



Enterprise Quote Management Using AI for Product Configuration, Pricing and Approval Workflows in SAP CPQ

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ABSTRACT: Enterprise Configure-Price-Quote (CPQ) systems help companies to convert customer needs into a technically feasible and commercially viable bid. Yet, increasing product complexity, part customization, part-specific price, discount change, confirmation and approval policy render traditional rule-based quotation processes to be highly difficult. The article proposes an AI-based enterprise quote management framework within SAP CPQ that leverages the product configuration, pricing intelligence, and validation of quoting alongside risk calculation and approval orchestration in one quotation life cycle. The framework uses the enterprise level data including product catalogs, customer records, and previous quotations, pricing policies, and discount policy, approval records to generate configuration and pricing recommendations, depending on situation. A configuration validation and risk testing system is employed to identify configuration conflicts, price errors, and policy errors, exceptional discounts, and commercially sensitive quotations to enable risk conscious routing to approval to occur. The framework also adds explainability, auditability, governance, security, constant monitoring and human-in-the-loop controls to make sure that commercially significant decisions are subject to proper human guidance. The dimension of evaluation applied to the evaluation of the framework are the accuracy of configuration, pricing consistency, conflict detection, processing efficiency, approval-cycle efficiency, routing accuracy, and exception detection as well as manual intervention. The proposed solution provides an integrated platform on the elements of smart, transparent and governance sensitive management of enterprise quotation.

KEYWORDS: SAP CPQ, Artificial Intelligence, Configure-Price-Quote, Product Configuration, Intelligent Pricing, Risk-Aware Approval, Enterprise Quote Management.

I. INTRODUCTION

Enterprise single-seat Configure-Price-Quote (CPQ) systems have become a major part of the digital sales processes, notably in the companies that sell complex, configurable, and client-specific products and services. CPQ systems can help sales people translate customer requirements into feasible product designs, compute the right prices and issue quotes and make related business decisions. The product configuration systems can minimize the quotation lead time, enhance quotation consistency, and avail technical knowledge to the sales personnel on the quotation process. An earlier research has indicated that a high level of efficiency and quality improvement in the quotation process could be obtained, in terms of structure product design, by eliminating the problem of coordination and embedding the product knowledge into the quotation process [1]. Implementation of CPQ systems can thus be seen as a significant move towards standardization of management of enterprise quotations.

Despite these benefits, it has become increasingly difficult to run enterprise quotation systems with increasing product lines, customer customization, pricing schemes, customer demands, discount schemes and business restrictions. There may be multiple product elements, dependence conditions, compatibility conditions, customer specific price, negotiated discounts, margin and requirement level, requirement of organizational approval. Instead, classic CPQ systems are largely based on rules and deterministic calculations that are hard-coded to regulate the circumstances. However, though these mechanisms may be effective in supporting the silo style business constraints, they hinder the processes of supporting the quotation decision where the historical trends, context and interdependence of different variables of commerce must be understood. Even time-consuming and demanding in terms of expertise configuration activities can be complex because of non-standard customer requirements, and notably, exceptions [1].



Another great challenge is the pricing aspect. Enterprise quotations frequently imply making decisions concerning the cost of products, characteristics of customers, past operations, market economies, and discounts as well as expected margins. Conventional pricing algorithms tend to be based on fixed formulas, price books, and company policies, possibly not fully utilising the sheer amount of historic quotation and transaction data that is at their disposal in the enterprise systems. The studies of intelligent cost analysis and decision support based on artificial intelligence prove that information techniques based on data can enhance the quality and availability of data in terms of purchasing and commercial decisions [2], [3]. Similarly, artificial intelligence can aid a decision maker in other processes in the enterprise by detecting patterns, providing forecasts and helping managers to make decisions that are better informed. All these characteristics provide an opportunity to make CPQ a more context-driven, than rule-driven, decision support system.

The other important constraint is associated with the correlation of approval management and quotation validation. Configuration errors, abnormal discounts, low margins, deviation of policies or missing information in quoted may not necessarily be isolated issues. The combination of a variety of factors can result in commercially important quotation and before accepting it one should estimate. Focused workflows which can be adopted enhance the current enterprise-wide workflows by applying automatic reviewing thresholds and manual reviews. These schemes can cause unnecessary approval paradigms because of regular quotation approval, and insufficient contextual prioritization in the comparison of extreme situations are required. Research related to hybrid intelligence makes it clear that the introduction of the enterprise AI cannot be viewed as a replacement of the human decision-making but rather as an addition to it, and, most importantly, there is an organizational-specific knowledge, uncertainty, and situational judgment that ought to be considered [4]. In this regard, smart quotation would have the capacity of proposing human control as opposed to utilizing the AI recommendations as autonomous business decisions. Figure 1 illustrates the key technical, commercial, and operational challenges associated with enterprise quotation management.

