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Cognitive Automation Frameworks Using Multi-Agent Reasoning for Proactive Enterprise Operational Intelligence

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Abstract

Enterprise Resource Planning (ERP) systems integrate essential business functions through a centralized database, but cannot respond autonomously to data updates. Optimizing these systems requires frequent, expert-level decisions. Recent advancements in AI—particularly optimization algorithms, reinforcement learning, planning, constraint satisfaction, and learning-to-plan techniques—enable autonomous, data-driven decisions. Such decisions enhance efficiency, adaptability, resilience, and profitability. AI agents can specialize in distinct aspects of ERP decision making and cooperate in planning and orchestration. These developments should reposition ERP systems as a foundation for business processes: decentralized ecosystems with emergent behavior, analogous to the transportation and aviation industries, rather than a monolithic backbone. Demand forecasting drives tailored inventory policies that determine order quantities and reorder points. Production planning incorporates capacity constraints, product sequencing preferences, lead times, resource bottlenecks, and sales forecasts to align supply with demand. Decision-makers expect immediate operational support, so these plans require timely updates based on unplanned events.

Three complementary perspectives are relevant in validating decision systems. Temporal accuracy quantifies how well decisions track changes in the real-world environment. Latency assesses the responsiveness of a decision system from the external environment to end results. Throughput accounts for processing demand across the entire planning horizon. Autonomous decision support offers substantial performance improvements; however, scrutiny of the results is essential. Two important facets of quality control relate to total cost of ownership and return on investment of the independent decision-making system or agent.

Keywords : Autonomous AI Systems,AI-Driven Decision Making,Enterprise Resource Planning (ERP) Optimization,Intelligent Process Automation,Predictive Analytics in ERP,Reinforcement Learning for Business Decisions,Self-Optimizing Enterprise Systems,AI-Based Resource Allocation,Autonomous Business Process Management,Data-Driven Enterprise Decision Systems,Cognitive ERP Platforms,AI-Powered Workflow Optimization,Real-Time Enterprise Analytics,Adaptive Business Intelligence Systems,Machine Learning for ERP Efficiency.

1. Introduction

Enterprise resource planning (ERP) encompasses a pivotal organizational architecture in which the flow of data and information sustains operational continuity and performance. Such structures thus assume a vital role for companies functioning in dynamic and discontinuous environments and are properly recognized as critical during the present era of uncertainty. Developing, running, and overseeing these ecosystems require regular, considered high-level decisions geared toward continual improvement, optimization, and a shifting strategic agenda. To this end, numerous techniques and technologies are available, but few processes are autonomous. Solutions that allow for an ever-increasing level of decision automation, aided by recent advances in artificial intelligence (AI), can thus hold significant appeal.

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The specific task currently addressed is the autonomous decision-making–aware optimization of ERP ecosystems by means of AI-driven decision systems. These solutions are capable of computing such improvements without human involvement through the application of core AI techniques at critical times throughout the ERP cycle or by expert inference as part of an assistant architecture. Working definitions of autonomous AI, decision systems, and such systems in an ERP context will serve to delineate the task more precisely.

Autonomous decision-making–aware optimization of Enterprise Resource Planning (ERP) ecosystems refers to the integration of AI-driven decision systems that can analyze, predict, and implement improvements within ERP processes with minimal or no human intervention. In this context, autonomous AI denotes systems capable of perceiving operational data, learning from patterns, and executing decisions independently to enhance efficiency, accuracy, and responsiveness across ERP modules such as finance, supply chain, and human resources. Decision systems act as the analytical core of this architecture, combining techniques such as machine learning, rule-based reasoning, and predictive analytics to evaluate operational states and recommend or automatically apply optimal actions. Within an ERP environment, these systems operate at critical points in the ERP lifecycle—such as planning, execution, monitoring, and optimization—allowing them to dynamically adapt workflows and resource allocations in real time. Additionally, expert inference mechanisms embedded in assistant architectures enable the system to replicate domain expertise, ensuring that decisions align with business rules and strategic objectives. Establishing clear working definitions of autonomous AI, decision systems, and their functional roles within ERP ecosystems helps delineate the scope of this task and provides a structured foundation for designing intelligent, self-optimizing ERP environments.

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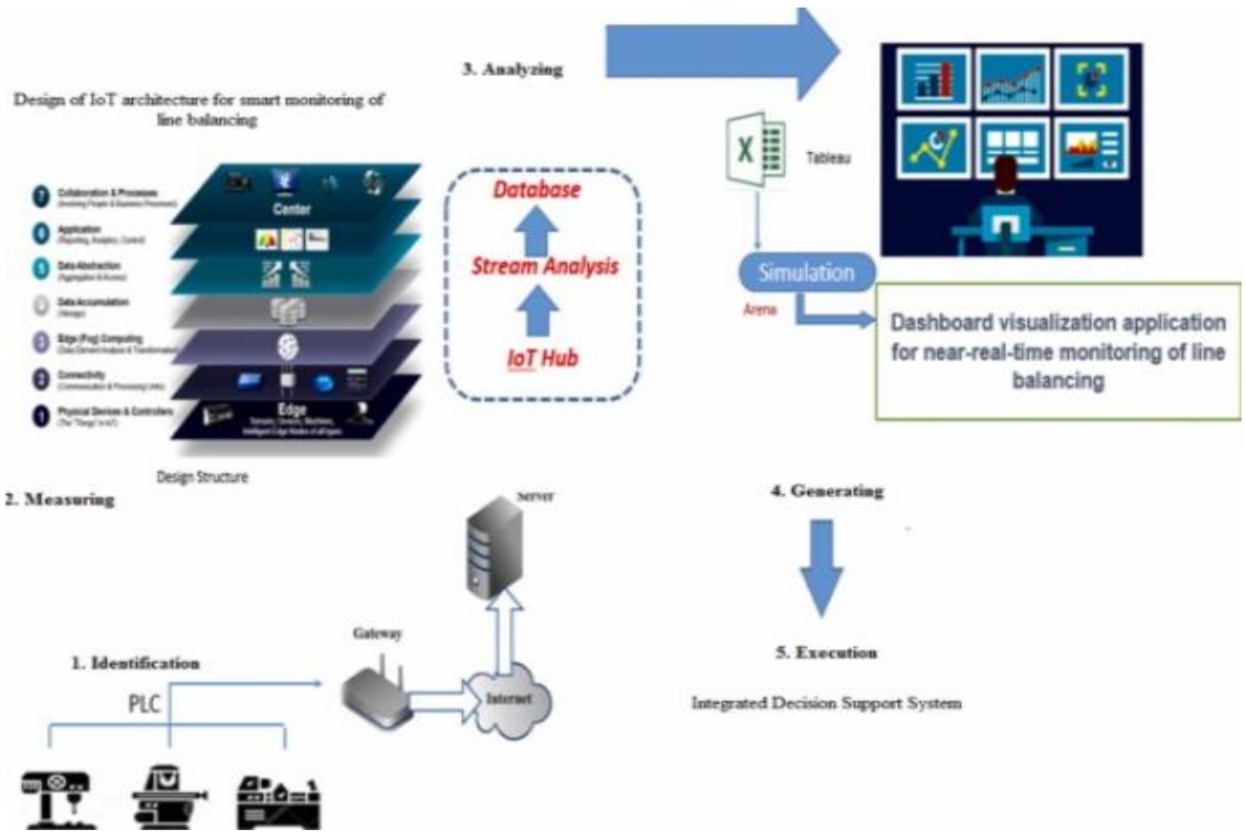

