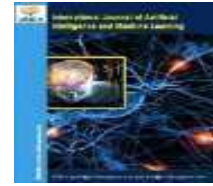




International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Human-AI Assisted Regulatory Documentation Automation in Health Insurance: A Design Science Reference Framework

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Abstract

Administrative complexity is a major contributor to healthcare spending in the United States, particularly within health insurance systems that rely on regulatory documentation, benefit configuration, and multi-step compliance workflows. This study proposes the Human-AI Collaborative Regulatory Transformation Framework (HCRTF) for converting unstructured regulatory documentation, redline files, and benefit tables into structured requirement templates in health insurance workflows. HCRTF combines AI-assisted parsing, requirement mapping, traceability, human validation, and feedback loops into one regulated workflow model. Using a design science research approach, the framework is evaluated through workflow decomposition, requirements-to-framework mapping, alternative workflow comparison, synthetic redline-to-requirement demonstration, and risk-control analysis. The study does not claim production deployment, measured time savings, extraction accuracy, or organizational adoption. Instead, it presents a design-stage reference framework for regulated healthcare administrative environments and defines the validation path needed for future empirical testing using real or de-identified regulatory documentation.

Keywords: Artificial Intelligence; Administrative Automation; Health Insurance Systems; Regulatory Documentation; Human-AI Collaboration; Enterprise AI Adoption

1. Introduction

The healthcare system in the United States is not affordable when compared to other countries (Himmelstein et al., 2020; Sahni et al., 2023). A substantial portion of healthcare spending in the United States is associated with administrative processes rather than direct patient care (Himmelstein et al., 2020). These inefficiencies may add friction to insurance operations and affect the overall experience of patients and members (Sahni et al., 2023). The U.S. healthcare system is technologically advanced, but it continues to face administrative complexity, operational stress, and cost inefficiency (Angus et al., 2025). But there is little attention to administrative workflows, which primarily support the insurance systems and the regulatory implementation (Cho & Miller, 2024; Lavoie-Gagne et al., 2025; Wong et al., 2026).

Despite increasing attention in artificial intelligence, majority of the research is mainly focused on clinical operations, which includes diagnostics, predictive analytics, and medical imaging (Angus et al., 2025; Bajwa et al., 2021). To address this challenge, this study proposes Human-AI Collaborative Regulatory Transformation Framework (HCRTF) that directly integrates the enterprise AI productivity tools with the analyst's driven regulatory interpretation, which will in turn support the systematic structuring of healthcare filing documents into implementation-ready requirement templates (Bhuyan et al., 2025; Wong et al., 2026). Benefit and claims workflows often pass through multiple checkpoints without automation, delaying both care and reimbursement (Pingili, 2025). This involves large volumes of redline documents containing policy updates, cost sharing tables, and regulatory language revisions that must be carefully analyzed and should be properly maintained into a structured format before something is implemented and proceeded further (Pingili, 2025). At a broader level, these workflow inefficiencies may contribute to the administrative factors associated with healthcare cost growth (Kakatum Rao et al., 2025).

In large health insurance environments, transforming regulatory documentation into structured operational requirements is a critical step for accurate benefit configuration, compliance validation, and timely publication of plan documentation (Nasser, 2025). However, limited mechanisms exist for converting unstructured regulatory content into structured requirement formats, creating workflow bottlenecks that may increase administrative workload and delay downstream implementation (Khayatbashi et al., 2025). This elaborates a human-centered approach in which the AI functions as a productivity tool while the domain experts retain their acumen of regulatory interpretation and compliance validation (Upadhyay, 2025). This approach examines how

practical AI adoption within healthcare administrative environments can support mechanical document-processing tasks, improve structure in requirement preparation, and provide a more organized pathway for implementing regulatory changes across health insurance systems (Khanna et al., 2022; Wong et al., 2026). This study adopts a structured, framework-based approach to systematically analyze and optimize administrative workflows using human-AI collaboration within enterprise healthcare environments. The traditional workflow described above is illustrated in Figure 1.

While existing research shows the value of AI in administrative automation, there are few studies that examine the actual process of changing the regulatory filing documents into structured implementation requirements. Analysts must review redline documents, identify changes across benefit structures, extract relevant tables, and organize the information into structured requirement templates for analysis and implementation. Although parts of this workflow resemble document processing or business automation, the process is distinct because it requires regulatory understanding, business analysis, and compliance oversight.

This work is positioned within the broader discussion of healthcare system improvement through administrative innovation and workflow optimization. Prior work has examined healthcare affordability through primary care redesign (Rayabarapu, 2026) and technology-driven infrastructure modernization (Nayeem & Rayabarapu, 2026), providing related context for the present study's focus on administrative innovation and workflow optimization. Together, these contributions highlight a consistent theme: improving healthcare efficiency requires not only clinical innovation but also administrative transformation. By focusing on regulatory documentation workflows, this research contributes to a more specific understanding of how human-AI collaboration can support structured, traceable, and scalable administrative processes in healthcare systems.

