

# Leveraging Artificial Intelligence in Configure-Price-Quote (CPQ) Systems for Healthcare Manufacturing

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**Abstract:** Healthcare manufacturing operates under stringent regulatory requirements, high product complexity, and increasing demand for customer-specific configurations. Configure-Price-Quote (CPQ) systems translate customer intent into manufacturable and compliant offerings, yet they often struggle at scale when relying solely on static rules and manually maintained knowledge bases. This paper presents an Artificial Intelligence (AI) enabled CPQ approach for healthcare manufacturing that combines knowledge-based configuration with governed, data-driven intelligence. We propose a validation-aware reference architecture and a digital-thread integration pattern that connects CPQ outputs with downstream PLM/ERP/quality systems to preserve traceability. Practical use cases are discussed: configuration recommendation, pricing and contract guidance, conversational access to catalog and release content, and compliance-oriented explainability, along with governance controls required for regulated environments.

**Keywords:** Artificial Intelligence; CPQ; Healthcare Manufacturing; Medical Devices; Pricing Optimization; Digital Thread; Trustworthy AI

## I. INTRODUCTION

Healthcare manufacturing has progressively evolved from producing fixed-configuration products to delivering highly configurable systems composed of hardware options, embedded software features, accessories, and service entitlements. In this setting, CPQ is more than a quoting tool: it functions as an enterprise computing platform that converts customer intent into a system definition that must be legally valid, manufacturable, and supportable across regions.

In regulated environments, errors introduced at configuration or pricing time propagate across manufacturing execution, quality assurance, logistics, and post-market service. The consequences include rework, delays, and audit findings; therefore, CPQ increasingly represents a convergence point of business policy enforcement, decision logic, and inter-system communication [1] [7] [9].

Traditional CPQ deployments rely on rule-based configuration and manually maintained product models. While deterministic rules are essential for enforcing hard constraints, they become difficult to sustain under configuration explosion, frequent catalog releases, and unstructured inputs such as Request for Proposals (RFP) and clinical requirement narratives. AI can complement rule engines by learning from historical outcomes, providing contextual recommendations, and enabling conversational access to complex catalogs while

remaining governed by validation and approval controls [2] [3].

This work is presented as an applied architecture and systems design contribution, rather than a statistical or algorithmic performance study. The contribution is a practical reference architecture and a set of integration and governance patterns that enable AI capabilities inside CPQ workflows without sacrificing auditability or compliance.

## II. CPQ CHALLENGES IN HEALTHCARE MANUFACTURING

CPQ systems in healthcare manufacturing must address technical, commercial, and regulatory complexity simultaneously. Product offerings are often modular and software-defined, creating large configuration spaces where only a subset of combinations is valid. Constraints vary by geography and clinical use case, while pricing is frequently governed by contracts, tenders, and policy-driven approvals [1] [7] [9].

Rule-based CPQ platforms encode complexity through compatibility constraints, pricing matrices, and approval workflows. As portfolios expand, the volume and interdependence of rules increase, raising maintenance cost and the risk of semantic drift. Catalog changes require coordinated updates across configuration logic, pricing artifacts, and documentation templates. Even small mismatches can produce downstream failure modes such as change orders, revalidation cycles, or incorrect deliverables.

CPQ must also communicate reliably with downstream platforms: Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and quality systems so that what was sold is what is built, verified, and serviced. This system-of-systems dependency elevates CPQ from a front-office tool to a lifecycle control plane, where traceability and reconstructability become first-class requirements [7] [9].

### III. AI-ENABLED CPQ CAPABILITIES

AI augments CPQ by introducing adaptive decision support while preserving deterministic rule enforcement. In practice, the most valuable capabilities are those that reduce cognitive load, increase quote accuracy, and prevent downstream rework without bypassing governance controls.