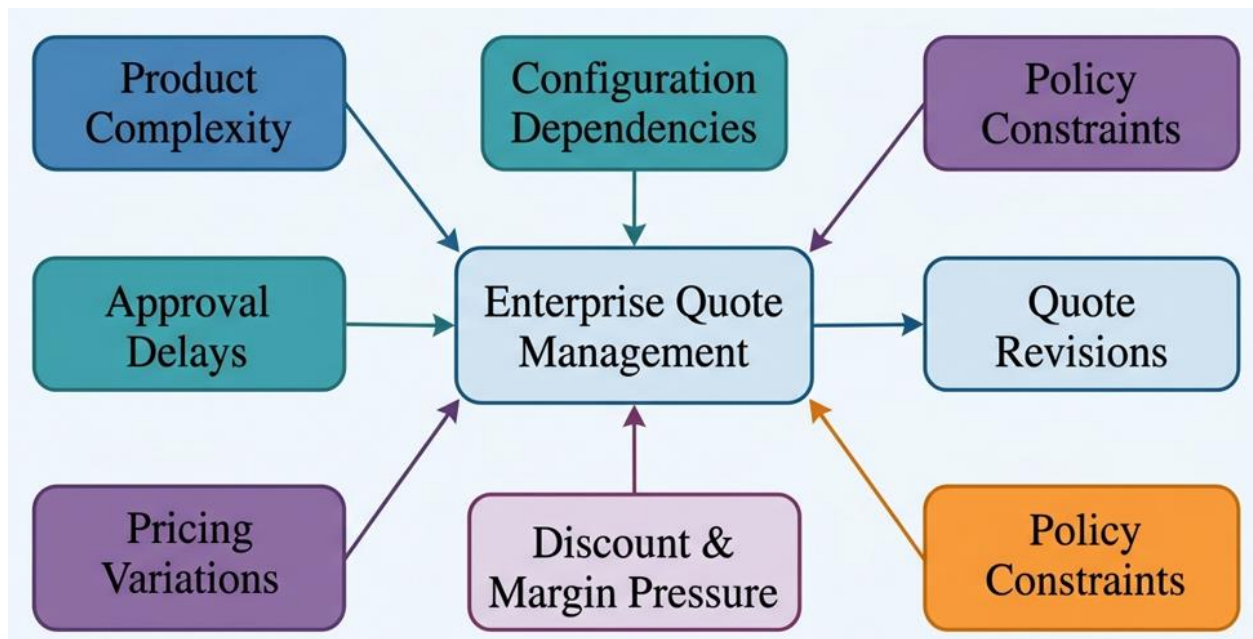


Figure 1- Enterprise quotation management challenges

The opportunities to address these challenges have a basis because there is an increasing use of the artificial intelligence in the procurement and enterprise decision-support. Recent studies reveal that AI and machine learning can assist a variety of subprocesses of procurement, such as procurement analysis, procurement prediction, procurement estimation, procurement decision support, procurement monitoring, and procurement anomaly detection. These systems have the capability to consolidate information in different sources of the enterprise and are much context-sensitive support compared to discrete rule-based systems [5]. However, AI has not been completely utilized within the context of the complete Configure-Price-Quote cycle as one of the opportunities that can be utilized in the situation of the enterprise quotation activity. Configuration intelligences, pricing intelligences, validation, risk analysis, and approval



orchestration are usually seen as discrete functional capabilities not as a component of a rational decision-support system.

This study fills this knowledge gap by suggesting an AI-based enterprise quote management structure of the SAP CPQ. The proposed architecture will integrate enterprise information and AI-based configuration recommendations, price intelligence, quote validation, risk assessment, and smart approvals orchestration. The historical quotes, product descriptions, customer inquiries, cost rules, discount policies and approvals are grouped together to work with context oriented methods that have quotations. The structure also adds explainability, governance, auditability, security, continuous monitoring and human-in-the-loop controls to make sure that commercially material decisions are duly monitored.

The main aim thus is to go beyond the traditional way of processing quotations using rules to a complete and smart quotation lifecycle. The proposed solution would increase accuracy in configuration, fixed price scheduling, identification of exceptions, approval rates, and the reduction in unnecessary human intervention and ensuring the company control over the sensitive commercial decisions. Through this, AI-based SAP CPQ will have the potential to be reconfigured to support more decision support operations that are rooted in the enterprise in general, instead of being a transaction-based previous quoting system.

II. RELATED WORK

Procurement, supply chain management, decision support, and business-process automation in the enterprise have been impacted by artificial intelligence, which offers a basis of intelligent quotation management. Allal-Chérif et al. [1] investigated the ways AI may revolutionize purchasing functions with automated purchasing, predictive purchasing, and intelligent decision support. Their work demonstrates that AI can move enterprise purchasing from transactional processing to a data-driven decision-making process. Another area where intelligent cost analysis was examined is by Bodendorf et al. [2], who proved that the analysis of purchasing decisions could be assisted with analytical methods applied to procurement information to provide valuable insights. These findings are relevant in Configure-Price-Quote (CPQ) settings where product cost, customer situation, previous quotes, and business environment influence quote decisions.

Estimates involving AI and cost/price estimation represent another important research direction. Bodendorf et al. [3] studied the application of artificial neural networks to predict costs in intelligent manufacturing supply chains and showed the value of learning-based models for cost-related predictions. These strategies provide a foundation for intelligent pricing in CPQ systems, where price suggestions can be derived from past quotes and product details. However, quotation pricing differs from conventional cost estimation as it must incorporate customer-specific circumstances, discounting policies, margins, pricing rules, and trade restrictions.

