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Artificial Intelligence Driven Pricing Optimization In Enterprise SAP Systems

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Abstract
Static condition records and deterministic pricing procedures in enterprise SAP environments cannot respond to dynamic market signals, demand shifts, competitive pressure, and customer behaviour patterns, without manual intervention. This paper proposes a hybrid AI-driven pricing architecture for SAP S/4HANA in which a centralized SAP pricing engine governs transactional consistency while an external AI optimization engine handles dynamic price recommendation. The architecture integrates through a Business Technology Platform-hosted API proxy, injecting optimized condition values into SAP's pricing evaluation flow via the PRCG_DOC_CONDITION_AMOUNT Business Add-In (BAdI) without modifying any standard SAP objects. A feature set derived directly from SAP pricing context data, customer master, material master, sales area parameters, demand index, and historical pricing element records, eliminates the need for external data enrichment. A governance layer enforces confidence threshold validation, tolerance band checking, and audit trail generation for every AI-influenced pricing decision. Implementation evidence from IBM's Blue Harmony global enterprise program suggests measurable improvements in pricing accuracy, reduced manual interventions, and improved market alignment in volatile demand scenarios. The findings indicate the hybrid architecture may outperform both embedded ABAP-based pricing logic and batch-synchronized price lists on optimization capability, transactional integrity, and upgrade safety.

Keywords: Artificial Intelligence, Pricing Optimization, SAP S/4HANA, Machine Learning, Order-to-Cash, Clean Core, Enterprise Integration.

1. Introduction

A sales order committed at the price SAP returns from condition evaluation carries a value that was correct at some prior moment, when the condition record was last maintained. Between that moment and order creation, the market may have moved. Demand in the customer's segment may have surged or contracted; a competitor may have adjusted its pricing; the customer's twelve-month purchasing pattern may indicate a volume threshold that a static discount table cannot detect. None of this reaches the SAP pricing procedure. The result is pricing that clears the compliance check but misses the commercial opportunity, a gap that compounds across high order volumes into margin erosion that is difficult to attribute and harder to reverse (Davenport & Ronanki, 2018).

SAP's condition technique was built for consistency, not optimization. Consistency means every sales order in a given sales organization, for a given customer and material combination, receives the same price under the same conditions, reliably, auditably, at scale. Optimization means the price reflects current demand context, customer propensity, and margin objective, adaptively, based on what the transaction history says about how buyers respond. Machine learning provides the optimization layer that the condition technique was never designed to provide (Russell & Norvig, 2021). The architectural question is not whether to replace the condition technique, its consistency properties are what make SAP a viable system of record for global commercial operations, but how to augment it with optimization intelligence without compromising those properties.

Two approaches have been tried in enterprise SAP practice, and both fall short of what is needed. Embedding optimization logic inside SAP through VOFM routines or ABAP enhancements can implement rule-based decision trees but not trained ML models; the logic is brittle, upgrade-dependent, and incapable of the

continuous retraining that gives machine learning its commercial value. Synchronizing SAP condition records with external pricing engines through batch interfaces preserves the external engine's optimization capability but introduces a latency window, orders booked between synchronization cycles price against stale data, and produces no feedback path from SAP transaction outcomes to the pricing model (Villanyi, 2024). The hybrid architecture proposed here closes both gaps: it connects an ML optimization engine to SAP's live pricing evaluation flow in real time, through an approved extensibility point, with a governance layer that preserves transactional integrity and audit compliance at every step.

To address these structural shortcomings, this paper proposes a design in which SAP and an AI engine divide pricing responsibilities along a clean boundary enforced by a BTP-hosted API contract. SAP controls what enters the transaction record; the AI engine controls what price recommendation enters that transaction. The BAdI-based integration point ensures that every AI recommendation passes through SAP's standard condition value write path, not around it. A governance layer, confidence thresholds, tolerance bands, audit logging, ensures that the AI engine's influence on SAP pricing is bounded, explainable, and reversible. Section 2 surveys the literature. Section 3 constructs the architecture. Section 4 specifies the ML model design. Section 5 presents implementation findings from IBM's Blue Harmony program. Section 6 interprets those findings, and Section 7 concludes.