Fig 1: AI-based decision support systems

1.1. Background and Significance

Enterprise resource planning (ERP) encompasses the coordinated management of an organization's shared data, supporting cross-functional flows of information among interdependent tasks—supply, demand, financial, HR, etc.—and enterprise-level records of decisions past and present. Enterprise business outcomes are routed through various such tasks, with physical execution and performance monitoring increasingly entrusted to robotic process automation, robotic outcomes, or similar techniques. Yet deciding at such scales is still largely left unsupervised to human decision-makers—often with adverse effects on enterprise performance. Autonomous AI-driven decision systems can offer timely, accurate input to such scales of resource planning through analysis and optimization at different stages of the ERP cycle.

The term autonomous AI denotes a loosely coupled ecosystem of multi-agent decision systems making use of a variety of AI techniques to execute the four key resource-planning tasks of optimization, forecasting, planning, and constraint-checking, as well as their interconnection through functionality-by-design data pipelines. The use of such systems, however, is usually limited,

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and adoption remains piecemeal rather than entering a fully orchestrated cycle for the mutual benefit of all tasks involved. Strongly autonomous techniques in demand forecasting or inventory optimization, for example, could enable organizations to take decisions closer to an optimal point in terms of costs, service levels, and safety stock levels—provided that such decisions are clearly communicated and integrated back into the procurement planning task.

1.2. Research design

Emerging trends in enterprise resource planning (ERP) optimization and the relevant core autonomous AI technologies indicate a growing potential to realize autonomous, AI-driven decision systems that adjust operational parameters such as forecasting and inventory policies without human intervention. The goal of these technologies and methods is to mitigate the burden of manual configuration, dynamically adapt to changing business environments, and thus enable faster, more frequent, and more efficient decision making. At the same time, new paradigms for decision governance must be established, enabling AI-manufactured operational parameters to be sufficiently accurate and trustworthy to allow autonomous execution.

The work draws on 15 years of experience teaching, developing, and deploying AI-driven solutions for ERP optimization in a wide range of operational contexts. Real-world case studies and empirical evidence are analyzed from previous implementations and documented AI decision-making methods to derive formal criteria and processes for autonomous systems. As an initial contribution to the definition of autonomous AI-driven decision systems, focus is placed on the optimization of ERP business cycles rather than enterprise systems as a whole. Multiple concepts are discussed, namely AI-based forecasting and optimization algorithms, computational reinforcement learning, planning, constraint satisfaction, learning-to-plan schemes, modular AI agents, decision orchestration, data pipelines, ETL/ELT procedures, proximity-based streaming, monitoring, structural alignment, API-based data and application integration, and demand-supplyintegration for ERP optimization.

Equation 1: Example forecasting equation: moving average (what I graphed)

A 4-period moving average forecast for the next period is:

$$\widehat{D}_{t+1} = \frac{1}{4}\sum_{i=0}^{3} D_{t-i}$$

Step-by-step derivation (just algebra):

1. Choose the last $k = 4$observations: $D_t, D_{t-1}, D_{t-2}, D_{t-3}$
2. Add them: $S_t = D_t + D_{t-1} + D_{t-2} + D_{t-3}$
3. Average them: $\widehat{D}_{t+1} = S_t/4$

2. Foundations of Autonomous AI in ERP

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As the business landscape becomes increasingly turbulent, with heightened market competition and external market shocks, organizations are compelled to establish agile internal processes that enable rapid adaptation to changes and exploit new opportunities. The growing complexity of business operations has triggered considerable changes in the paradigms of Enterprise Resource Planning (ERP) and Business Intelligence (BI) systems. Data-driven decision systems — autonomous systems that leverage advances in Artificial Intelligence and Machine Learning to make ERP decisions based on real-time information without requiring interaction with human staff — can be developed independently of proprietary platforms, opening relevant research avenues. Such systems should be understood as modules that automate specific phases of the ERP or BI cycles, fulfilling particular roles in a broader ecosystem of interconnected and interdependent decision systems.

A review of published works using relevant keywords reveals that the realm of autonomous AI-based enterprise decision systems, capable of making systematic decisions with impact on one or more business subsystems, has been only partially explored. Coverage has focused primarily on data-related modules; use cases concerning internal business subsystems have received little attention, and most investigation has centred on planning-adjacent topics. In fact, Business Intelligence and Enterprise Resource Management comprise numerous cycles — Demand Forecasting, Inventory Policy Definition, Supply Planning, Sales and Operations Planning, Production Planning, Production Scheduling, and others — that should be understood as independent endeavors that run in recurrent cycles and can be interspersed with cycles of shorter duration that react to events affecting execution.

— Data lineage represents the map of data movement and transformation throughout the whole processing lifecycle. This map should not only show the origin and history of each data artifact, but also the environment in which it resides and the condition of the data.