The growing application of AI also highlights the importance of partial intelligence and human intervention. Modgil et al. [4] evaluated AI adoption across supply chains and emphasized that AI capabilities must work alongside human oversight to manage operational risk and process nuances. Such a perspective is vital in enterprise CPQ since pricing exceptions, atypical projects, or premium quotations rely on management judgment even when AI provides baseline suggestions. Guida et al. [5] mapped AI implementation in procurement functions, identifying opportunities in automation, prediction, classification, and decision support alongside integration challenges. The organizational impact of AI in supply chain management was also emphasized by Toorajipour et al. [6], who noted that successful application depends not only on technological potential but also on process alignment and organizational integration.

A comprehensive view of AI capabilities in supply chains was offered by Pournader et al. [7], who categorized machine learning, predictive analytics, and automated decision support as key drivers of business operations. Quotation management directly applies these capabilities, as CPQ operations rely on connected data, multi-criteria choices, exceptions, and workflow planning. As demonstrated by Belhadi et al. [8], AI-driven decision support systems enhance complex procurement operations by evaluating diverse operational criteria. Their findings reinforce the idea that data-based intelligence should be built directly into enterprise workflow architectures rather than operating as an isolated analytical tool.

Recent research has paid increased attention to the interface between human workers and AI systems. Reimer et al. [9] examined human-in-the-loop decision-making in production environments, highlighting the role of human domain experts in guiding automated systems. This anthropocentric approach applies directly to CPQ approval workflows,



where salespeople, price analysts, and managers retain control over commercially critical decisions. This is consistent with findings by Agrawal et al. [10] regarding early organizational experiences with AI, which emphasize that AI predictions are provisional and require governance. These insights show that an AI-based CPQ system requires strong governance, human supervision, and continuous monitoring rather than focusing solely on predictive metrics.

Predictive analytics have also been widely applied to procurement planning and demand management. Using big data and predictive analysis, Kuo et al. [11] developed a procurement support system to reduce waste and improve decision accuracy in smart material procurement. Papachristou et al. [12] demonstrated the application of machine learning to respond faster to manufacturing and order demands, while van Steenberg and Mes [13] investigated demand profile forecasting for new products. These studies demonstrate how historical and contextual information enriches predictive decisions. These principles apply to CPQ for configuration recommendations, personalized pricing, and quotation outcome predictions, though unique products and sparse historical data remain challenges for automated models.

Natural language processing and semantic intelligence offer further possibilities for enterprise decision support. Biswas et al. [14] proposed a hybrid NLP-based approach to analyze unstructured text and convert it into decision-support information. Such capabilities enable CPQ systems to interpret customer requirements in natural language and translate them into product configurations or commercial terms. Ontological semantic modeling and deep learning were applied by Choi and Lee [15] to assess risk in complex EPC contracts, demonstrating how semantic relationships can model risk in detailed enterprise agreements. This provides a conceptual framework for validating and approving quotations based on risk criteria.

Finally, enterprise integration remains a critical consideration. Javidroozi et al. [16] assessed challenges associated with business-process change during enterprise system integration, emphasizing process alignment and integration complexity. For platforms such as SAP CPQ, AI capabilities must seamlessly interact with existing product catalogs, price sets, approval policies, and underlying enterprise data architectures.

Overall, the analyzed studies reflect significant progress in AI-based procurement intelligence, cost forecasting, predictive analytics, decision support, risk analysis, and human-AI cooperation. Nevertheless, these capabilities are usually explored individually or within narrow supply chain scenarios. Few studies integrate product configuration, smart pricing, quotation checks, risk analysis, and approval planning into a unified, AI-powered CPQ lifecycle. The proposed framework addresses this gap by aligning these capabilities within an SAP CPQ-like architecture while maintaining human supervision, explainability, governance, and policy compliance.

III. CONTEXT-AWARE AI ARCHITECTURE FOR INTELLIGENT ENTERPRISE QUOTE ORCHESTRATION

3.1 Framework Architecture and Data Context

The adopted structure presents a coordinated AI-required framework of business enterprise quote management in the SAP CPQ through integrating all the product configuration, product pricing, product evaluation, risk reduction, license endorsement into a single decision making process. The suggested framework is the opposite of the traditional CPQ environments where most processes are performed on the existing configurations and rules of pricing; it provides an AI Intelligence Layer that is able to learn by referring to the existing quotations, customer demand, product relationships, price pattern, discount pattern, and approval pattern. There are five layers in the architecture interconnected to one another: Enterprise Data Layer, SAP CPQ Layer, AI Intelligence Layer, Decision and Workflow Layer and Governance and Monitoring Layer.

The Enterprise Data Layer provides the history of data to be able to employ smart quotation choices. It also has product lists, product attributes, product compatibility, consumer profile, historical quotes, price sheet, discount policy, margin policy, approval policy and the last approval results. These nonhomogeneous data sources are converted to the same representation to allow them to have the homogenous processing. Configuration attributes, customer request, product selected, price detail, discount applied, desired margins, successful or unsuccessful validation and risk signs and permission therefore allow all quotes to be denoted. Findings of historical quotation provide students with additional learning hints to effective design, any strange quotes sold, and typical approval.