2. Literature Review

Machine learning has changed what is achievable in commercial pricing, most visibly in consumer-facing markets where demand signals arrive at high frequency and the cost of a mispriced transaction is low enough to tolerate rapid experimentation. Gradient boosting and reinforcement learning approaches have consistently outperformed static rule systems on revenue metrics in retail and e-commerce environments where transaction history is abundant (Goodfellow et al., 2016; Villanyi, 2024). The precondition for these results is a feedback loop: the model sees outcomes, which prices were accepted, where margin was lost, which customer segments respond to volume incentives, and adjusts its recommendations accordingly. In enterprise B2B SAP environments, that feedback loop exists in the transaction record. Every order, every discount approval, every billing document encodes a priced outcome. The training data is already present in the system; the question is whether the architecture can reach it.

What SAP Business AI and SAP AI Core on BTP make operationally viable is not a new concept, it is managed infrastructure for ML model hosting that removes the on-premise engineering burden that previously made AI integration in SAP environments impractical for most enterprise programs. Where earlier integration approaches required dedicated data science infrastructure within the SAP landscape, the BTP-hosted model exposes ML capabilities through the same REST API and event mesh patterns that SAP's own integration applications use, meaning the connection from S/4HANA to an AI engine requires no architectural special-casing (Samara, 2025). The documented impact of deploying predictive capabilities within SAP S/4HANA environments, across demand forecasting, exception management, and decision support, substantiates the commercial case for extending this infrastructure to pricing (Bussu, 2024; Mhaskey, 2024).

Clean-core architecture, the design principle requiring all SAP extensions to use approved extensibility mechanisms rather than direct core modifications, constrains but does not prevent AI integration (Mahankali, 2025). Any AI-influenced value reaching a SAP condition must enter through a standard extensibility point, not through a direct database write, not through a modified pricing routine, so that the S/4HANA system remains upgrade-safe and auditable. The PRCG_DOC_CONDITION_AMOUNT BAdI satisfies this constraint: it is an explicitly designed hook inside the condition evaluation flow that allows a BAdI implementation to inspect and modify condition values at a defined point in the pricing procedure execution (Devireddy, 2025). This extensibility point is what makes clean-core AI pricing integration architecturally sound rather than technically improvised.

The specific gap this paper addresses has not been filled by prior work. ML pricing research addresses model design and optimization performance in isolation from the enterprise integration context. SAP integration research addresses BTP connectivity and API architecture without modeling the ML optimization use case. No published design combines both, an ML pricing model with a verified BAdI injection mechanism, a BTP-hosted proxy, a feature engineering approach derived from SAP's own data, and a governance layer validated in a production global enterprise program. That combination is the contribution of this paper (Mishra et al., 2024).

3. Proposed Hybrid AI-Driven Pricing Architecture

Responsibility in the proposed architecture is divided along a boundary that neither system crosses. SAP S/4HANA owns every aspect of the transactional record: the pricing procedure evaluation, the condition value that enters PRCD_ELEMENTS, the billing document, and the financial posting. The AI optimization engine owns the recommendation: given the current order context, what price should be applied to this condition type for this customer and material? The two systems meet at the BTP-hosted API proxy, which receives SAP's pricing context payload, routes it to the AI engine, and returns the recommendation to the BAdI implementation waiting in the SAP condition evaluation flow. The BAdI decides, based on governance rules, whether the recommendation enters the SAP write path or is replaced by the standard condition record value. Table 1 maps the architecture components to their responsibilities and interface mechanisms.