Unlike existing studies that focus primarily on clinical AI applications or generic process automation, this research specifically addresses the transformation of regulatory documentation workflows within health insurance systems. The proposed framework differentiates itself by integrating domain-driven human expertise with AI-assisted document structuring under real-world enterprise constraints, thereby offering a practical and implementation-oriented approach rather than a purely theoretical or fully automated model.



Figure 1. Traditional Healthcare Regulatory Documentation Workflow

This figure illustrates the conventional end-to-end workflow for processing healthcare regulatory filings, beginning with redline document review and progressing through change identification, content extraction, requirement structuring, validation, system configuration, and final publication. The process is predominantly manual, requiring significant analyst effort across multiple stages, which contributes to increased turnaround time and variability in outcomes.

2. Related Work and Design Science Foundation

2.1 Healthcare Administrative AI and Workflow Automation

Existing research shows growing interest in the use of artificial intelligence to support healthcare administration, including billing, insurance-related workflows, documentation support, and operational process improvement (Cho & Miller, 2024; Lavoie-Gagne et al., 2025; Pingili, 2025). These studies establish that

AI can support administrative efficiency, but much of the literature remains focused on broad administrative automation rather than the specific transformation of regulatory documentation into structured implementation requirements. This creates a gap for health insurance workflows that depend on redline review, benefit-table extraction, structured requirement preparation, validation, and downstream configuration.

2.2 Document Processing and Insurance Workflow Transformation

AI-assisted document processing has practical relevance for healthcare and insurance workflows because these environments rely heavily on unstructured documents, tables, policy language, and recurring documentation updates (Khayatbashi et al., 2025; Pingili, 2025). Prior work in insurance automation and intelligent document processing supports the value of extracting and structuring information from complex documents. However, general document automation does not fully address regulated health insurance workflows where source traceability, analyst validation, compliance interpretation, and exception handling are required.

2.3 Human-in-the-Loop AI in Regulated Administrative Environments

Human-in-the-loop design is especially important in healthcare administrative settings because AI-generated outputs may be incomplete, inconsistent, or contextually inaccurate without expert review. In regulated workflows, AI should assist with parsing, extraction, comparison, and structuring, while human analysts retain responsibility for interpretation, validation, compliance review, and final approval. This supports the central design principle of the proposed HCRTF: AI accelerates document handling, but human experts control the regulatory and business interpretation.

2.4 Design Science Research Foundation

This study follows Design Science Research because the primary contribution is a designed artifact: the Human-AI Collaborative Regulatory Transformation Framework. Design Science Research is appropriate when a study develops and evaluates an artifact, method, model, or framework to address an identified organizational problem. The design science literature emphasizes problem identification, artifact construction, design evaluation, and communication of design knowledge as core elements of this research approach (Hevner et al., 2004; Peffers et al., 2007). Because the present study evaluates the framework before production implementation, the evaluation follows an ex ante design evaluation logic, where the artifact is assessed through design requirements, comparison, synthetic demonstration, and risk-control analysis (Venable et al., 2016).

3. Methodology

3.1 Design Science Research Approach

This study adopts a Design Science Research approach to develop and evaluate the Human-AI Collaborative Regulatory Transformation Framework (HCRTF) for healthcare administrative documentation workflows. The design problem addressed in this study is the lack of a structured and traceable method for converting regulatory filing documents, redlines, benefit tables, and unstructured policy language into implementation-ready requirement templates in health insurance workflows. The HCRTF is the artifact developed in this study, and it defines how AI-assisted document parsing, structured requirement mapping, source traceability, analyst validation, exception handling, and feedback-driven refinement can be integrated into regulatory documentation workflows. The design objective is not to prove operational performance, but to construct a structured framework that addresses an identified workflow problem in health insurance administration. This study does not include controlled experimental data or quantitative modeling and is therefore positioned as a framework-based design study rather than an empirical performance evaluation or quantitative implementation study. The artifact construction process followed workflow decomposition, identification of repetitive documentation tasks, separation of AI-supported and analyst-controlled activities, and development of framework layers, validation checkpoints, and feedback loops. The evidence source for the design was process observation and task-level analysis of health insurance regulatory documentation workflows. The evaluation criteria include completeness, source traceability, requirement accuracy, table extraction support, analyst correction need, and risk-control coverage. The refinement process was based on prompt comparison, output review, human validation, and adjustment of control points during design-stage evaluation.

3.2 Problem Context and Workflow Decomposition

This methodology follows a case-informed workflow decomposition approach. It has all the existing administrative processes, which are being analyzed and it identifies the inefficiencies and all the repetitive tasks and how AI-assisted augmentation can be used as an opportunity. This study deals with life cycle of the redline documents (policy updates, benefit tables, regulatory language modifications). These documents act as input for the requirement preparation, configuration, validation, and publication workflows.