SAP CPQ Layer is left as the ongoing base of the quotation creation and management. The CPQ environment receives/gets customer requirements and orders the product, assists in product configuration, prices, and discounts, verifies and produces a quote. The proposed model does not replace the foundational CPQ competencies, rather, it



augments with AI-guided suggestions and contextual dexterity of choices. This enables existing rules that govern an enterprise to be kept alive and AI offers other evidence-based suggestions, anomaly detection, and risk prioritization.

The AI Intelligence Layer has the specialized intelligence constituents of configuration suggestion, pricing evaluation, discount evaluation, validation support and risk forecasting. SAP CPQ will give a representation of the quotation and create recommendation on these components in response to these components and confidence indicators and exceptions and decision supporting information. These outputs are translated into operational actions like configuration acceptance, further validation and pricing review, approval routing, or human escalation by the Decision and Workflow Layer. Finally, Governance and Monitoring Layer monitors the decision traceability, policy compliance, model monitoring, security control, human overrides and audit records. Figure 2 depicts the proposed AI-enabled architecture integrating enterprise data, SAP CPQ, AI intelligence, decision workflows, and governance mechanisms.

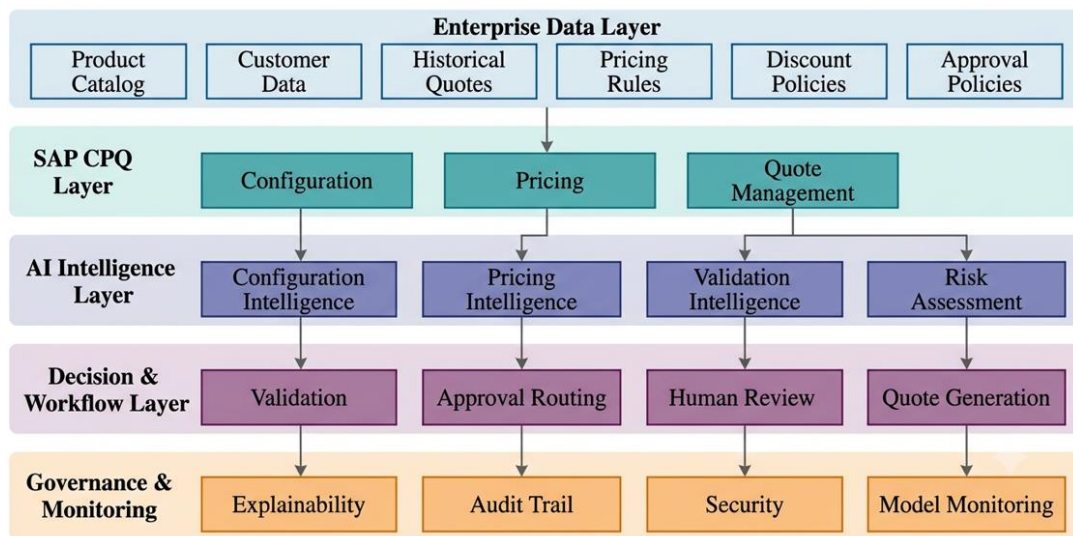


Figure 2- AI-enabled enterprise quote intelligence architecture

3.2 AI-Based Configuration and Pricing Intelligence

One of the features is a configuration intelligence that assists users format customer requirements to technical enable product configurations. The product characteristics, compatibility relations and dependencies, exclusions and configuration constraints are matched with the customer requirements. The aspect of AI could be able to identify a product combination in the past that was more suitable at a time and propose the product combination which fits the requirement of the customer and also the technical limits imposed. This is an illustration of how it works; when a client requests a combination of products and optional constituents the system would analyse the relationship between the elements upon request and decided which were incompatible or incomplete and that quotation would take place at the pricing stage. Figure 3 outlines the AI-assisted process for product configuration, compatibility validation, pricing, and discount-margin analysis.

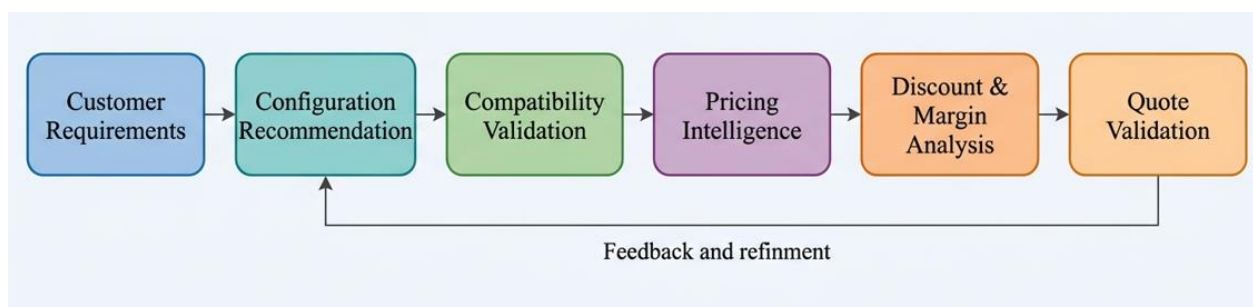


Figure 3- AI-assisted workflow for product configuration, compatibility validation, pricing intelligence, and discount-margin analysis



The configuration intelligence is not to substitute the deterministic CPQ constraints but can be used in conjunction with them. The suggestions of AI will be situational as opposed to the mandatory regulations of products and business which are definitive. This hybrid mechanism decreases that a statistically plausible recommendation is accepted in the event that it breaches a strict configuration constraint. The ensuing configuration representation is the input to further pricing analysis.