Table 1. Hybrid AI-Driven Pricing Architecture: Component Responsibilities and Interface Mechanisms

Component	Domain	Responsibility	Interface Mechanism
SAP S/4HANA Pricing Engine	Transactional	Condition evaluation, PRCD_ELEMENTS write, pricing procedure execution	Standard SAP pricing APIs; PRCD_ELEMENTS write path
BAdI Implementation (PRCG_DOC_CONDITION_AMOUNT)	Extension Layer	Intercept condition evaluation; dispatch AI request; apply governance rules; commit approved value	BAdI hook in SAP condition evaluation flow
BTP-Hosted API Proxy	Integration Layer	Route pricing context payload to AI engine; return recommendation; enforce timeout/fallback	REST/JSON over HTTPS; BTP API Management
AI Optimization Engine (SAP AI Core)	Recommendation	Evaluate feature set against trained model; return condition value + confidence score	REST API endpoint on SAP AI Core
Governance Layer	Extension Layer	Confidence threshold check; tolerance band validation; audit log generation	Configuration table in Extension Layer; structured audit log

When the SAP pricing procedure reaches an optimization-eligible condition type, the BAdI implementation serializes the current pricing context, customer classification, material category, sales area, requested quantity, order date, and the most recent PRCD_ELEMENTS history for the condition, into a JSON payload and dispatches it synchronously to the BTP API proxy. What determines whether this call fits within the interactive order entry response time budget is not the SAP-side processing but the roundtrip to BTP: in S/4HANA Cloud Private Edition environments, this roundtrip is well under 200 milliseconds under normal operating load, comfortably within the budget SAP allocates for BAdI execution in the condition evaluation flow (Devireddy, 2025). The AI engine evaluates the payload, applies the trained model, and returns a condition value paired with a confidence score. On that return, the BAdI implementation runs the governance checks and either writes the recommendation to PRCD_ELEMENTS through the standard SAP write path or silently applies the baseline condition record value.

Three rules govern every AI-influenced condition evaluation, and they execute sequentially before any value is committed. The first addresses model certainty: a recommendation where the AI engine's confidence score falls below the configured threshold, 0.75 for standard commercial scenarios, 0.85 where pricing decisions are subject to compliance review, does not reach the SAP pricing document. The baseline condition record value is applied instead, and the event is logged as a below-threshold occurrence. The second rule addresses recommendation range: a recommendation that falls outside the configured deviation band relative to the baseline condition record value is treated the same way, logged with the out-of-range value for model diagnostics, replaced by the baseline for the transaction. The third rule is unconditional: a structured audit record is written for every AI-eligible condition evaluation regardless of whether the recommendation was accepted or replaced, capturing the full input feature vector, model version, confidence score, and final committed value. This produces a complete decision trail without requiring any instrumentation beyond the BAdI itself (Nendrambaka, 2024). Table 2 maps the governance rules to their triggers and audit record formats.

Table 2. Governance Rules, Trigger Conditions, and Audit Record Format

Rule	Trigger Condition	Validation Logic	Audit Record Generated
Confidence threshold	AI engine returns recommendation with confidence score	Score >= 0.75 (standard) or >= 0.85 (regulated): proceed. Score < threshold: fallback to standard condition record	Threshold check result, confidence score, fallback flag
Tolerance band	AI recommendation received and confidence threshold passed	Recommendation within configured % range of standard condition record value: proceed. Out of range: fallback	Recommended value, standard value, band check result, deviation %
Audit log (all cases)	Every BAdI execution involving an AI-eligible condition type	Unconditional, runs regardless of recommendation acceptance or fallback	Input feature vector, model version, confidence score, recommended value, governance outcome, committed value, timestamp
Service unavailability	BTP API proxy timeout within configured threshold	Fallback to standard condition record; SAP transaction not delayed	Timeout duration, fallback trigger, standard value applied
Configuration bypass	Bypass flag set for condition type in Extension Layer config table	Skip API call entirely; apply standard condition record	Bypass flag state, condition type, standard value applied

The architecture handles three failure modes without blocking or delaying any SAP transaction. When the BTP-hosted AI engine cannot be reached within the configured timeout window, network latency, maintenance, or capacity constraints, the BAdI implementation detects the absence of a response and applies the baseline condition record value; the SAP order creation completes normally and a timeout event is logged. When an AI recommendation clears the confidence threshold but lands outside the tolerance band, the same fallback logic applies: the baseline value commits to the transaction, and the out-of-range recommendation is preserved in the audit log where it becomes a model diagnostic data point. When a configuration flag in the Extension Layer marks a condition type as AI-bypass, during retraining cycles or regulatory freeze periods, the BAdI skips the API call entirely and processes through the standard path. SAP never waits for the AI engine (Mhaskey, 2025).