This study has data that is directly taken from the process observation and the task level analysis. The iterative workflow evaluation is performed across different stages of administrative operations. Some of them include

document review, identification of modified sections, and extraction of structured and unstructured content, transformation into requirement templates, and preparation for downstream implementation. The workflow observation was conducted from the perspective of healthcare business analysis practice, with attention to how regulatory documentation moves from source review to structured requirement preparation and downstream implementation. Workflow observations were organized around five problem categories: unstructured source documentation, repeated manual review, table and language extraction, requirement-template preparation, and validation handoffs. These categories were used to derive the framework requirements shown in the requirements-to-framework mapping table.

3.3 Framework Design Process

A different aspect of this methodology is the main use of human-AI collaborative operating model, where both the experienced experts and the technical capability members together contribute to the transformation in this workflow. The senior professionals are always there with all the acumen that they have, along with regulatory expertise. While the junior and the technically skilled people can contribute to AI tool utilization, prompt engineering, and development of automations. This way of collaboration ensures that AI adoption is grounded in domain knowledge while still leveraging the technical capabilities within the team.

As illustrated in Figure 2, the framework emphasizes the central role of human experts in interpretation, validation, and decision-making, which were supported by AI-driven document parsing, extraction, and structuring. The inclusion of continuous feedback loops provides the necessary requirement on the feedback and prompt evaluation mechanisms understand the feedback, which further enables the refinement and controlled adoption within the enterprise environment. This validation-driven approach is particularly important in enterprise environments, as AI-assisted systems may be susceptible to inconsistencies or data integrity risks, reinforcing the need for human oversight and controlled evaluation mechanisms (Nayem, 2025).

The entire approach of the study is always aligned towards useful AI adoption in regulated environments. Standards that have to be maintained here are accuracy, traceability, and human accountability which are necessary for healthcare administration systems, which makes totally automated or experimental methods less practical. This approach is particularly suitable for enterprise healthcare environments where controlled experimentation is limited due to compliance, data privacy, and operational constraints. The design cycle followed four stages: problem identification, framework construction, design-stage evaluation, and refinement of control points. The framework was refined to separate AI-supported tasks from analyst-controlled tasks, ensuring that automation supports document handling while human experts retain responsibility for interpretation and approval.

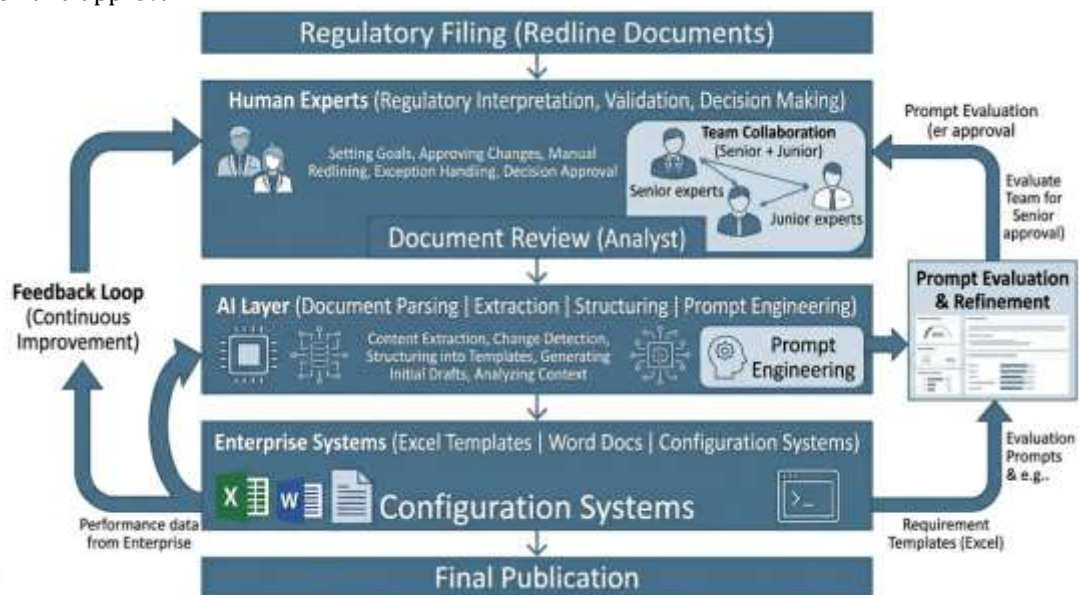


Figure 2. Human-AI Collaborative Automation Framework for Regulatory Transformation

This figure presents a layered framework highlighting the integration of human expertise and AI-assisted capabilities within healthcare regulatory workflows. Human experts lead interpretation, validation, and decision-making processes, while AI supports document parsing, extraction, and structuring through prompt-driven interactions. The framework emphasizes continuous feedback loops, prompt evaluation, and

collaboration between senior and junior team members to ensure controlled, incremental adoption and consistent output quality.