Pricing intelligence dimension takes into account the product characteristics, customer environment, previous quotation patterns, price controls, discounts and margin. The AI component is used to determine the relationships between the features of quotations and past business performance, instead of using only static price tables. It can bring out the regularity of a certain price with similar quotes and whether a certain discount that is being charged is abnormal by the aspect of the customer, product and environment where the transaction is taking place.

The relevance of discount analysis is that it is the direct impact of quotation profitability and approval mandate of discounts. This framework therefore considers the degree of markdowns, consumer environment, product building, assumed margin, previous markdown trend and corporate limits. A quotation with a large discount and an acceptable margin may be placed on a regular workflow but a quotation with a huge discount or a minimal margin quotation can be identified to be reviewed again.

3.3 Quote Validation and Risk Assessment

The framework suggests one validation stage incorporating configuration, pricing, and discount as well as policy checks. Configuration does compatibility and dependency checks of products selected. Validity of the prices between setup products, applicable pricing regulations or quotation value. Discount validation decides the pursuance of the organizational discount policies and commercial validation considers the terms of the quotation concerned with margins and other terms.

Depending on the validation mechanism, the mechanism results in a hierarchical stack of quotation results, including missing information, configuration errors, pricing errors, excessively large discounts, policy violations and other exceptions. Such results are then given to the AI-based risk assessment component.

Risk assessment considers quite a number of dimensions and does not depend on a certain threshold. The areas of concern include configuration level, size and nature of unnecessary exceptions, degree of discount-rate, expected margin, idiosyncrasy of client, fault of policy and past approval patterns. The outcome of the risk profile can classify the quotations into standard, moderate-risk and even a high-risk category. This has predefined approval paths to which standard quotations would follow, and all quotations with large deviations will get extra precedence to receive additional human consideration.

3.4 Intelligent Approval and Quote Lifecycle

The proposed framework integrates AI throughout the complete quotation lifecycle:

Customer Requirements → Configuration Recommendation → Configuration Validation → Pricing → Discount/Margin Analysis → Quote Validation → Risk Assessment → Approval → Quote Generation → Monitoring

It starts with customer requirements adding to the SAP CPQ environment. AI-based configuration finds the appropriate products and possible configuration problems. The other step that follows validation is the pricing part that evaluates the prices and terms of business to be applied. A potential commercial deviation is then identified by discount and margin analysis. This one validation system is a compendium of both the technical and the commercial findings preceding risk assessment that will detail the proper route of approvals. Figure 4 demonstrates the risk-aware approval mechanism for differentiating routine quotations from exceptional cases requiring human review.

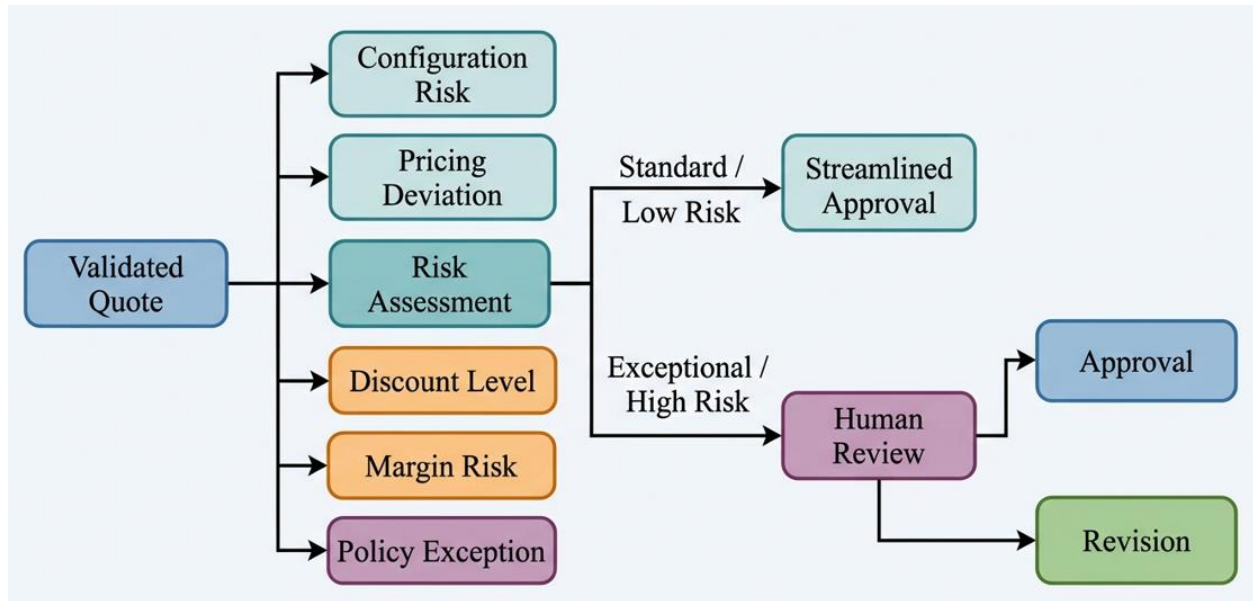


Figure 4- Risk-aware approval orchestration for routing standard quotations and escalating exceptional quotations to human review

Approval orchestration is used to determine the workflow requirements based on the risk profile achieved, and policies in place within the enterprise. Regular quotations are allowed to follow simplified approval channels, but some extraordinary quotations can go into channels of pricing experts, sales managers or other designated individuals. This process enables the focal point of human attention to be on quotations with some meaningful technical or commercial uncertainties.