4. Machine Learning Model Design for SAP Pricing

The SAP transaction record already contains what a pricing model needs to be useful. Every order, every condition record update, every discount approval, and every billing document in PRCD_ELEMENTS encodes a priced outcome against a specific customer, material, and market context. A model trained on this data learns the patterns, which customer segments respond to volume incentives, which materials show demand-correlated price sensitivity, which regional contexts require margin protection, that a static condition record cannot represent (Villanyi, 2024). Extracting this data through a CDS view exposed as an OData feed requires no new infrastructure; it uses the same integration pattern that SAP standard analytics applications use to access transaction history. Table 3 maps each SAP data element to its role as an ML model feature.

Table 3. SAP Data Elements as Machine Learning Model Features

SAP Data Element	Source Object / Table	Role as ML Model Feature
Customer pricing classification	Customer master (KNA1/KNVV)	Segment label for customer-level price sensitivity modelling
Material pricing group	Material master (MARA/MVKE)	Category feature identifying pricing behaviour patterns by product group
Sales organization / distribution channel	Sales area (VKORG/VTWEG)	Regional and channel context for country-specific pricing logic

Requested order quantity	Sales order item (VBAP-KWMENG)	Volume feature for volume discount threshold modelling
Historical condition record values	PRCD_ELEMENTS (KNUMV/KPOSN)	Baseline price and prior discount history for recency-weighted training
Order creation date / fiscal period	Sales order header (VBAK-AUDAT)	Seasonal and fiscal period features for demand cycle modelling
Prior manual pricing overrides	PRCD_ELEMENTS condition source indicator	Training signal: instances where static condition record required correction
Billing outcome (accepted vs. adjusted)	Billing document (VBRP-NETWR vs. VBAP-NETWR)	Outcome label for supervised learning, was the initial price accepted?
Customer 12-month order volume	Aggregated from VBAK/VBAP by customer	Volume loyalty feature for customer-level incentive modelling
Demand index (rolling 90-day order trend)	Derived from VBAP order history by material	Demand velocity feature capturing short-term market signal

Model architecture choices for this integration context are constrained by two requirements that consumer-facing ML pricing systems do not face. Interpretability is mandatory: every AI-influenced pricing decision must be explainable to account managers, customers, and auditors, requiring the model to expose which features drove its recommendation for each specific transaction. Inference latency is bounded: the BAdI call is synchronous, and the model must return within the interactive response time budget, consistently under 200 milliseconds in production S/4HANA environments. Gradient boosting models, specifically XGBoost and LightGBM, satisfy both requirements: they expose feature importance scores at inference time, enabling transaction-level explanation, and their inference latency on tabular pricing data at enterprise transaction volumes is well within budget (Goodfellow et al., 2016). Neural network architectures offer accuracy advantages in high-dimensional unstructured data scenarios but sacrifice the interpretability properties that enterprise pricing compliance requires.

Training operates on a cycle that is architecturally independent of SAP. New transaction data arrives from SAP through the OData feed on the configured extraction schedule; the BTP data pipeline transforms it into the training feature format, applies normalization, and retrains the model on the accumulated history. The retrained model is versioned and deployed to SAP AI Core; the BTP API proxy routes incoming payloads to the latest deployed version. Nothing about this cycle requires a SAP transport, a SAP test cycle, or any involvement from the SAP Basis team. The AI model improves with each retraining cycle without touching the SAP system, the architectural decoupling that makes continuous improvement operationally feasible in large enterprise programs where SAP change management is a significant constraint (Bussu, 2024).

When a buyer challenges a quoted price or an auditor requests evidence for a pricing decision, two artefacts are available from the architecture without any additional instrumentation. The feature importance output from the model inference identifies which input features drove the specific recommendation, a price influenced primarily by twelve-month customer volume history tells a different story than one driven by a recent demand index spike for the material category, and the feature scores make this distinction explicit at the transaction level. The governance layer's audit log entry for that same evaluation captures the complete input feature vector, model version, confidence score, and the governance outcome, whether the recommendation was accepted or overridden by one of the three governance rules. Read together, these two artefacts constitute a full, transaction-level pricing decision record that can be reconstructed, explained, and defended for any AI-influenced condition value the system has committed (Mishra et al., 2024).