3.4 Ex Ante Evaluation Strategy

Because this study does not include production deployment, statistical testing, or measured implementation outcomes, the framework is evaluated through an ex ante design evaluation approach. This study is positioned as a qualitative, practice-oriented research investigation supported by workflow observation and task-level analysis within enterprise healthcare environments. Data sources include real-world administrative processes, document handling workflows, and iterative evaluation of AI-assisted outputs across multiple scenarios. The validation approach is based on comparative output analysis, where AI-generated results are systematically compared across varying prompts, formats, and use cases to assess consistency, reliability, and practical applicability. Figure 3 illustrates the iterative validation and adoption model used to support design-stage evaluation, including prompt testing, human validation, output comparison, feedback review, and controlled refinement of AI-assisted workflow outputs.

The evaluation focuses on whether the proposed framework addresses the identified workflow requirements, preserves human validation, supports traceability, and provides a structured pathway for converting regulatory documentation into implementation-ready requirement templates. Since this is a design-stage study, the paper does not report a fixed sample size, document count, participant count, time-saving percentage, or statistical performance score.



Figure 3. Iterative Validation and Adoption Model for AI-Assisted Regulatory Workflows

This figure illustrates the iterative process used to evaluate and refine AI-assisted workflows through prompt testing, human validation, output comparison, and team-based feedback. The model highlights a controlled and incremental approach to AI adoption in regulated environments.

3.5 Study Boundaries and Limitations

Several boundaries should be noted because this study is workflow-based and design-stage in nature. Different enterprises may also have different AI capabilities, security restrictions, access limitations, and tool-performance constraints. The findings are influenced by the specific context of health insurance documentation workflows and should be validated in other organizational environments before broader generalization.

The study does not claim that the proposed framework has been validated through full organizational deployment, controlled comparison, or measured operational improvement. Future research should test the framework using real or de-identified regulatory documents, defined evaluation criteria, analyst feedback, processing-time comparison, output consistency measures, and implementation outcomes.

Limited AI-assisted language refinement was used for minor editorial support during manuscript preparation. No AI tool was used to generate or analyze study data, develop the framework, prepare the figures, or make interpretive decisions. All scientific content, workflow analysis, framework design, and final manuscript decisions were completed by the author.

4. Framework Evaluation and Illustrative Demonstration

4.1. Human-AI Collaborative Regulatory Transformation Framework (HCRTF)

The Human-AI Collaborative Regulatory Transformation Framework (HCRTF) is designed as a hybrid operational model that integrates artificial intelligence into healthcare administrative workflows while maintaining strong human oversight, domain expertise, and organizational alignment. The framework is built on the principle that sustainable AI adoption requires not only technological capability but also structured collaboration, gradual implementation, and continuous evaluation.

As shown in Figure 2, the HCRTF consists of three connected layers: an AI-assisted document processing layer, a domain-expert validation layer, and a feedback-driven refinement layer. The input to the framework includes regulatory filing documents, redline files, benefit tables, and unstructured policy language. The expected output is a structured requirement template that can support downstream configuration, validation, and implementation activities.

The main control point in this framework is human validation. AI supports parsing, extraction, comparison, and structuring, while analysts retain responsibility for regulatory interpretation, requirement accuracy, compliance review, and final approval. The proposed HCRTF is technology-agnostic but assumes a hybrid AI workflow that may include enterprise AI assistants, prompt-based extraction, document intelligence tools, rule-based mapping, and human review checkpoints. The AI component is expected to support parsing, section identification, table extraction, semantic comparison, and first-pass structuring. The rule-based component supports template alignment, source tagging, and routing of extracted content. The human-validation component confirms regulatory meaning, resolves ambiguous changes, reviews low-confidence outputs, and approves the final requirement template. Table 1 presents the requirements-to-framework mapping used to evaluate whether the proposed HCRTF addresses the main workflow requirements identified in health insurance regulatory documentation processes.

Table 1. Requirements-to-Framework Mapping

Workflow requirement	Framework component	AI role	Human validation role
Extract changed benefit language	Document parsing layer	Identifies changed text and relevant sections	Analyst confirms regulatory meaning
Structure redline content into requirements	Requirement structuring layer	Organizes extracted content into template format	Analyst verifies completeness and intent
Handle benefit tables and policy language	Content extraction layer	Extracts tables, sections, and language blocks	Analyst checks accuracy against source documents
Maintain traceability	Audit and source-reference layer	Links extracted output to source content	Analyst confirms source alignment
Support compliance-sensitive review	Validation checkpoint layer	Flags uncertain or incomplete outputs	Analyst approves, rejects, or revises the output

The framework evaluation uses five design-stage criteria: completeness, source traceability, requirement accuracy, table extraction support, and analyst correction need. Completeness refers to whether relevant regulatory content is captured in the structured output. Source traceability refers to whether the output can be linked back to the original regulatory document, redline section, or benefit table. Requirement accuracy refers to whether the structured output preserves the intended benefit or regulatory meaning. Table extraction support refers to whether tabular benefit content can be carried forward into structured templates. Analyst correction need refers to the extent of human review required before the output can be used for downstream implementation.