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Fig 2: AI in ERP Systems

2.1. Core AI Techniques for Resource Planning

Enterprise resource planning (ERP) applications support business operations across multiple functional areas, thereby producing large amounts of data. Advanced analytics, including machine learning, utilize this data for better decision-making in support of specific operations, teams, and departments. Typically, these decisions are the outcome of a dedicated analysis using highly specialized and costly-to-develop algorithms like simulation, optimization, planning, or forecasting. Performing these analyses at scale is not yet possible. Autonomous systems can manage the entire decision process end-to-end and – when trained with sufficient domain knowledge – can produce high-quality solutions with little to no human intervention.

Autonomous decision-making systems, guided by an appropriate AI architecture have thus far been used in ERP applications addressing demand, supply, and production. The most pressing issues – that is, demand forecasting, inventory management, production planning, and scheduling – appear in most manufacturing, trade, and service industries; additional, less frequently encountered topics, such as pricing, transportation management, and personnel planning or scheduling also appear. Seven queues of decisions in inventory management – forecasting, service-level determination, safety-stock calculation, and decisions in procurement, replenishment, stock transfer, and disposal – may also lend themselves to near-autonomous resolution.

Equation 2: Forecast error and accuracy (the paper explicitly calls for “accuracy” beyond curve fitting)

Autonomous AI-Driven Decision S…

Define error:

$$e_t = D_t - \widehat{D}_t$$

Then common accuracy metrics:

MAE

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} | e_t |$$

RMSE

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$$

MAPE (percentage)

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$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n} \left| \frac{e_t}{D_t} \right|$$

2.2. Data governance and quality in ERP ecosystems

In the context of data pipelines within ERP, data governance encompasses a wide-ranging policy framework involving people, processes, and technology, which ensures high-quality, consistent, and trustworthy data that comply with the established internal and external regulations. Several components need to be taken into consideration: data lineage, data stewardship, data quality metrics, data metadata, data access control, data privacy, and data synchronization across the different business modules of an enterprise.

— Data stewardship encompasses the definition of responsibilities in relation to data governance and data quality control. These responsibilities can comprise the review of data access requests, the definition of business-related objects used in the ETL, supervision of data quality checks, definition of data lineage, definition of data dictionary with business definitions for all objects, supervision of data privacy, review of organizational control objectives, and communication to users on data-related issues.

— Data quality metrics include availability, timeliness, integrity, accuracy, completeness, consistency, and uniqueness. The presence of any deficiency in one of these metrics should activate a properly defined control procedure.

— Data metadata are information that describe the data and can enrich its usage. The building of data metadata should be planned and followed.

— Data access control is a mechanism rooted in data privacy and data protection regulations. The access control definition can include, for instance, roles or business teams that have analytical access to the data.

— Data privacy includes laws and regulations that determine how to deal with sensitive information. These privacy preservation means should be defined before using data in an analysis.

— Data synchronization captures the condition of data stored in systems that have a different frequency for data update. When two data repositories that require analytical integration have different frequencies for data update, a synchronization mechanism should be defined.

3. Architectural Paradigms for Autonomous ERP Systems

The architecture of autonomous AI-driven decision systems in ERP optimization encompasses design patterns for modular AI agents, a requisite data pipeline, and integration mechanisms to form a coherent architecture. The agent design considers the level of autonomy, while coordination patterns between agents dictate decision latency, decision failover, and GPA considerations. A thorough analysis of the various data sources and data movement across the ERP ecosystem creates the data architecture that underpins any AI-based decision-making.

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Autonomous ERP has emerged as an extension of the broader trend toward autonomous decision-making in business and technology. An ERP system produces vast amounts of data through modules such as material management, warehousing and logistics, sales and distribution, production planning, quality management, and financial accounting. The information from each of these modules is highly interdependent—demand forecasts drive procurement, and production scheduling must take into consideration resource capabilities and availability, inventory levels, and demand from customer orders. Changes to one module's data, particularly in a high-velocity environment, are likely to necessitate changes in several other areas. The ability to adjust decisions quickly is therefore critical.