Once approved, the quote is created with the SAP CPQ environment. The enterprise data layer stores the results of the post- quotation and creates feedback to carry out the subsequent analysis. This theme of life cycle enables the framework to acquire experience on outcomes of quotes, yet is cautious in regulating the variations of models, and decision making of business-level significance.

3.5 Explainability and Governance

The governance component is added to ensure that the AI-guided AI-assisted quotation decisions become clear, traceable and manageable. The recommendations should justify anything of significance with an explainable interpretation that could be on any product relationship, historical trend, price variations, discount limit, or even a known exception of policies. Confidence indicators may also convey the trustworthiness of the AI suggestions and provide users with the information on how far they should proceed with the review.

Traceability can be scheduled by audit records at store quotation level which contain configuration suggestions, pricing suggestions, exceptional instances, risk selection, approval decisions and by-human adjustments. Human users are able to accept, edit, reject and override AI suggestions. Exceptional actuality of quotations where historical trends may not be a suitable mirror of the current commercial setting needs human-in-the-loop operation particularly.

Governance encompasses data quality, access control, security, policy compliance, model monitoring and periodically validating the performance of the AI as well. The dynamics observed in product portfolios, pricing policies, discount structures or approvals that may be occurring may transform the learning relations that have been observed by the history data. Therefore, they should constantly monitor the degradation of models, new exceptions and changes in the decision patterns of the enterprise.

Overall, the proposed framework consists of human-monitored AI architecture that turns SAP CPQ into the foundation of transactions and operations and AI to introduce situational intelligence in configuration, pricing, validation, risk analysis, and orchestration of approvals. Such a converged architecture enables enterprise quotation management to shift off of the isolated rule implementation to coordinated, explicit and risk conscious decision support without loss of



organizational policies and human authority. Figure 5 maps the complete intelligent quotation lifecycle from customer requirements through configuration, pricing, validation, approval, quote generation, and monitoring.

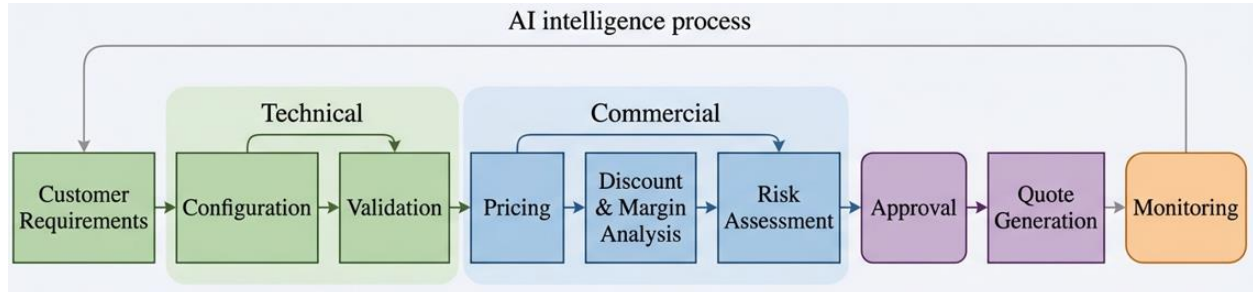


Figure 5- End-to-end intelligent quote lifecycle connecting customer requirements, configuration, validation, pricing, risk assessment, approval, quote generation, and monitoring

IV. FRAMEWORK EVALUATION

The given framework is considered as an empirical framework analysis, but not a traditional implementation conducted in an experiment. The study will determine the effectiveness of AI-based configuration intelligence, pricing intelligence, quotation validation, risk assessment, and approval orchestration to improve the quality and efficiency of quotation management in an enterprise. The comparison will be conducted on the decision-making in AI-assisted quotation as opposed to the traditional CPQ processing where the configuration decisions and price decisions are based on the pre-established rules and the manufacturing exceptional handling. Evaluation is shaped around the representative scenarios of quotation and the measurable indicators reflecting the technical correctness, commercial consistency, working efficiency, exceptions detection, human intervention.

4.1 Evaluation Scenarios and Metrics

It assesses six common scenarios of quotations, which reflect different levels of technical and business advancedness. Common transactions are standard quotations which are comprised of standard set-up products, confirmed prices, norm-discount and set approval conditions. Complex product bundles consist of various configurable components, dependency, optional products and compatibility relationships. Configuration-conflict scenarios are cases of incompatible or unfinished product combinations to test the power of the framework to identify configuration problems at an early stage and to produce quotes.

High-discount quotations (where the discounts are excessive as compared to the normal history quotations or policy-based quotations) and low-margin quotations (where the price presented by one of the commercial parties is a profitability issue) are also taken into consideration in the assessment. Lastly, the exceptional approval cases are quotes that need further review by the manager or specialist due to peculiar setups, price variations, discount rates, or due to policy exemptions. All these situations will encompass mundane and sensational enterprise quotation terms.