4.2 Redline-to-Requirement Transformation Pipeline

The most important part of this entire framework is the dual-layer collaboration model, in which there will be two layers. The first layer consists of different domain experts involved, who have a deep understanding of the

requirements, the benefit structures, and the compliance standards. The second layer consists of contributors who focus on using AI tools, developing different prompt strategies where they can predict what the output will be, and building different workflows. This framework starts with AI-assisted document processing and identifying where AI tools are mostly used to process large documents and identify the relevant sections, and if there are any modifications to be made. The next stage includes mapping the available content into a structured format. We usually call them spreadsheets or ready-to-configure documents. The main reason for following this process is to avoid repetitive formatting and changing the task as per needed while preserving the original content as it was for validation.

This transformation process of changing the documents into structured requirements follows a systematic process that combines AI-assisted processing with mapping techniques. As shown in Figure 4, this pipeline includes document parsing, change detection, content extraction, and template-based structuring, ensuring that all the inputs we ingest into it are converted into consistent outputs that are ready to analyze. Figure 4 represents the redline-to-requirement transformation pipeline. The workflow begins with source document intake, continues through AI-assisted parsing and change identification, and ends with structured requirement preparation for analyst review. The validation checkpoint prevents the AI-generated output from moving forward without human confirmation. Table 2 provides an illustrative synthetic redline-to-requirement demonstration. The examples are fictional and are used only to show how the proposed framework would classify and route changes during design-stage evaluation.

Table 2. Synthetic Redline-to-Requirement Demonstration

Previous language	Revised language	AI classification	Required analyst action
Specialist visits require a \$40 copayment after deductible.	Specialist office visits require a \$50 copayment. The deductible does not apply.	Modified	Confirm cost-sharing change and deductible rule.
No prior-year language is available for virtual urgent care.	Virtual urgent care visits are covered with a \$25 copayment.	Added	Confirm whether the new benefit should be added to the requirement template.
Nutritional counseling is covered when medically necessary.	No matching language appears in the revised document.	Deleted	Confirm whether the benefit was intentionally removed or relocated.
Routine eye exams are covered once every 12 months.	Routine eye exams are covered once every 12 months.	Unchanged	Confirm that no requirement update is needed.
Prior authorization is required for advanced imaging services.	Advanced imaging services require prior authorization under the radiology management section.	Relocated	Confirm that the requirement meaning is unchanged and update the source location.
Rehabilitation therapy may require review based on medical necessity.	Rehabilitation therapy requires review when medical necessity criteria are not clearly documented.	Ambiguous	Escalate to analyst review because the operational meaning may differ.
See benefit table for applicable outpatient surgery cost sharing.	Outpatient surgery cost sharing varies by facility type and network status.	Low-confidence	Review source table manually and confirm worksheet mapping before use.

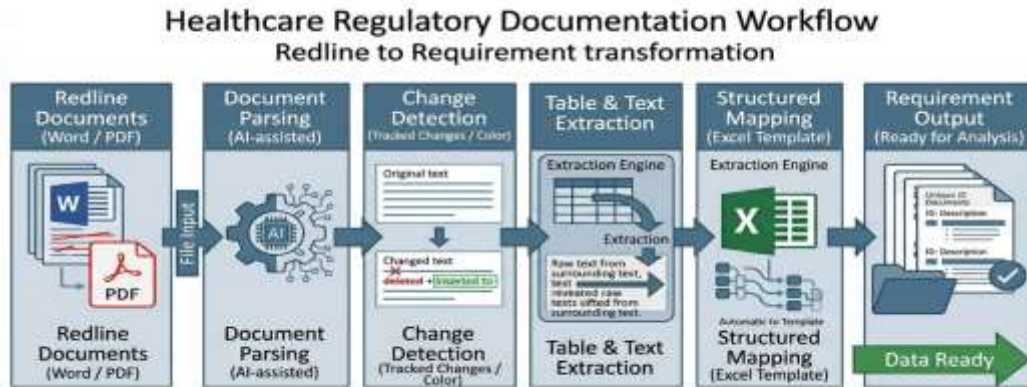


Figure 4. AI-Assisted Redline-to-Requirement Transformation Pipeline

This figure depicts the proposed transformation pipeline for converting unstructured regulatory redline documents into structured requirement outputs. The process includes AI-assisted document parsing, change detection, content extraction, template-based structuring, and analyst validation. The figure should be interpreted as a design-stage workflow model rather than evidence of measured performance improvement.

4.3 Enterprise AI Integration Architecture

One of the most important units in this particular framework is prompt engineering and Evaluation, where different people use different prompts in different situations as input and generate the desired output, which are continuously tested and evaluated. Results are analyzed to identify different approaches, making sure that outputs meet the quality expectations during different use cases. This particular framework also involves an adoption strategy, whereas AI implementation has some constraints, as said before, like limitations and organizational policies. AI usage is expanded by continuously monitoring the outputs and comparing them with the expectations that we initially had. The full layered architecture of AI integration is shown in Figure 5, where its capabilities are embedded with different applications like Word and Excel while working under constraints related to security and data access. This entire architecture exposes the importance of maintaining human intervention to validate the outputs.