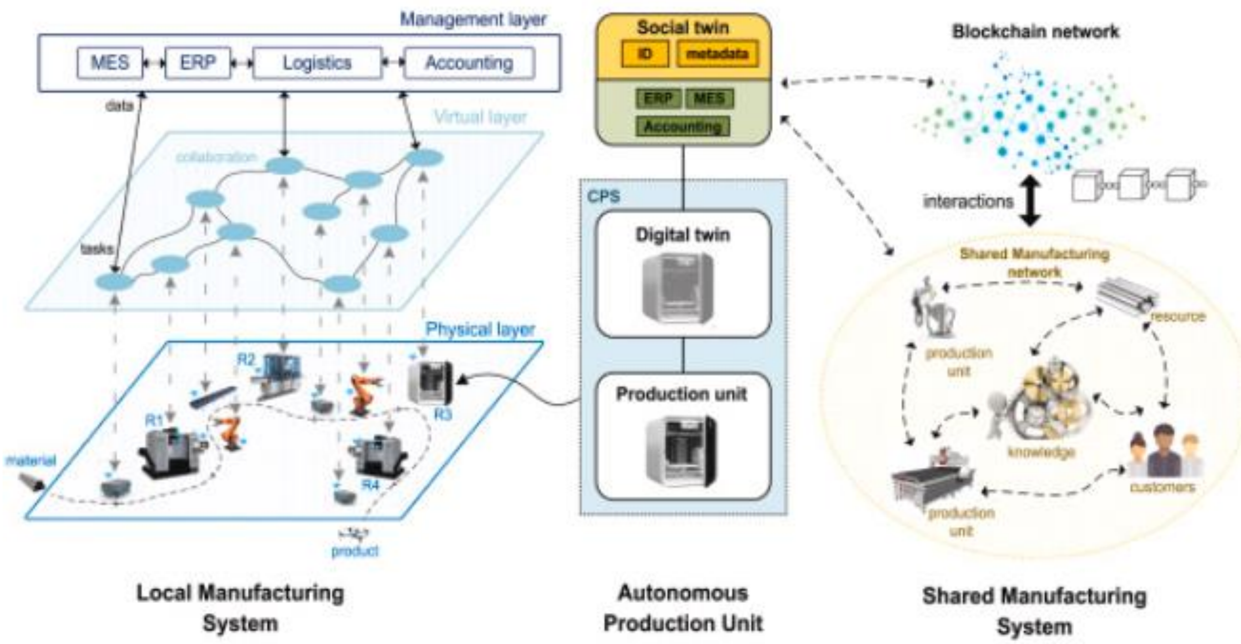

Fig 3: Architectural Paradigms for Autonomous ERP System

3.1. Modular AI agents and orchestration

The design of modular AI agents suitable for enterprise resource planning (ERP) systems is an active area of research. Modularization aims to balance the advantages of independence and specialization of agents with the benefits of orchestration and coordination. A dedicated module can be developed for each part of an ERP cycle (for example, forecasting, inventory optimization, and production planning) without any dependence on the other modules, which operate independently with infrequent decisions. Coordination typically arises because the demand used for inventory optimization can be generated by the forecasting agent, the inventory policies obtained can be applied to the procurement module, and the aggregation of supply across products and warehouses is important for production planning. Keeping decisions independent enables the use of highly efficient algorithms (for example, shallow search trees for warehousing inventory optimization), as long as significant decision latency can be tolerated.

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Latency in decision-making is a key attribute of ERP. Unlike event-driven architectures, which focus on reducing overall latency and are designed for a set of business processes that take at most a few seconds to complete, ERP systems typically support decision cycles that can take hours or days to execute. Consequently, the emphasis is to minimize latency of each specific decision and to decide whether the risk of making a decision later depends on the decision latency of other interdependent agents. While the decision time is the algorithm execution time, the scenarios selected by the agent for real-time execution can be performed on different instances of the algorithm running in parallel mode to improve the overall latency. In case of failure of the main instance, responsibility can shift to an instance providing a result after a longer period.

3.2. Data pipelines, integration, and interoperability

In an enterprise resource planning ecosystem, the activities in the various modules typically correspond to well-defined stages in a company's business processes. For example, demand-side transactions (sales orders) create need signals in the systems/modules associated with supply-side processes (supply planning and inventory management). As such, the underlying data sources for the demand-side modules, databases required for running ETL processes, and data destination objects are all evident. However, it is the integration and interoperability across these modules that determines the effectiveness of the overall system or solution from an enterprise perspective. One of the major advantages of autonomous AI decision systems should be the exploitation of data streams within a module, across modules, or in the wider ecosystem for decision-making processes with limited or no human intervention.

Data pipelines supplementary to those supporting basic transactional operations must therefore be established to avoid delays in the availability and timeliness of critical information. Key aspects for enabling such data pipelines and, consequently, autonomous AI decisions are the data sources for the decision system, the ETL or ELT methods adopted, the methods supporting data transfer—streaming-based as opposed to batch-based—the need for schema alignment, the API used for interoperability across different software stacks, and data governance across these areas.

Equation 3: Lead-time demand distribution

Assume:

- Lead time L(in periods)
- Per-period demand mean μ, stdev σ
- Independent demand per period (common baseline assumption)

Then lead-time demand is:

$$D^{(L)} = \sum_{i=1}^{L} D_i$$

Mean

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$$\mu_L = \mathbb{E}[D^{(L)}] = \sum_{i=1}^{L} \mathbb{E}[D_i] = L\mu$$

Variance

$$\mathrm{Var}(D^{(L)}) = \sum_{i=1}^{L} \mathrm{Var}\,(D_i) = L\sigma^2$$

Standard deviation

$$\sigma_L = \sqrt{L}\sigma$$

4. Optimization Strategies and Use Cases

The trade-offs across inventory policies (service level, safety stock, fast-moving items) can be explored using various demand forecasting techniques for a predefined planning horizon. Demand forecasts can serve as input to determine procurement schedules and inventory replenishment triggers for (near) autonomous integration into the relevant ERP modules. Also, the relevance of the upstream and downstream supply chain to the demand of each product family should be considered, aiming for reduced overall investment tied to working capital.

Production planning and scheduling efforts are generally concerned with capacity constraints, sequencing, lead times, bottleneck analysis, and real-time adjustment of the schedule and execution priority to accommodate unforeseen changes. The planning task seeks to assure that sufficient production capacity is available to meet anticipated demand, while scheduling determines which goods will be produced when. Planning and scheduling approaches often focus on a subset of the available production resources or consider a limited period

Demand forecasts, planning production capacity, and scheduling production execution are frequently executed in distinct and isolated operations, yet these processes should be rather tightly interlinked to deliver an optimal overall result. Distinct but intertwined explanation frameworks for the underlying models can be pursued: demand forecasting methods shape decisions on desired services levels or safety stocks—together with risk considerations and working-capital expenditures—while production planning and scheduling mainly address capacity limitations within the ERP framework.

Specifically, the demand forecast should be regarded as a primary upstream steering mechanism for the entire supply chain. It can be argued that demand forecasts can be refined, modified, or replaced more easily than the capacity that should be set up and then maintained to achieve the desired services levels.

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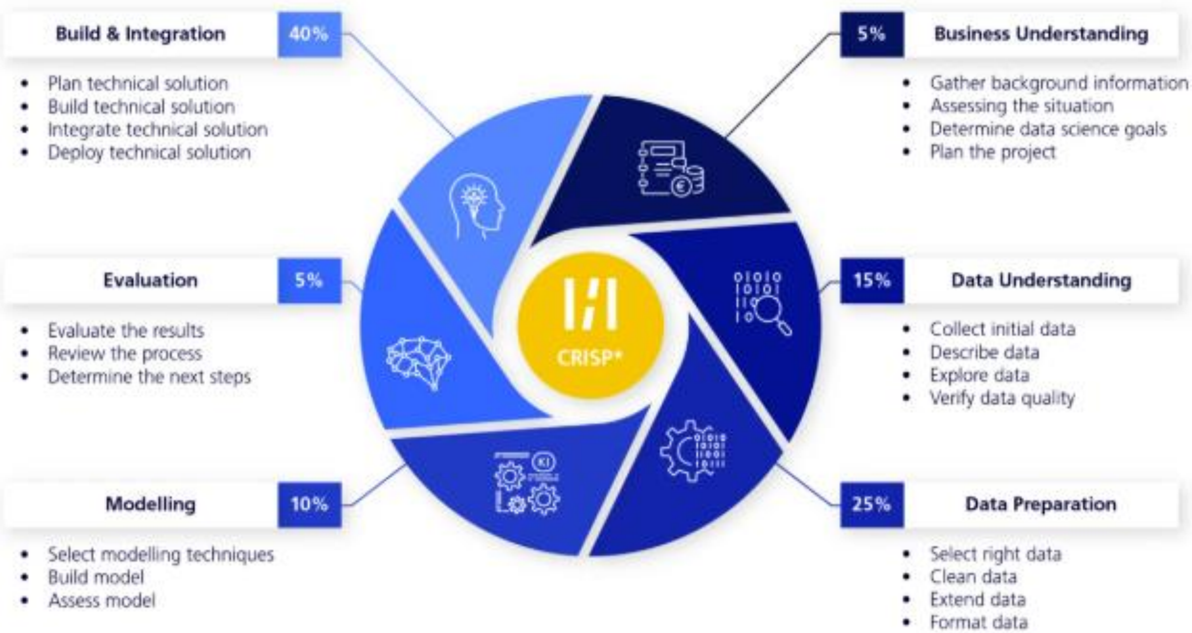