#### A. Intelligent configuration assistance.

Recommendation models can propose valid product bundles, default attribute selections, or upgrade paths by learning from historical quotes, outcomes, and install-base context. In regulated manufacturing, recommendations must remain bounded by constraint validation: AI proposes, rules validate, and users confirm. This separation reduces risk while improving speed and consistency [2][3].

#### B. Pricing and contract guidance.

Pricing in healthcare manufacturing is shaped by list prices, regional price pages, customer-specific contracts, and discount approvals. AI can provide decision support by suggesting discount ranges, identifying pricing anomalies, and recommending contract types based on contextual signals and historical behavior. These outputs should be treated as guidance and remain subject to approval workflows and policy thresholds [5][9].

#### C. Conversational access to catalog and release knowledge.

Natural language interfaces can reduce time spent searching catalogs and documentation. Users can ask questions such as what changed in a release, which options are valid for a modality, or which bundles are typical for a given configuration intent. This capability is particularly useful when release notes and master data are distributed across repositories, and it supports more consistent quoting during periods of frequent change [2][3].

#### D. Compliance-oriented explainability and quote reasoning.

AI services can assist in generating explainable summaries of configuration choices, highlighting why certain options were added or blocked, and producing human-readable diffs between quote versions. These explanations improve trust and reduce avoidable rework, especially when preference rules or catalog dependencies introduce unexpected line items.

Specific algorithmic choices are intentionally abstracted, as the contribution focuses on system-level integration and governance rather than model design [4][6][8].

### IV. REFERENCE ARCHITECTURE

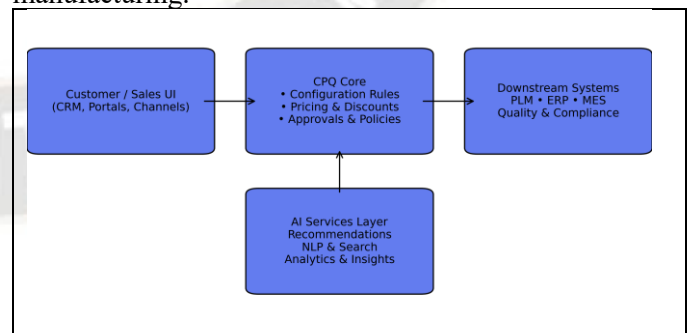
The proposed architecture retains rule-based configuration as the deterministic core while adding AI services as governed, assistive components. This design ensures that safety- and compliance-relevant constraints remain explicit, testable, and auditable, while AI improves usability and decision quality.

Customer and sales interfaces interact with the CPQ core, which executes configuration rules, pricing logic, and approval workflows. AI services operate alongside the core engine to provide recommendations, natural language query capabilities, and analytics. AI outputs are validated by configuration and pricing rules and, where required, routed through human approvals.

Fig. 1 summarizes the architecture.

A digital thread connects CPQ outputs with downstream PLM, ERP, MES, and quality systems, preserving configuration identity and version semantics across the lifecycle. This integration supports reconstructability (determining what was sold, built, verified, and deployed), which is critical for regulated environments [7] [9].

Fig. 1. AI-enabled CPQ architecture for healthcare manufacturing.



### V. GOVERNANCE AND TRUSTWORTHY AI

In healthcare manufacturing, AI adoption is gated by trust, auditability, and regulatory acceptance. AI-enabled CPQ must therefore include controls for data provenance, model versioning, and immutable logging of recommendations and user actions. These controls support explainability and

enable audits to reconstruct what the system recommended and what the user ultimately approved [4][6][8].

Human-in-the-loop patterns are critical. AI can assist by prioritizing options or highlighting risk signals, but accountability for final decisions must remain with authorized users. Approval workflows, validation checkpoints, and policy enforcement ensure that adaptive intelligence does not bypass governance [4][6].

Quantitative performance evaluation is intentionally out of scope, as the focus is on architectural patterns, governance, and system integration rather than model benchmarking.

