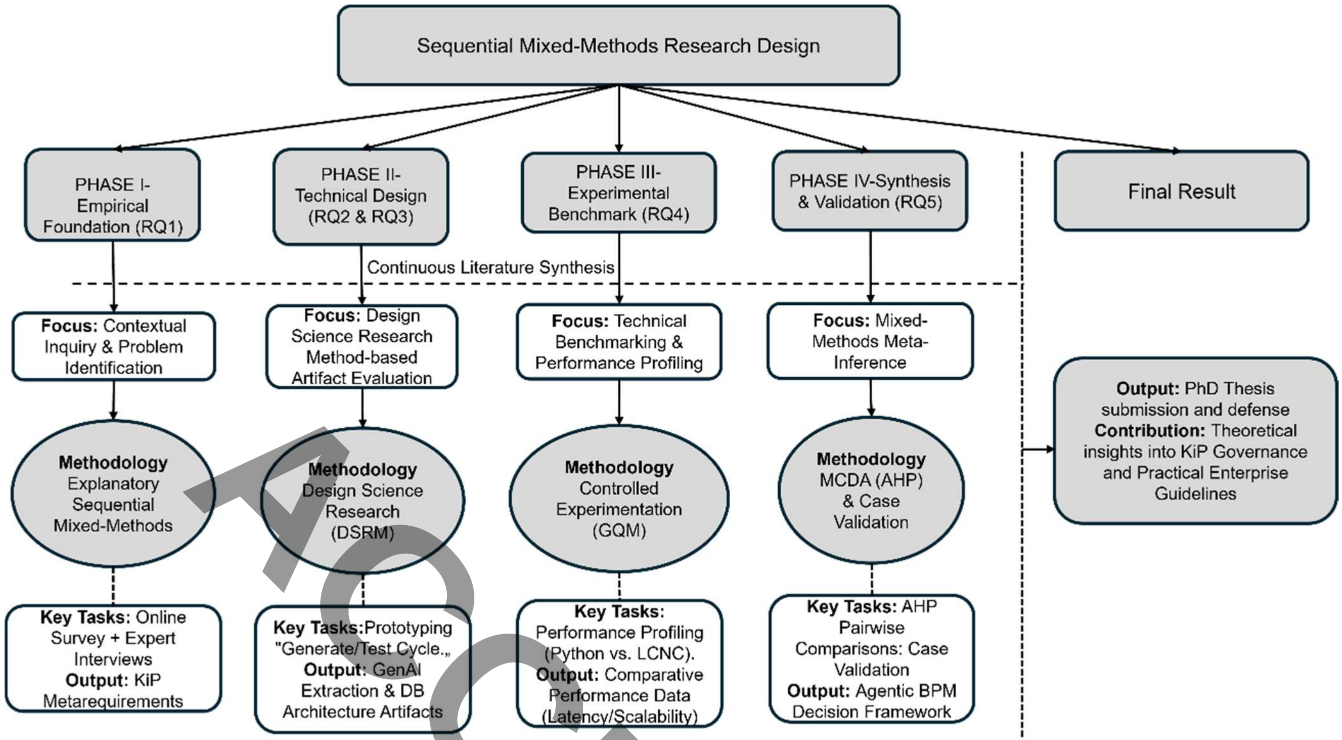

Figure 2-Research Roadmap

Phase 4: Technical Performance Benchmarking (RQ4)- To compare Python-based automation pipelines and LCNC implementations, this study employs a Controlled Experiment to establish cause-and-effect relationships [24]. Following the GQM (Goal-Question-Metric) framework, objective and quantifiable information regarding latency and throughput is collected under formally defined hypotheses [11, 24].

Phase 5: Governance and Decision Framework (RQ5)- The final governance framework is developed using a Multi-Criteria Decision Analysis (MCDA) approach. Specifically, the Analytic Hierarchy Process (AHP) is employed to derive relative ratio scales from expert judgment regarding conflicting criteria such as operational efficiency versus compliance [20]. The framework is then validated through a case study approach to investigate its applicability in a real-life enterprise context [24, 25], ensuring the practical utility of the final decision support artifact.

5 Preliminary Results: Qualitative Domain Analysis

The qualitative phase provides empirical grounding for the Expert Frustration Gap identified in the domain pillar.

As illustrated in Figure 3, thematic analysis of 208 coded segments from twelve semi-structured interviews reveals that organizational friction is most concentrated in Structural Fragmentation (24%, n=50) and Operational Burden (22.1%, n=46). Experts categorized the urgency of governance as "Highest Priority" (Rank 5), citing non-negotiable drivers such as audit-related financial risk and tax compliance. These bottlenecks - specifically Automation Constraints (21.6%) and Usage Transparency (9.1%), provide evidence for the need for Agentic BPM. Participants characterized current workflows as reactive firefighting cycles, where manual data entry and fragmented reporting consume significant resources. Notably, experts with 20+ years of experience estimated waste premium ranging between approximately 20% and 40% of total software expenditures.