Fig 4: AI-Driven Process Optimization

4.1. Demand forecasting and inventory optimization

Accurate, timely demand forecasts are essential, enabling optimal inventory levels that align with demand patterns while meeting service objectives. Forecast uncertainty drives buffer stock levels, with excess inventory accumulating holding costs. Insufficient inventory compromises service quality. Reliable forecasts facilitate seamless inventory replenishment. Several statistical methods for forecasting, including supervised ML and multivariable models, predict upcoming demands. Inventory policies identify the order quantity and timing, accounting for costs and service aspirations. Differentiated service levels among products influence product-class buffers and underpin product prioritization. Operating under an inventory policy defines a procurement plan for raw materials or semi-finished goods.

Group demand patterns offer predictability and classification for products. Service-level constraints that rely on forecast accuracy can be incorporated into safety-stock calculations. Using a batch-forecasting approach, forecast horizons are aligned with provisioning terms specified by procurement or production planning. Integrating budgetary limitations establishes framework conditions for model executions, and safety-stocking calculations enable inventory policy definition, determining order quantities and timing for next-level inventory elements such as finished-goods or distribution-center stocks. Integrating service-level aspirations into inventory optimization examines trade-offs among service levels, inventory spending, and budgetary ceilings. Due-date-driven procurement policies regulate replenishment in sync with lead times. Multiclass inventory policies generate differentiated service levels that emerge from demand-distribution characteristics. Safety stock performs well under disequilibrium situations driven by lead-time mismatches.

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Simultaneous safety-stock and order-up-to-level specification ensures cohesion between inventory-absorption capacity and replenishment volume. Cost-sensitive demand-class forecasting acknowledges inventory-investment shaping and budgetary ceilings by generating a procurement plan, home-actuating buffers, and prioritized demand-class fulfillment. Safety stock performs adequately while tracking total-lost-sales criteria. Safety-stock levels shaped by variance- and skill-driven corridor thresholds account for budgetary limitations. Active collaboration between demand-forecasting, sales-operations-planning, and demand-sensing groups can mitigate demand-forecasting errors. Bridging the leaf-and-root-class forecast patterns using serviceful apex-forecasting patterns reduces holding costs.

Equation 4: Order-up-to level (periodic review)

If review period is $R$and lead time is L, protect over $L + R$:

$$S = \mu_{L+R} + z\,\sigma_{L+R}$$

with

$$\mu_{L+R} = (L + R)\mu, \sigma_{L+R} = \sqrt{L + R}\,\sigma$$

Order quantity each review:

$$Q_t = \max(0, S - IP_t)$$

where $IP_t$is inventory position (on-hand + on-order − backorders).

4.2. Production planning and scheduling

Production planning and scheduling are critical components of manufacturing management that aim to align supply with demand in a timely manner while ensuring accurate order fulfilment at minimum cost. Production planning provides an overall plan for a specific time period (i.e., volume across product families), supported by materials supply and inventory replenishment plans, while production scheduling specifies how resources, such as machine tools and manpower, will be allocated to production tasks in the near term. Both problems must be solved repeatedly by an enterprise on a daily, weekly, and monthly basis due to the fluctuating nature of demand and the uncertainties introduced by the (semi-)perishable nature of products in the manufacturing process, in supplier reliability, and in supplier delivery times.

Demand forecasting serves as a stepping stone to production planning and control so that supply can closely follow demand. Basically, a demand forecast provides the basis for assessing the inventory levels needed in order to meet a pre-specified service level. Inventory policies—for example, order-up-to-level policies—state when to replenish the stock level and when to firm up the orders. Inventory management is thereby integrated with procurement planning. The level of safety stock is then used to determine the service level at which the product can be offered to customers. Care should be taken, however, that safety stock or safety lead time does not induce mismatch in production planning and procurement schedules. Production planning represents a major part of the manufacturing budget. Any underutilization of the production plant increases the cost per unit manufactured and may also lead to an indirect cost through higher prices to customers. Conversely, overtime increases the cost significantly. In a

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two or more-stage operation, two or more of the production family groups may have to be sequenced together to optimize the usage of bottleneck resources.

5. Evaluation, Validation, and Metrics

Autonomous AI-Driven Decision Systems for ERP Optimization

Performance metrics for autonomous decisions encompass accuracy, latency, throughput, return on investment, total cost of ownership, and overall decision quality. Accuracy refers to the goodness of fit for forecasted values, but curve fitting alone is often insufficient to assess performance in a business context. Latency and throughput are key for high-velocity decisions, and for long-term decisions, return on investment and total cost of ownership support a broader evaluation. For evolving decisions, quality goes beyond classical measures, accounting for stability across multiple dimensions.

Robustness under perturbations is important when decisions cannot be supervised. Fairness across products/assets helps mitigate economic disparity. Explanations are crucial for decisions without calibrators, and bias mitigation shields models from dangerous learning. The above metrics guide the design of autonomous AI decision systems, spanning demand forecasting, inventory optimization, production scheduling, and performance management. Case studies of ERP systems emphasize demand forecasting and production scheduling, demonstrating the applicability of reinforcement learning, statistical process control, control charts, etc., with classic and lightweight architectures. Work to enhance fairness and mitigate bias provides additional angles for exploration.