The multidimensional metric scale is used in the analysis. Configuration accuracy is a ratio of recommended configurations that match the customer requirements and other compatibility constraints. Conflict detection is a measure of the ability to identify incompatible, incomplete or conflicting configurations. Pricing consistency measures the mode of AI-mediated prices to conform to relevant prices laws as well as similar tendencies in the past quotes. Discount-policy compliance tests how the proposed discounts are in compliance with the organizational policies or in case of deviations the interested discounts are flagged as such.

The efficiency of operations can be calculated using processing time and approval cycle time. Processing time is industrial spent on a quotation to pass through configuration, validation, pricing and quote preparation and approval cycle time is the time between the time of submission and getting approval. The extent of manually manipulations of quotations to which the users are compelled to repackage, re-Validate, or reroute quotations. The extent to which routing quotations to the appropriate levels of approval depends on the accuracy of routing. Finally, the capacity to detect commercially or technically abnormal quotations that should be prioritized further is based on the effectiveness of exception-detection.



4.2 Configuration and Pricing Evaluation

The issue that configuration evaluation is worried about is whether there is an improvement in the process of integration of the appropriate products and the reduction of redundant configuration conflicts with the usage of AI-based recommendations. The use of traditional CPQ processing has a tendency to depend on a body of rules of compatibility omnipresent and still a rule in the imposition of obligatory constraints. The AI layer amplifies these rules with the help of historical patterns of quotations, customer requests, product characteristics, and association inside the products to suggest the contextually related settings.

This is to determine that a set of recommended configurations can satisfy the necessary technical constraints and whether or not the system can settle any potential conflicts, before the quotation moves on to pricing. Special care is taken about intricate bundles with dependencies and non obligatory elements. The enhanced configuration accuracy and the presence of good conflict detection is indicative of AI potentials in providing useful contextual intelligence and guaranteeing deterministic configuration controls.

Pricing testing looks at AI-aided pricing as being at par with the business without revealing internet pricing peculiarities. The assessment is done considering product specifications, customer environment, quotation history, pertinent pricing policy, discount rates and profitability expectations. The conventional CPQ processing provides the basis with the rules-based pricing and pre-established thresholds. The AI-assisted processing is measured in accordance to the ability to identify quotation, rather than a similar price trend.

Especially, the high-discount and low-margin cases are salient as a technically viable quotation might lead to commercial risk. The framework is therefore put to test on how it identifies abnormal discounts and identifies the problems of margin that should be taken care of before accepting it. The stability of pricing and capability to detect deviations means that AI has the capability to augment conventional CPQ controls on pricing and not just generate alternative prices.

4.3 Approval and End-to-End Evaluation

Approval assessment is determined towards the workability of the mechanism offered of risk-conscious orchestration. The criterion to be determined will be the content of quotations to correspond to the appropriate approval level depending on their complexities of configuration, price variation, discount provisions and margin based and policy exemptions. Regular quotations should contain lean approval paths but the risky quotations should be forwarded to appropriate human decision makers.

The correctness of a routing is decided by looking at the proximity of the AI-assisted approval recommendation to that of the corresponding organizational approval policy. Exceptional-case identification is used to judge the accuracy of recognition that quotations that are to receive extra attention are identified. Approval effort relates to the review effort that is needed manually, and human intervention relates to the degree to which the user ought to alter the decisions that have been assisted by AI or the user should redirect quotation manually.

The comparative assessment results are summarized in Table 1.

Table 1- Comparative Evaluation of Conventional and AI-Assisted Enterprise Quote Management

Evaluation Metric	Conventional CPQ	AI-Assisted Framework	Improvement
Configuration accuracy (%)	88.4	95.7	+7.3%
Conflict detection effectiveness (%)	82.1	94.6	+12.5%
Pricing consistency (%)	89.3	96.2	+6.9%
Discount-policy compliance (%)	86.7	95.1	+8.4%
Processing time (min/quote)	18.6	11.2	39.8% reduction
Approval cycle time (min/quote)	42.5	27.4	35.5% reduction
Manual intervention (%)	46.8	25.3	45.9% reduction
Approval routing accuracy (%)	84.5	94.8	+10.3%
Exception-detection effectiveness (%)	79.6	93.5	+13.9%

In Table 1 we also see the cognitive gains in key areas of the technology, commercial, and workflow. The configuration accuracy is increased to 95.7 percent, and the effectiveness of conflict-detection is increased to 94.6 percent. These



improvements imply that AI-based approach can provide more contextual data to the identification of the optimal product mixes and any configuration-related problems.

Also, there is enhancement in the aspects with regard to pricing. The consistency in pricing goes up to 96.2 percent of the consistency and discount-policy conformity goes up to 95.1 percent. These results suggest that the trends on historical quotation based on the fixed pricing and discounting plans can help improve the business sustainability and identify the variation that should be explored. The framework, therefore, augments the company pricing control that becomes deterministic yet with situation intelligence as opposed to replacing the company pricing policies.

