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# Data-Driven Decision Intelligence: Leveraging AI and Cloud ERP Analytics for Strategic Enterprise Agility and Risk Governance

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## Abstract

Organizations are increasingly operating in volatile, uncertain, complex, and ambiguous (VUCA) business environments. To remain competitive, they must be agile, make fast & accurate strategic decisions, and effectively govern risk. Cloudbased ERP systems hold vast operational, financial, supply chain, and human resource data. Coupled with Artificial Intelligence (AI) and advanced analytics, these data assets can enable decision intelligence: the ability to anticipate trends, simulate scenarios, and guide strategic action. However, realizing this promise requires overcoming significant challenges: data silos, data quality, latency, model trust, risk of bias, regulatory compliance, and alignment with governance frameworks.

In this paper, we propose a comprehensive framework titled AIDriven Decision Intelligence for Cloud ERP Analytics aimed at enabling enterprise agility and strengthened risk governance. The framework integrates modules for realtime analytics, predictive forecasting, scenario modeling, prescriptive recommendations, and continuous risk assessment. It builds on cloud ERP to provide integrated dashboards, anomaly detection, stress test simulations, and policy compliance modules. Key features include data ingestion and cleansing pipelines; AI/ML models for demand forecasting, cash flow, supply chain disruption, fraud detection; management of model governance (explainability, fairness, version control); and embedding risk governance and audit layers consistent with regulatory and enterprise risk frameworks.

We evaluate the framework in a case study of a midsized manufacturing enterprise using a cloud ERP deployment, across modules: supply chain, finance, and operations. Performance metrics include forecasting accuracy (e.g. demand, cash flow), speed of decisioncycle, reduction in risk incidents (inventory stockouts, supply disruptions, financial anomalies), and agility measures (time to respond to disruptions). Results show that predictive forecasting improved demand forecast accuracy by ~2530%, supply chain disruption alerts reduced lead time to respond by ~40%, and risk incidents in finance dropped by ~20%. The agility of planning cycles improved, enabling scenario simulations that allowed leadership to test "whatif" supply or demand shocks. Model governance mechanisms helped improve trust among stakeholders; results also highlight tradeoffs: more aggressive forecasts can generate false alarms; cleaning data and ensuring data quality impose overhead; regulatory compliance may slow down deployment of certain analytics.

We discuss the advantages of the framework: strategic alignment, risk mitigation, faster decisionmaking, improved resilience, and competitive responsiveness. Disadvantages include increased complexity, need for skilled personnel, cost of setting up data pipelines and governance, and risk of overreliance on models that may not generalize in novel conditions.

In conclusion, AIdriven decision intelligence via cloud ERP analytics offers promising capacity for enterprise agility and robust risk governance. Future work includes refining explainability, integrating external data (market, geopolitical, climate), realtime simulation and digital twin integration; exploring transferability to different industries; and establishing standardized benchmarks for decision intelligence performance and risk governance in cloud ERP settings.


**Keywords:** Decision Intelligence; Cloud ERP Analytics; Strategic Agility; Risk Governance; Predictive Analytics; Prescriptive Modeling; Model Governance; Scenario Simulation; Enterprise Data Quality; Business Intelligence.

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## Introduction

Modern enterprises are under growing pressure to operate more agilely: to anticipate market shifts, respond to supply chain disruptions, manage financial risk, and adapt operations quickly. Traditional decisionmaking processes—often retrospective, manual, or siloed—are inadequate for highly dynamic environments. Meanwhile, cloudbased Enterprise Resource Planning (ERP) systems have become central hubs of integrated operations: finance, supply chain, procurement, manufacturing, HR, etc. They accumulate vast quantities of transactional, operational, and financial data, often in real time or near real time.

AI and analytics overlayed on cloud ERP offer a powerful opportunity: to turn that voluminous data into decision intelligence. Decision intelligence refers to systems and processes that not only report past performance (descriptive analytics) but forecast future trends (predictive analytics), evaluate alternative options (scenario or simulation modeling), and prescribe recommended actions (prescriptive analytics). These capabilities are crucial for strategic planning, risk governance, and enabling enterprise agility—i.e. the ability to pivot in response to changing internal or external circumstances.

Yet, enterprises face challenges in realizing this potential. First, data issues: data in ERP systems may be siloed across modules, inconsistent, delayed, or incomplete. Second, analytical challenges: selecting appropriate models, ensuring forecast accuracy, handling uncertainty, measuring risk. Third, governance, trust, and ethics: stakeholders must trust AI models—explainability matters; bias, fairness, and compliance with regulations (financial, privacy) are important. Fourth, organizational readiness: culture, skills, metrics, leadership support, and alignment of analytics with strategic objectives matter. Finally, technical/infrastructure concerns: cloud ERP analytics must integrate data pipelines, ensure security, scale performance, support scenario modeling, and provide easy dashboards.

This paper proposes a framework—AIDriven Decision Intelligence using Cloud ERP Analytics—to help enterprises enhance agility and risk governance. Our contributions are:

*Framework design*

We design a modular architecture combining cloud ERP data, predictive analytics, scenario modeling, prescriptive decision support, and governance layers for risk oversight.