Complete results indicate that, even when predictions are inaccurate, a well-designed and quickly evolving process can achieve high overall performance, minimize cost, protect against stockouts, and generate net profit while decreasing operational effort with increasing volume. Such performance can be achieved without using such techniques and with relatively unskilled operators. Acknowledging the possible use of other AI techniques and with a different distribution of work across the demand nodes serves mainly to showcase the application of method and their augmentation. Future studies will address the performance and impact of structuring the decision under the modular-parallel perspective proposed for autonomous AI systems.

Equation 5: Production planning with capacity constraints (optimization model)

- $x_{p,t}$: units of product $p$produced in period t
- $I_{p,t}$: ending inventory of product $p$in period t

Inventory evolves as:

1. Start with last period inventory $I_{p,t-1}$
2. Add production $x_{p,t}$
3. Subtract demand $D_{p,t}$

$$I_{p,t} = I_{p,t-1} + x_{p,t} - D_{p,t}$$

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Let $a_{p,r}$ be capacity consumption of product p on resource r (e.g., machine hours/unit), and $C_{r,t}$ available hours:

$$\sum_{p} a_{p,r}\ x_{p,t} \leq C_{r,t} \forall r, t$$

$$\min \sum_{p,t} \left(c_p^{prod} x_{p,t} + c_p^{hold} I_{p,t} + c_p^{back} B_{p,t} \right)$$

5.1. Performance metrics for autonomous decisions

Decision systems producing autonomous decisions require specific performance metrics that may differ from traditional business analytics systems. Besides the standard metrics of accuracy, response latency, throughput, return on investment, and total cost of ownership, adherence to user-defined decision quality criteria is also essential. Metrics provide business stakeholders with high-level indicators on the achieved performance of autonomous decisions and indicate whether the implemented decision system is delivering with the expected quality.

The majority of autonomous decisions in enterprise resource planning systems are discrete in nature, in that one decision is made for a specific point in time and decision space. Therefore, the impact of all autonomous decisions can be treated as a set of independent decisions. Decision latency and throughput determine the system's ability to cope with business analysis needs in a timely manner. However, unlike business analytics systems, which represent schedules and reports that assist human decision-makers, those metrics indicate the capability of the autonomous decision system to produce results at the required frequency for integration back into the business process and execution cycle.

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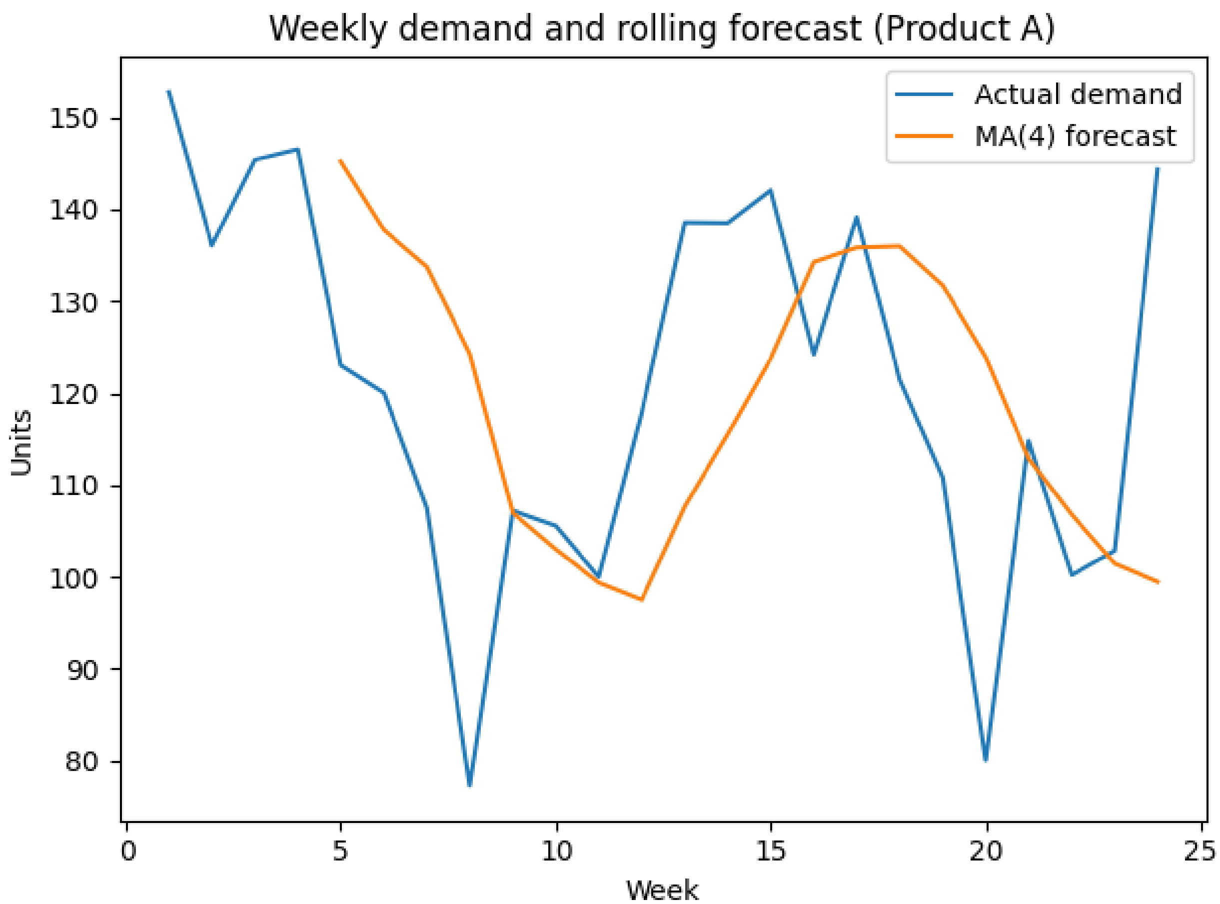

5.2. Robustness, fairness, and bias mitigation

The robustness of an autonomous decision system accounts for the quality of its decisions under changes in inputs and operating conditions. It is essential to detect weaknesses in a decision system by perturbing inputs and validating its decisions against expected outcomes. In the case of demand forecasting models, performance can be evaluated using cross-validation, assessing the effect of outliers, and analyzing changes in prediction accuracy across different products. During inventory optimization, it is crucial to analyze the service-level attainment under different demand scenarios. Pipeline capacity decisions must be tested under possible sales-volume scenarios and also under predicted stock imbalance resulting from demand forecasts. Performance under adverse conditions, such as supply-chain disruptions, stock-outs, or extreme weather events, is equally important. Performance must not only be assessed as a whole but also segregated across products to ensure fairness (Perez et al. 2021).