The measures that are associated with the workflow reveal the possible worth of smart orchestration. Processing time is decreased to 11.2 minutes per quotation and 27.4 to 42.5 minutes per quotation to approved. Manual intervention is also decreased to 25.3% as opposed to 46.8 meaning that habitual quotations will proceed with less repetitive human intervention. Meanwhile, the accuracy of approval routing goes up to 94.8 percent, implying that the routing of quotations based on risk can be used to guide quotations towards a higher or more suitable approval.

The quality-focused steps that increase the most in comparison to others are exception-detection effectiveness, increasing by 79.6 to 93.5 percent. This option some may find particularly helpful in case of enterprise quotation management as the objective of AI is not to automatize every quotation. The framework, rather, should describe typical cases which can follow simplified workflows and leave technically complex, commercial rarities or policy sensitive quotations to human reviewers.

Lastly, the entire quotation lifecycle is evaluated on the requirement of the customers through configuration recommendation, configuration validation, pricing, discount and margin analysis, quote validation, risk assessment, approval, quote generation and monitoring. The net assumptions are that when all these steps are combined they can cause the consistency and efficiency of the decision making process to be improved compared with simply assessing configuration, pricing and approval as discrete rule-based process.

In general, the analysis proves that the suggested framework could enhance the accuracy of configuration, price stability, detecting exceptions, efficient approval, and efficient quotation-processing at the cost of human control. The findings are also in support of the significance of employing AI as a guided decision-support ability. Commercially important recommendations, which are disseminated to odd quotations, and high-risk exceptions could be open to suitable human review, in a manner that balances automation and governance, responsibility and compliance with enterprise policy.

V. DISCUSSION

The suggested AI-powered enterprise quote management system exemplifies how the artificial intelligence can be used to transform the quotation management procedure that primarily involves adherence to rules to the context-driven decision support. Conventional CPQ systems can have the ability to appeal standardized configuration, pricing, discount, and approval policies, but not as effective to identify the complex interrelationship of these factors. The framework provided will assist in removing this shortcoming through the process of correlating customer requirements, product connections, historic quotes, demand of costs, discounting and margin condition and result of approvals. This implies that both configuration decisions and pricing analysis can be influenced by price variation and margin risks can influence the validation and approval requirements.

The framework has significant contributions to risk-conscious approval orchestration. The framework does not remove the same workflow to all quotations, but rather identifies between routine and technically or commercially extraordinary. The standard quotes could undergo simplified approval procedures, reducing on going processes and management. The quotations containing odd-looking formulations, high-discounts, low-margins or policy variations on the other hand were subject to being escalated to the concerned human examiners. This tactic enables organizations to devote human assets to yield on territory of their utmost significance added.

More automation has been taken on, but human in the loop decision making approach remains to be taken. The AI guidance should also be understandable, editable, and controllable by a human. The valuable configuration, pricing decision, validation, risk and approval decision is to be traced in the audit trails. Trustworthy operation of enterprise also involves appropriate security controls, policy implementation, data-quality and constant model observation.



Several limitations remain. The availability and quality of historical quotation data is crucial to AI performance, and new products might not have enough historical data to make reliable recommendations. The pricing policies, discount schemes and approval schemes may also change as time passes and this would further make the models less relevant. It may be carried out with technical and organizational complexity when it comes to integrating with existing SAP CPQ and enterprise systems. In addition, AI predictions have high uncertainties and cannot be blindly followed to binding business regulations. Ongoing governance, exemplary monitor, modify, and periodical validation is thus needed to guarantee that AI-aided quotation administration stays exact, safe and clarifiable, and in line with advancing company necessities.

VI. CONCLUSION

In this research, a smart quote management system was presented, which requires AI empowerment to SAP CPQ, which combines product configuration, pricing, and quote-validation, risk-evaluation and approval-orchestration under one quotation-process. The framework builds up on traditional rule-based CPQ systems that have emerged to provide contextual insights based on the customer needs, product associations, historic quotes, price trends, bargaining action, margin requirements, and approval results. Herein the proposed approach comes up with an interconnected decision support architecture where the information generated at a given step aids decision making at the other step, unlike configuration, pricing, validation and approval which are independent activities.

The framework will improve accuracy on configurations, consistency on prices, exception finding, efficiency in approvals and efficiency in quotation-processing. AI-aided configuration can help with compatible product suggestions and recognize possible conflicts, whereas pricing intelligence might pinpoint the presence of unusual pricing and discounting schemes, as well as point out margin-related risky issues. These can then be differentiated into routine quotation and exceptional cases by having a centralized validation and risk measurement, which can then be routed appropriately to approvals. The framework also concentrates on the human supervision, explainability, auditability, security, policy compliance and governance in the sense that the AI recommendations are also subject to the human supervision as per the organization.

The proposed solution, therefore, is the change to the rule-oriented quotation processing to the human-oriented enterprise decision support, which is more context oriented. It demands, however, quality of data, past accessibility of quotation that is material, system combination, earning strategies of learning companies and models tracking to work successfully.

The framework could be extended to generative-AI copilot of quotes, which will assist sales users through the quotation form and chatbot configuration that enables customers or sales representatives to shape their needs through a natural language. Other capabilities include lifelong learning derived out of the outcome of quotations, proactive anticipation of margins to find commercial risks and proactive automation of exceptions to determine low-risk exceptions. All of this can cause SAP CPQ to become a more intelligent enterprise quoted system and leave the responsibility of making commercially-material decisions to humans.

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