*Model governance and risk governance integration*

Embedding explainability, bias detection, audit trails, versioning, and alignment with enterprise risk management (ERM) and regulatory compliance (e.g. financial controls).

*Strategic agility enhancement*

The framework enables faster decision cycles, scenario simulations (whatif), and proactive alerts for risk conditions (inventory, cash flow, supplier disruption).

*Empirical demonstration/case study*

We apply the framework in a manufacturing enterprise using cloud ERP, and show improvements in forecasting accuracy, reduction in risk incidents, improved responsiveness.

*Analysis of tradeoffs & challenges*

Not all analytics are costfree; we examine complexity, model trust, false positives, resource demands, data cleansing, and alignment with governance.

The rest of this paper is structured as follows. In Section 2, we survey the literature on ERP analytics, decision intelligence, risk governance, and strategic agility. Section 3 describes the methodology and framework design. Section 4 presents case study, results, and discussion. Section 5 concludes, with directions for future research.

## Literature Review

Below is a structured survey of prior work relevant to this topic, organized by themes: ERP analytics & BI; decision intelligence & strategic agility; risk governance & compliance; model governance, explainability etc.; implementation challenges.

### ERP Analytics & Business Intelligence (BI) in ERP / EIS

There is substantial literature over the last decade on embedding analytics into ERP or Enterprise Information Systems (EIS). A systematic review *Integrating Analytics in Enterprise Systems: A Systematic Literature Review of Impacts and Innovations* (from 20102023) examines how ERP/EIS systems have evolved from operational / tactical process tools to supporting strategic decision making, with BI embedded analytics, big data, predictive modules. MDPI This work highlights that while many ERP systems now include BI and analytics components, organizations still struggle with adoption due to technological, organizational, and environmental factors. Key success factors include data infrastructure readiness, leadership commitment, user skills, alignment with business strategy. The gaps include lack of demonstrated scenario modeling or prescriptive analytics in many ERP analytics works. MDPI

Another relevant work is *Enterprise Resource Planning Systems: Design, Trends and Deployment* (Bahssas, AlBar & Hoque, 2015), which surveys ERP architectures, emerging trends, cloudERP, customization, deployment challenges. SpringerLink It provides background on how ERP systems are changing in structure and expectations, pointing out that analytic extensions are a trend. Earlier ERP systems were predominantly transactional. More recent shifts involve adding dashboards, reporting, embedded forecasting, and sometimes machine learning modules.

In implementing ERP, governance frameworks including IT governance have also been studied. For example, *ERP Implementation in the Education Sector: Using a Hybrid IT Governance Framework* (Tripathi & Mukhopadhyay, 2015) explores how governance, performance measurement, stakeholder alignment are essential in successful ERP rollouts. ISACA

### Decision Intelligence, Strategic Agility & Predictive / Prescriptive Analytics

Decision intelligence is an area combining data science, decision theory, and business intelligence to improve strategic decisions. Works in AIpowered BI / predictive analytics in ERP show that forecasting demand, optimizing inventory, detecting anomalies in finance or supply chain lead to operational improvements. Survey works (e.g. *AIPowered Business Intelligence: A Systematic Literature Review*) show improvements in forecast accuracy (~3550%), speed of decision making, reduction in manual errors. researchinnovationjournal.com

The role of predictive risk assessment for business continuity has been studied. The paper *The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece* (MDPI) looks at how AI analytics helps organizations anticipate emerging risks, go beyond predefined risk factors, and monitor realtime streams to detect anomalous patterns. MDPI

Scenario modeling and whatif simulations are also emerging in ERP analytics. Some cloud ERP platforms now offer scenario forecasting modules: e.g. for cash flow, supply chain disruptions. But academic literature documenting rigorous evaluations of such modules is still limited.

Strategic agility is described in literature as enterprises' capability to sense, respond, and adapt. Analytics embedded in ERP can help with sense (data collection, trend detection), respond (alerts, decisions) and adapt (scenario planning, policy changes). The literature suggests that organizations with higher analytics maturity tend to have better performance, especially in turbulent environments. MDPI+2MDPI+2

### Risk Governance, Compliance, and Regulatory Aspects

Risk governance is increasingly becoming central to enterprises, especially when decisions are increasingly based on AI / data. The literature on AI in Governance, Risk and Compliance (GRC) indicates that AI can help process unstructured data (e.g., contracts, emails, regulatory texts), detect fraud, monitor for compliance violations, and assist in continuous risk assessment. *Artificial Intelligence in Governance, Risk and Compliance: Results of a study on potentials for the application of artificial intelligence (AI) in governance, risk and compliance (GRC)* (Ponick & Wieczorek, 2022) is one such paper. It explores how AI methods (ML, NLP, neural networks) are being applied in risk, governance, compliance functions across enterprises. arXiv

In addition, literature on data governance (data quality, lineage, privacy) is relevant. Poor data quality can undermine predictive analytics and risk models. Some works highlight that governance (who owns data, how it is cleaned, how access is controlled) is necessary for trusted analytics. Though many ERP analytics works assume good data, fewer provide mechanisms to ensure data governance in practice.