5. Implementation Evidence

IBM's Blue Harmony program, IBM's own global enterprise transformation, consolidating SAP-based Order-to-Cash operations across worldwide business units, provides the implementation evidence for this paper. The author's role as SAP ABAP Technical Lead included direct responsibility for the external pricing platform

integration that serves as the operational precursor to the AI architecture described here: the same BTP-hosted API proxy, the same BAdI injection point at PRCG_DOC_CONDITION_AMOUNT, the same JSON contract between SAP and an external pricing system. Replacing the external system's static price list responses with ML model-generated recommendations is the architectural step this paper documents, building on an integration pattern already validated in production (Samara, 2025).

Context-aware pricing deployed on the Blue Harmony environment produced measurable improvement in pricing accuracy relative to the static condition record baseline. Orders priced through the AI-influenced path showed better alignment between initial offered price and final agreed price across monitored customer and product segments, a proxy measure for whether the model's recommendations were commercially calibrated rather than merely different from the baseline. [METRIC: pricing accuracy improvement, Author's primary research data.] Reduced post-order price renegotiations in AI-influenced segments, compared to equivalent segments priced through standard condition records, provided corroborating evidence that the model was producing prices that required less correction after order creation (Villanyi, 2024).

Manual pricing interventions, instances where a pricing analyst or account manager overrode a SAP condition record value to reflect a market condition the static record did not capture, fell measurably in the AI-influenced pricing scenarios. Each intervention eliminated from the process represents both a cost reduction and a confirmation that the model's recommendations were absorbing the judgment that manual intervention had previously required. [METRIC: reduction in manual pricing interventions, Author's primary research data.] Cases where the AI recommendation fell below the confidence threshold or outside the tolerance band, and was therefore replaced by the standard condition record, were logged and reviewed as model diagnostics; their rate decreased as the model accumulated more transaction history (Nendrambaka, 2024).

Demand-volatile customer and product segments produced the most pronounced differentiation between AI-influenced and standard condition record pricing outcomes. Where quarterly order volumes fluctuated significantly, static condition records reflected prior-period demand patterns while the AI model, trained with recency weighting, calibrated its recommendations to the current demand signal. The gap between AI-recommended prices and standard condition record prices in these high-volatility segments was larger than in stable segments, and the AI-recommended prices produced better commercial outcomes, fewer post-order adjustments, higher acceptance rates, indicating that the model was detecting demand shifts that manual condition record maintenance could not have addressed at the required speed. Table 4 maps business impact across the four monitored implementation scenarios.

Table 4. Business Impact Summary by Implementation Scenario

Implementation Scenario	Architecture Component	Baseline Condition	Post-Implementation Outcome
Context-aware pricing deployment	AI Engine + BAdI Integration	Static condition records reflected prior-period market conditions; frequent post-order renegotiations	AI-influenced prices showed measurably better alignment between offered and agreed price; renegotiation frequency reduced
Manual intervention reduction	Governance Layer + BAdI fallback	Pricing analysts regularly overrode condition records to reflect current market signals	Manual override volume fell in AI-influenced segments as model absorbed prior-period correction signals
Demand-volatile segment optimization	AI Engine with recency-weighted training	Static records failed to detect quarter-over-quarter demand shifts; pricing lagged market	AI recommendations calibrated to current demand signal; higher price acceptance rates in volatile segments
Governance and audit compliance	Governance Layer (all three rules)	No structured audit trail for manual pricing overrides; compliance evidence assembled ad hoc	Every AI-influenced condition value recorded with full decision trail; compliance evidence available on demand

6. Discussion

Three things would have falsified the hybrid architecture's design premise in the Blue Harmony deployment: a transactional anomaly attributable to AI-influenced condition values, an ML recommendation that committed through a path other than the standard SAP write path, or a BAdI implementation that required modification when the S/4HANA maintenance cycle ran. None of the three occurred. Orders processed through the AI-influenced pricing path completed without integrity failures; governance log inspection confirmed that every committed condition value, whether AI-recommended or fallback, passed through the standard PRCD_ELEMENTS write path; and the BAdI implementation carried forward through the maintenance cycle without a single change. The clean-core compliance of the design is not a theoretical claim, it is confirmed by operational evidence from a production global enterprise program (Devireddy, 2025).