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Decision systems are fundamentally biased toward older data if left unchecked. Fairness, therefore, also implies a meaningful distribution of data across the training intervals. External sources can help mitigate the bias, but generally speaking, fairness requires applying different considerations in the architecture of each decision system. Metrics should focus on specific assets being treated. Bias in demand forecasts may affect service-level attainment recommendations, while forecast errors may influence inventory costs and profits and inventory errors may affect freshness costs.

6. Governance, Risk, and Compliance Considerations

Ethical and legal implications: accountability and transparency of autonomous systems; consent for data consumption and model training; vendor risk management; compliance with existing and emerging legislation.

Auditability and traceability: external and internal logging requirements; provenance of autonomous decisions and data products; reproducibility and external auditing as criteria of trustworthiness.

The relevance of Governance, Risk and Compliance is twofold: fostering the adoption of Autonomous AI throughout organizations and industries, and ensuring that Vulnerability Management and Mitigation Plans remain within reasonable boundaries. These two aspects are addressed below.

Accountability and transparency are mandatory for Autonomous AI systems. Organizations shall be able to explain the reasons behind every decision made, validate and check for adherence before executing, and attribute responsibility for failures. Consent of data owners is essential for any model relying on data harvested elsewhere. Therefore, a consensus among stakeholders can favor the development of Autonomous AI in sectors demanding availability. It should also be possible for organizations to share trained models with third parties for faster consumption, and service-level agreements would mitigate vendor risk. Moreover, emerging legislation on the ethical use of data and AI (such as the EU AI Act) imposes restrictions on the adoption of these technologies in sensitive areas, making compliance essential. Legal exposure can also come from the use of decision outputs in a context that was not foreseen initially. External audit can help validate transparency and exposed logic.

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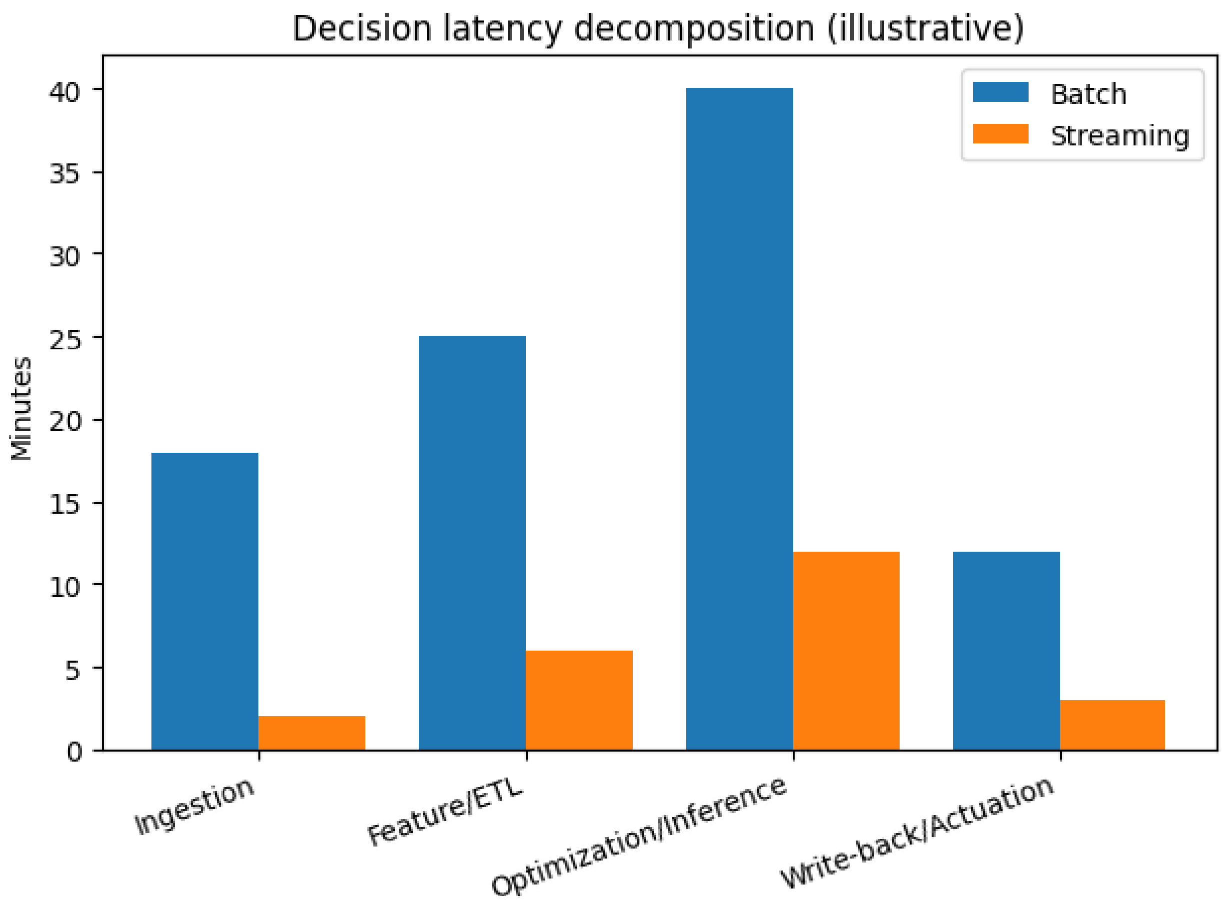

6.1. Ethical and legal implications

A solid governance, risk, and compliance framework is crucial to creating trust in autonomous AI-based decisions. The absence of governance mechanisms that define who is accountable for the decisions can hinder their adoption. For example, when an ERP module automatically decides to advance an order in the production schedule and the order is missed, results point to the production planning module. But is it due to a bad decision or to the bad data or an unacceptable bias baked in the training data? It can also be difficult to determine what constitutes an acceptable decision by the module. The introduction of GRC ensures that these questions are answered. Determining who should provide consent to the decisions is also essential. For example, if credit risk assessment is automated within the ERP system and leads to a credit block for a product by a supplier in the supply layer, should the supplier or the consumer need to give consent? Vendors also need to be evaluated to ensure that they adhere to GRC principles. The risk associated with the vendor should also take into account their training set and whether it contains known bad

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outcomes so that the deployed model reflects only known good outcomes. Similarly, regulatory alignment ensures that attribution, transparency, consent, vendor risk exposure, and other related aspects are covered.