Figure 5 connects the proposed framework to the enterprise environment by showing how AI-assisted capabilities can operate within existing document tools, spreadsheet workflows, security restrictions, and human review points. The figure supports the central argument that AI adoption in regulated health insurance workflows should be embedded into controlled enterprise processes rather than treated as a standalone automation tool. Table 3 compares the proposed HCRTF framework with common workflow alternatives. This comparison is used as a design-stage evaluation rather than a measured performance comparison.

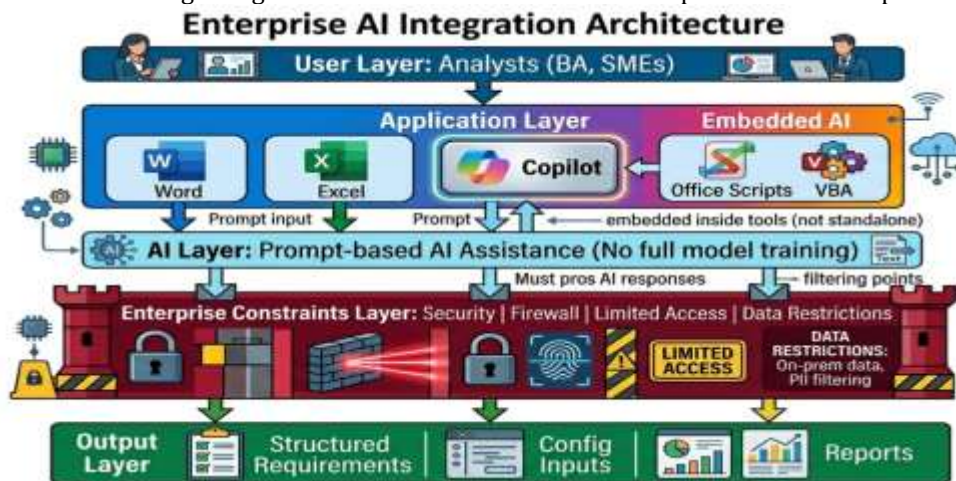


Figure 5. Enterprise AI Integration Architecture under Operational Constraints

This figure illustrates the integration of AI capabilities within enterprise healthcare systems, emphasizing the role of existing tools such as Word, Excel, and embedded AI assistants. The architecture highlights the constraints imposed by enterprise environments, including data security, access limitations, and compliance

requirements. Human validation remains a critical control layer to ensure that AI-generated outputs meet regulatory and organizational standards.

The comparison ratings in Table 3 are based on a design-stage functional-fit rubric. “Yes” indicates that the workflow option directly supports the criterion as part of its expected operating model. “Moderate” indicates that the workflow option may support the criterion with manual setup, prompt refinement, or additional configuration, but not consistently as a built-in control. “Limited” indicates that the workflow option does not reliably support the criterion without substantial manual intervention. “Requires manual review” indicates that human review is possible but is not embedded as a structured validation checkpoint. “Designed for scalability” indicates that the proposed workflow includes repeatable components, source traceability, human validation, and feedback loops intended to support repeated plan-document processing. These ratings are not measured performance scores; they are design-stage judgments based on the workflow requirements identified in this study.

For interpretation, “Yes” represents strong functional fit, “Moderate” represents partial functional fit, and “Limited” represents weak functional fit. The purpose of the table is to compare expected workflow suitability, not to report empirical performance.

Table 3. Alternative Workflow Comparison

Workflow option	Handles redlines	Supports tables	Provides traceability	Supports human validation	Manages risk	Can scale across plan documents
Manual review	Yes	Yes	Limited	Yes	Moderate	Limited
VBA/macros	Limited	Moderate	Limited	Requires manual review	Limited	Limited
Copilot-only workflow	Moderate	Moderate	Limited	Requires manual review	Moderate	Moderate
Power Automate-only workflow	Limited	Moderate	Moderate	Requires manual review	Moderate	Moderate
Proposed HCRTF framework	Yes	Yes	Yes	Yes	Stronger through validation checkpoints	Designed for scalability

4.4 Administrative Effort Redistribution

A comparative assessment between traditional manual workflows and AI-assisted processes reveals a consistent pattern of effort redistribution. Tasks such as document parsing, table extraction, and requirement structuring demonstrate a pathway in reducing manual effort, while analytical and validation tasks gain increased focus. In this study, administrative effort redistribution is treated as an expected design outcome rather than a measured operational result. The framework suggests that AI-assisted parsing, extraction, and structuring may shift analyst effort away from repetitive document-handling tasks and toward interpretation, validation, and compliance review.