#### VI. EVALUATION METRICS (SYSTEM-LEVEL)

Even without model benchmarking, organizations should evaluate AI-enabled CPQ using system-level operational and quality metrics. Recommended measures include quote cycle time, first-pass configuration validity, approval turnaround time, frequency of downstream change orders, and the rate of policy exceptions.

For AI-assisted recommendations and conversational access, effectiveness can be assessed through user effort reduction (e.g., fewer manual steps), retrieval precision for catalog and release questions, and the reduction of rework caused by incorrect or incomplete configurations. These metrics align with the practical objectives of regulated manufacturing: accuracy, traceability, and predictable downstream execution [9].

#### VII. CONCLUSION

AI-enabled CPQ systems transform quoting from reactive rule execution to proactive decision support. By combining deterministic validation with governed intelligence, organizations can improve quote accuracy, reduce avoidable downstream rework, and accelerate commercial workflows while preserving compliance.

While motivated by healthcare manufacturing, the architectural patterns and governance principles discussed are applicable to other regulated, high-complexity enterprise computing environments, including aerospace and industrial equipment.

Industry documentation is cited where peer-reviewed literature on CPQ system implementation remains limited, consistent with the applied research focus of this study.

#### II. REFERENCES

- [1] Conga, "Managing product rules," Conga Documentation Portal, 2026. Available: <https://documentation.conga.com/en/cpq-for-salesforce/current/cpq-for-administrators/managing-product-rules>
- [2] SAP, "Introduction to SAP intelligent product recommendation," SAP Help Portal, 2026. Available: [https://help.sap.com/docs/SAP\\_INTELLIGENT\\_PRODUCT\\_RECOMMENDATION/7e21c4f1857e4ee99699a4e7a9c9702a](https://help.sap.com/docs/SAP_INTELLIGENT_PRODUCT_RECOMMENDATION/7e21c4f1857e4ee99699a4e7a9c9702a)
- [3] Oracle, "AI-generated product recommendations," Oracle Configure, Price, Quote Cloud - What's New, 2026. Available: <https://docs.oracle.com/en/cloud/saas/readiness/sales/25c/scpq-25c/25C-cpq-wn-f39290.htm>

- [4] K. Lekadir et al., "FUTURE-AI: International consensus guideline for trustworthy and deployable artificial intelligence in healthcare," *The BMJ*, vol. 388, 2025. doi: 10.1136/bmj-2024-081554
- [5] H. Ravilla, "The role of CPQ automation in pricing consistency and revenue forecasting," *Data Science and Big Data Analytics*, Springer, 2026. doi: 10.1007/978-3-032-05377-0\_1
- [6] Mishra A, Saha S, Makhija S, Sinha S, Raychoudhury V, CC S. Empirical study of dynamics of amoebiasis transmission in mobile ad hoc networks (MANETs). *Int J Commun Syst.* 2020;33:e4186. <https://doi.org/10.1002/dac.4186>
- [7] S. Jenko et al., "Artificial intelligence in healthcare: How to develop and implement safe, ethical and trustworthy AI systems," *AI*, vol. 6, no. 6, 2025. doi: 10.3390/ai6060116
- [8] Conga, "Conga configure price quote (CPQ) data sheet," Conga, 2022. Available: <https://appexchange.salesforce.com/partners/servlet/servlet.FileDownload?file=00P4V000010LKQnUAO>
- [9] C. Bagwe, "Explainable AI (XAI) in compliance audits: Bridging the gap between AI and regulatory transparency," *International Journal of Scientific Engineering and Science*, vol. 9, no. 3, 2025. Available: <http://ijses.com/wp-content/uploads/2025/03/50-IJSES-V9N3.pdf>
- [10] B. Karnani, "The evolution of CPQ (configure, price, quote) systems: AI integration and revenue impact," *International Journal of Research in Computer Applications and Information Technology*, vol. 8, no. 1, pp. 3370-3387, 2025. Available: <https://www.researchgate.net/publication/389368660>