Auditability of the decision must also be addressed. All decisions must be logged to ensure provenance—where the data come from and how they influenced the decision—and reproducibility, so that the same decision can be repeated using the same data. Additionally, decisions must be audit-ready to allow an external audit to verify that GRC is being followed. Failure to adhere to these principles will complicate the adoption of autonomous AI-based decisions.

6.2. Auditability and traceability

Auditability and traceability requirements are stringent in decisioning-critical domains such as finance and public safety, and are increasingly demanded in other business functions as well. Every decision taken should be logged, together with information that allows for a full provenance check, including how the input data was generated, which particular agents executed which parts of the decision-making process, how requests to external services were formulated and answered, how the outputs were generated based on all of the above, and how any relevant supra-agents or human users reacted to, commanded, or were influenced by the process out. Furthermore, auditability should also extend to the feasibility of re-running the decision-making process for given input values without alterations to the system and environment states. This is important to evaluate the decision quality or any future appeal of the decision. Techniques such as digital fingerprinting could be employed to ensure that re-running the process for a given input values truly yields the same results. Any inconsistency would point to hidden changes in the AI agent's reasoning, the data generation process, or the remote services that the agent relies on. Lastly, stakeholders must be able to audit the input-output behaviour of the automated decision-making in a zero-knowledge fashion, meaning they must be able to ascertain that patterns do not introduce unfairness or hidden biases across different agents, product lines, assets, or classes of service provision, while ensuring that no sensitive private details enter the decisioning process and no sensitive private details can be inferred from it at any point.

7. Conclusion

The trajectory of enterprise resource planning research during the last decade suggests increased sophistication of ERP decision-making. It appears that decision automations will leverage continuous improvement cycles with a dual aim of enhancing the performance of the process itself and also creating a higher-quality support environment for the remaining human decisions. In fact, the pressure on enterprises reduces the margins of error on the decision that still rely on human intelligence, so those will need to be supported with the best possible data and prescriptions. Hence, it is natural to expect the emergence of hierarchical systems composed of decision agents that have different levels of data automation. At the lower level, the data-intensive decisions will exploit autonomous AI-driven decision systems. These systems will extract information from internal and external data sources in order to generate decisions for the next time bucket following defined policies, while obeying constraints imposed by supervisory functions. They will therefore naturally take over the data-intensive and data-supporting decisions.

On one hand, they should be as flexible as possible to exploit the known algorithms that provide the best autonomous solutions for each decision type. On the other hand, the supervising function should guarantee that the quality of these decisions remains acceptable, that is, they shouldn't drift too far from the acceptable margins defined by the upper layer actor. The exploration of quality margins determined by the supervising function will provide a level of reinforcement learning to the different decision

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types. The introduction of such agents represents a first realisation of the virtuous circle of participative cooperation among systems, where every agent is involved and benefits from the others acting competently and efficiently in their own domains. The autonomously driven decisions will therefore provide a powerful orchestration of the overall organisation, supporting better-quality human decisions at higher levels of the hierarchy and automatically acting on a high number of decision time buckets.

In complex organisational systems, decision-making agents should be designed with a balance between autonomy and oversight. On one hand, these agents must remain flexible enough to utilise specialised algorithms that generate the most effective autonomous solutions for each type of decision. On the other hand, a supervisory function is essential to ensure that the outcomes produced by these agents remain within acceptable quality margins defined by higher-level actors. This supervisory layer monitors and evaluates decisions, preventing them from drifting beyond the boundaries of acceptable performance. By exploring and adjusting these quality margins, the system introduces a form of reinforcement learning that continuously improves the behaviour of the agents across different decision categories. The integration of such intelligent agents establishes a virtuous cycle of participative cooperation among systems, where each agent contributes its expertise while benefiting from the competent actions of others within their respective domains. As a result, autonomously driven decisions enable a powerful orchestration of organisational processes, reducing complexity and enhancing efficiency. This not only automates numerous operational decision timeframes but also supports higher-level human decision-making with more reliable and timely insights.

Product	MAE	RMSE	MAPE_%
A	17.83	23.12	16.36
B	18.56	22.28	25.88
C	10.99	12.45	24.77

Table : Forecast accuracy metrics (synthetic example)

7.1. Emerging Trends

The quest for autonomous systems has accelerated with developments in artificial intelligence, notably the emergence of generative AI. The evolution of large language models fuels progress toward the convergence of statistical-learning-based AI, symbolic AI, and mathematical optimization into an all-encompassing framework for “artificial life.” Modern environmental and data-economics paradigms stress the importance of improving enterprise efficiency, especially resource allocation, waste minimization, and the implementation of low-cost workers in all decision processes. In the context of ERP systems development, building remains an important option. Especially as the autonomous product service business ecosystems emerge, the service ecosystem provides the necessary command and data feedback. The long-standing goal is to allow virtualization of the entire decision-making chain of all resource-and-time-consuming products and services.

The future of these developments envisions an emerging autonomous virtual enterprise for real-time collaboration and production in multi-enterprise ecosystems. Consolidating these visions leads to the definition of a synthesis of demand forecasting and inventory optimization PCP case; production planning and scheduling. Automation of the “SAP APO” toolbox by integrated modular AI agents. Providing critical explanation by classifying these agents built-in reflex level. As well as building business-

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ready autonomous orchestration services to provide fully autonomous resource planning. Technology and market conditions may differ, but the need for autonomous ERP optimization remains a priority for almost all enterprises independent of their sector characteristics. Early adoption cases and proof of concepts pave the way for a maturing ecosystem.

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