Figure 6 illustrates this design-stage redistribution of effort between manual document-processing activities and higher-value analytical activities. This figure should be interpreted as a conceptual workflow comparison, not as evidence of measured time savings. Prior research supports the relevance of AI-assisted administrative automation in healthcare workflows (Cho & Miller, 2024; Lavoie-Gagne et al., 2025). However, the present study does not report measured time savings, error-rate reduction, document-count analysis, or analyst-level performance scores. Table 4 presents the risk-control matrix used to evaluate the framework’s safeguards for regulated healthcare administrative workflows.

Table 4. Risk-Control Matrix

Risk	Example	Severity	Likelihood	Control
AI misses regulatory nuance	Benefit rule interpreted incorrectly	High	Medium	Analyst validation required.

Wrong section mapping	Table linked to wrong requirement	High	Medium	Source traceability and review checkpoint.
Hallucinated content	AI adds unsupported text	High	Medium	Source-only extraction rule and mandatory human approval.
Incomplete extraction	A benefit table row is missed	Medium	Medium	Manual comparison against source document.
Low-confidence output	AI is uncertain whether language is modified or unchanged	Medium	High	Escalation to analyst review.
Workflow overreliance	User accepts AI output without review	High	Medium	Mandatory human approval checkpoint.
Security or access restriction	AI tool cannot process restricted content	High	Medium	Enterprise-approved workflow boundary and manual fallback.
Ambiguous regulatory language	"May require review" is interpreted as a firm requirement	High	Medium	Analyst interpretation and compliance review.
Relocated requirement not detected	Same requirement appears under a different section	Medium	Medium	Semantic comparison plus source-location review.
Table formatting loss	Merged cells or footnotes are not extracted correctly	Medium	High	Manual table validation before downstream use.

5. Discussion and Conclusion

5.1 Principal Findings

The proposed framework suggests a redistribution of analyst effort from repetitive document-handling tasks toward higher-value analytical and validation tasks. This is relevant for document review, extraction, requirement preparation, and decision-making activities, as shown conceptually in Figure 6. In the context of this study, effort redistribution is presented as a proposed design outcome rather than a measured operational result.

The framework suggests that AI-assisted document parsing, extraction, and requirement structuring can support analysts by reducing repetitive document-handling effort and allowing greater focus on regulatory interpretation, validation, and decision-making. The framework was evaluated across multiple workflow scenarios including document parsing, requirement structuring, and validation cycles. These workflow scenarios were used for design-stage evaluation and do not represent a controlled empirical comparison or production deployment.

From a design science perspective, the HCRTF contributes a structured artifact that links a clearly defined organizational problem with a framework-based solution, design requirements, evaluation criteria, and risk-control mechanisms. The contribution is not limited to describing an AI use case; it presents design knowledge about how regulated healthcare documentation workflows can separate AI-supported tasks from human-controlled decisions.

For healthcare workflow automation, the framework contributes a practical model for moving beyond isolated tool use toward a controlled workflow structure. Instead of treating AI as a standalone automation layer, the framework positions AI within document intake, parsing, structuring, source traceability, analyst validation, exception handling, and feedback refinement. This is important because regulatory documentation workflows require both operational efficiency and compliance-sensitive review.

For human-AI collaboration, the framework clarifies the division of responsibility between AI systems and healthcare business analysts. AI is positioned to support repetitive and structure-oriented tasks, while analysts retain responsibility for regulatory interpretation, business-rule judgment, compliance review, and final approval. This role separation helps reduce the risk of overreliance on AI-generated outputs and supports safer adoption in enterprise healthcare environments.