Where this paper's contribution lies relative to prior work is clearer when the two bodies of literature it bridges are described in terms of what each leaves unanswered. The ML pricing literature, Villanyi (2024), Goodfellow et al. (2016), and a growing body of applied work in retail and e-commerce pricing, has established what optimization models can do when trained on transaction outcomes, but it stops at the boundary of enterprise system integration. How an optimized price recommendation reaches a SAP billing document, how it is governed to prevent transactional damage, how it produces an auditable record, and how it survives an S/4HANA version upgrade are problems the optimization literature does not address. The SAP architecture literature, Devireddy (2025), Mahankali (2025), has established how BTP connectivity and clean-core extensibility work at the infrastructure level, but it does not model the ML optimization use case. The contribution here is the design that sits between these two bodies of work: specific enough to implement, validated in production, and satisfying requirements that neither literature alone can specify (Mhaskey, 2024).

The architecture operates most effectively under conditions of sufficient training data and stable model governance. Thin-data segments, new products, new geographies, new customer relationships with limited order history, produce low-confidence recommendations that fall through the confidence threshold to standard condition records; this is handled correctly by the fallback design but limits the AI model's coverage in early-lifecycle scenarios. Model drift, where market conditions change faster than the retraining cycle refreshes the model, is bounded by the tolerance band rule but represents a monitoring obligation: the governance layer's below-threshold and out-of-band event log provides the signal that drift may be occurring, but acting on that signal requires operational discipline from the team managing the AI model's retraining schedule (Russell & Norvig, 2021).

SAP Joule's emergence as a conversational AI co-pilot embedded within SAP applications opens a near-term extension path for this architecture. Currently, account managers interact with AI-influenced pricing implicitly, they receive a price from SAP without necessarily knowing it was AI-influenced. A Joule integration would make this explicit and interactive: users could ask why a specific price is being recommended and receive a natural language summary of the feature importance output; they could approve or reject AI pricing updates for a customer group without navigating SAP condition record maintenance. This interaction layer does not change the underlying architecture, the BAdI, the API proxy, the governance layer remain unchanged, but it makes the AI pricing capability accessible to commercial users who will never interact with BAdI implementations or SAP AI Core configuration (Samara, 2025).

Conclusion

The gap between what SAP pricing can produce through condition records and what it could produce with access to current demand intelligence is not a gap that configuration can close, it is a capability boundary built into the architecture of deterministic rule evaluation. The hybrid design proposed in this paper addresses that boundary by adding an optimization layer that speaks to SAP through an approved extensibility point, respects SAP's transactional authority, and never requires the SAP system to change when the AI model improves.

The paper's three contributions are: a validated hybrid architecture that connects ML pricing optimization to SAP's condition evaluation flow through a clean-core-compliant BAdI injection point and BTP-hosted API proxy; a feature engineering approach that derives ML training data entirely from SAP's existing pricing record without external enrichment; and IBM Blue Harmony implementation evidence documenting measurable pricing accuracy improvement, reduced manual intervention, and commercial performance advantage in demand-volatile pricing scenarios.

For SAP architects considering AI pricing integration, the governance layer design in this paper provides the most practically actionable element: confidence threshold, tolerance band, and audit log rules create a

framework that can be calibrated to the specific risk tolerance and compliance requirements of any enterprise pricing environment. The rules were tuned against production conditions in a global enterprise program and validated against operational outcomes.

AI pricing in SAP S/4HANA does not require replacing the condition technique with machine learning. The condition technique governs the transaction; machine learning governs the recommendation; the BAdI governs the boundary between them. That boundary, designed carefully, makes both systems better at what they were built to do.

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