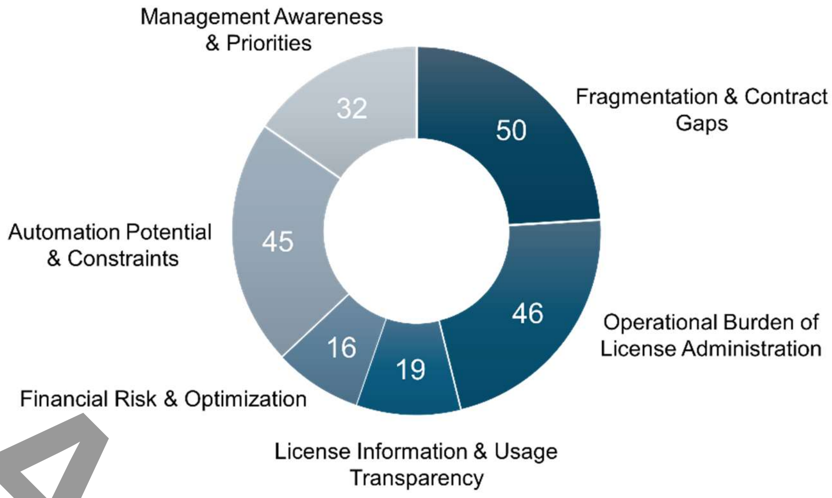

Figure 3-Distribution of Thematic Codes and Narrative Prominence

This comprises specialized labor loss from manual reconciliation and defensive over-licensing, intentional asset buffers maintained to mitigate financial and legal audit risks.These findings indicate that the 'Expert Frustration Gap' is not merely a matter of convenience but a structural deficiency in current deterministic automation. The high concentration of Structural Fragmentation and the resulting waste premium demonstrate that without the reasoning capabilities of GenAI, organizations remain trapped in high-risk, manual 'firefighting' cycles. Consequently, the transition to Agentic BPM is an economic and regulatory necessity to bridge the gap between rigid automation and KiP.

6 Discussion

6.1 Architectural Trade-offs in GenAI-driven Automation

The research reveals a trade-off between operational agility and regulatory control: Python-based pipelines offer fine-grained control for compliance, while LCNC platforms prioritize deployment velocity. However, LCNC's Accessibility Trap, rapid democratization creating governance gaps due to opaque orchestration, introduces Security Debt [1], as evidenced by Structural Fragmentation (24%) (see Section 5). Thus, Python's granular control is strategically critical for auditability in high-stakes Agentic BPM.

6.2 Reconciling KiP Complexity with GenAI

The thematic prominence of Structural Fragmentation (24%) confirms that KiP are inherently resistant to rigid standardization. The integration of GenAI offers a path to managing unstructured data yet amplifies challenges regarding reliability and explainability. The findings suggest that successful Agentic BPM implementation in KiP environments is not merely a technical challenge but a requirement for Meta-Framing [7], ensuring AI agents operate within defined regulatory and expert-led guardrails.

6.3 Theoretical and Managerial Contributions

This study advances the Agentic BPM paradigm by bridging architectural design and AI governance, though empirical validation via benchmarking remains future work. The five-pillar model provides a systematic diagnostic tool for enterprise architects. For management, the identification of a 20% to 40% waste premium due to defensive over-licensing provides a financial imperative for transitioning toward intelligent, autonomous monitoring. By aligning technical performance with compliance requirements, the framework supports a transition from isolated AI pilots to scalable, audit-ready enterprise automation.

7 Conclusion

This research has evaluated the structural and architectural requirements for integrating GenAI into KiPs. By applying **Design Science Research Methodology**, this study successfully synthesized qualitative domain insights with a multi-layered technical evaluation to address the inherent tensions between rapid automation and enterprise governance. The findings underscore that while **Agentic BPM** offers a viable path for managing unstructured industrial data, the selection of an underlying orchestration environment is a critical determinant of long-term process integrity.

The resulting **five-pillar framework** serves as a strategic roadmap for navigating the transition from static workflows to autonomous, agent-led execution. By highlighting the hidden risks of opaque low-code systems and the financial repercussions of manual coordination "firefighting," this work provides both a theoretical and a practical foundation for more resilient AI infrastructures. It suggests that moving beyond isolated AI prototypes requires a holistic focus on the **Control** and **Execution** pillars to ensure that autonomy does not come at the cost of auditability. Ultimately, this research demonstrates that bridging the "Expert Frustration Gap" requires moving beyond rigid scripts toward GenAI-driven frameworks that can transform high-cost manual work into scalable, governance-compliant enterprise assets.

While this study establishes a robust architectural baseline, it also identifies a clear trajectory for **ongoing empirical research**. Future efforts will prioritize the high-volume benchmarking of these heterogeneous pipelines to generate quantifiable performance metrics across varied industrial use cases. Ultimately, the objective remains the refinement of a validated decision-support system that empowers organizations to deploy scalable, compliant, and expert-aligned AI agents within the evolving landscape of digital enterprise transformation.

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