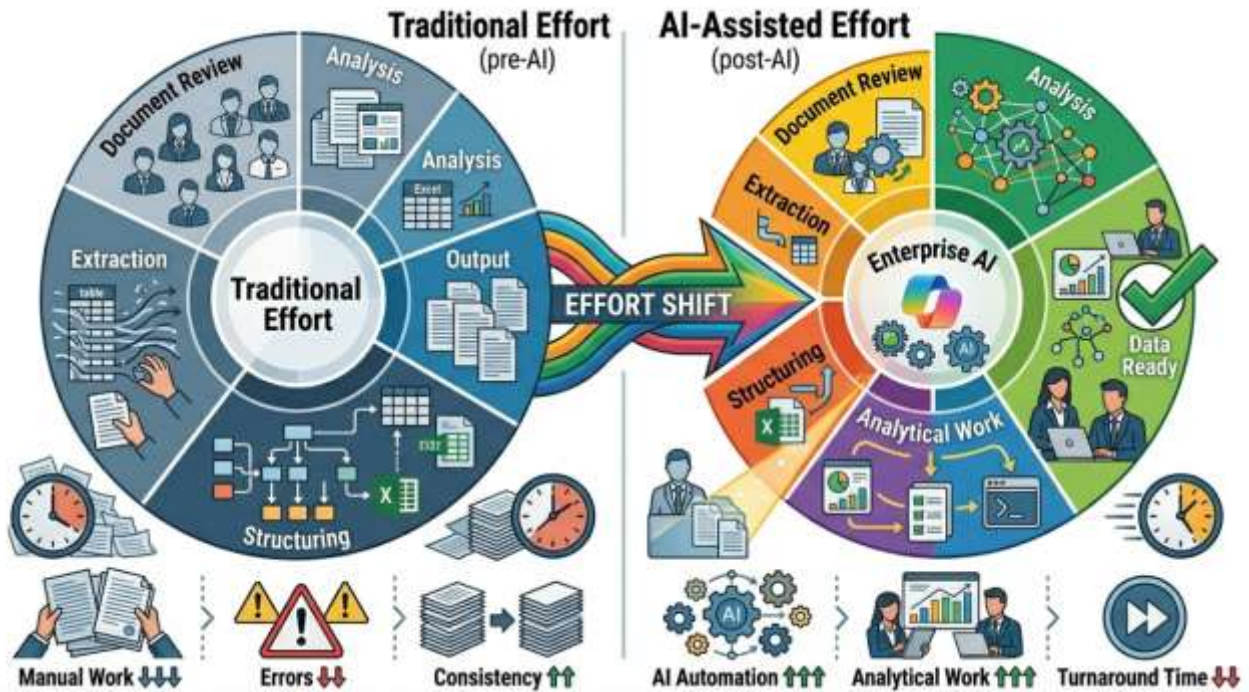


Figure 6. Administrative Effort Redistribution in AI-Assisted Regulatory Workflows

This figure presents a conceptual comparison between traditional manual workflows and AI-assisted regulatory documentation workflows. It illustrates how the proposed framework may shift effort from repetitive document review, extraction, and structuring toward higher-value analytical and validation activities. The figure does not represent measured time savings, measured workload reduction, or quantified accuracy improvement.

5.2 Limitations

Apart from all the positives it had, it also involves some challenges to face, which are related to the tool limitations and constraints, and the differences in the outputs, limited access to AI features, restrictions due to security concerns, and different document structures can effect efficiency as well. To track and put together all these improvements, a human-AI collaborative workflow is proposed, which helps in assisting and processing the structured validation points across all stages for the overall implementation. As shown in Figure 7, the entire workflow shows the step-by-step ingestion through different processes starting from parsing, extraction, requirement, structuring, configuration, and feedback loops.

This study does not report production deployment, organizational adoption, measured time savings, extraction accuracy, or analyst-level performance outcomes. The proposed framework is evaluated at the design stage through workflow mapping, synthetic demonstration, and risk-control analysis. Future research should validate the framework using real or de-identified regulatory documentation, analyst review data, processing-time comparison, and output consistency metrics.

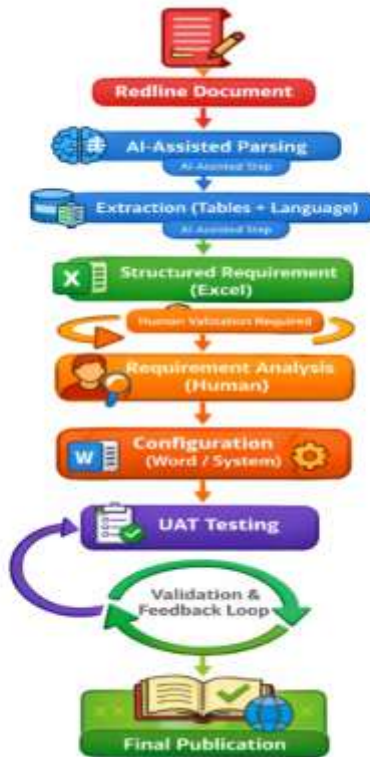


Figure 7. End-to-End Human-AI Collaborative Regulatory Processing Framework

This figure presents the proposed end-to-end framework integrating AI-assisted processing with human validation across the regulatory lifecycle. The workflow spans redline document ingestion, AI-driven parsing and extraction, structured requirement generation, human-led validation, system configuration, and iterative feedback through UAT cycles. The framework emphasizes controlled AI adoption, continuous performance monitoring, and collaborative decision-making to ensure reliable and scalable regulatory transformation.

5.3 Future Research and Conclusion

Future research can extend this work by applying defined performance metrics, testing the framework across organizations, and evaluating the impact of AI-assisted workflows on administrative efficiency, scalability, and output quality. Future research should also examine how the proposed framework performs across different types of regulatory documents, benefit structures, payer environments, and enterprise AI tool constraints.

This study presents the Human-AI Collaborative Regulatory Transformation Framework as a design-stage reference framework for regulated health insurance documentation workflows. Its main contribution is the integration of AI-assisted document parsing, structured requirement mapping, source traceability, human validation, and feedback-driven refinement into a single workflow model. The study does not prove healthcare cost reduction or operational performance improvement, but it identifies a structured path for future empirical validation in healthcare administrative environments.

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