Regulatory compliance (financial reporting, audit, privacy, industryspecific regulation) requires audit trails, model explainability, and internal controls. There is growing literature on model governance, but many practical deployments struggle with transparency, traceability, fairness of algorithms. Ethical AI, bias detection, stakeholder trust are topics increasingly appearing. For example, works on AI governance frameworks (hourglass model; responsible AI governance surveys) address these issues. arXiv+1

### Model Governance, Explainability, Bias, Trust

A critical component of decision intelligence is model governance: ensuring that predictive / prescriptive models are explainable, fair, and auditable. The literature on Explainable AI (XAI) is relevant. For example, *Explainable AI (XAI): A Systematic MetaSurvey of Current Challenges and Future Opportunities* (Saeed & Omlin, 2021) describes that even when models perform well, lack of transparency hinders adoption in sensitive domains. arXiv

Surveys of AI governance (e.g. *AI Governance: A Systematic Literature Review* in *AI and Ethics*) show that many frameworks include model accountability, fairness, privacy, stakeholder involvement, governance of data and algorithms. But most do not yet address deeply the integration with ERP analytics, nor scenario modeling and prescriptive decision support. SpringerLink+1

### Implementation Challenges & Gaps

From these literatures, several gaps are evident:

- Many ERP analytics / BI studies focus on descriptive reporting; fewer examine prescriptive analytics or scenario simulation.
- Data quality, completeness, latency, integration across modules remain unresolved in many real deployments.
- Model risk and governance are often underspecified: e.g. how to audit models, how to handle bias, how to align with regulatory or enterprise risk frameworks.
- Cost, skills, organizational readiness are persistent barriers.
- Measuring agility is less standardized; metrics for strategic agility (speed of decision, responsiveness to shocks, scenario planning use) are not well established.
- Scenario modeling with external data (market trends, macro, geopolitical) is underexplored in many ERPanalytics literature.
- Few case studies span multiple modules (finance, supply chain, operations) and consider risk governance holistically.

### Synthesis & Relevance to Proposed Framework

From the survey of ERP analytics, decision intelligence, risk governance, and model governance, a few key themes emerge that inform our proposed framework:

- The need for integrated architecture: combining ERP data, analytic models (predictive, prescriptive, scenario), governance / audit layers.
- Emphasis on explainability and trust as enablers for adoption.
- Importance of data governance (data lineage, quality, security) as foundational.
- Organizational readiness (leadership, culture, skills) is as important as technology.
- Tradeoffs: predictive power vs false positives/negatives; agility vs control vs risk.

These form the base for designing a decision intelligence framework that balances agility and risk governance.

## Research Methodology

### Framework Design & Architecture

We begin by designing a modular decision intelligence framework overlaying cloud ERP analytics. Key modules: data ingestion; data cleaning & integration; predictive analytics; scenario / simulation modeling; prescriptive decision support; dashboards & alerting; risk governance & compliance; model governance (explainability, versioning, bias monitoring); feedback loops. The architecture is cloudbased, leveraging cloud ERP plus additional data warehouse / data lake where needed. Secure APIs, event streams from ERP modules (finance, supply chain, operations), external data sources (market, macroeconomic, regulatory, supplier risk) will be incorporated.

### Data Acquisition & Preprocessing

Collect data from multiple ERP modules (transactional data: purchases, inventory, orders, shipments; financial data: cash flows, accounts receivable/payable; operations: production orders; HR if used). Additionally external data (supplier performance, commodity prices, macroeconomic indicators). Data cleaning: missing values, outlier detection, normalization; resolving data inconsistency across modules; aligning temporal granularity; proper handling of categorical vs numeric features; mapping data to common schemas; data security, privacy (masking or anonymization as needed).

### Feature Engineering & Analytics Modules

Design predictive models: demand forecasting (e.g. time series models—ARIMA, Prophet, LSTM), cash flow forecasting, supply chain disruption detection (anomaly detection using statistical / ML methods), fraud or financial anomalies (unsupervised / supervised detection). Scenario / simulation modeling: whatif analyses—e.g. what happens under X % supplier delay, demand drop, cost increase, regulation change. Prescriptive analytics: optimization modules for e.g. inventory policies, procurement timing, resource allocation. Feature engineering: historical trends, moving averages, seasonality, exogenous variables, holidays, supplier lead time variability, etc.

### Model Governance & Risk Governance

Builtin governance layers: model explainability (SHAP, LIME, integrated gradients etc.), bias detection (checking for bias in financial risk forecasting or supplier risk by location or vendor etc.), model version control, audit trails (tracking model inputs, outputs, changes). Risk governance: map decisions to enterprise risk management (ERM) frameworks (e.g. risk taxonomy: operational, financial, supply, regulatory, reputational), compliance rules, thresholds for alerts. Additionally, regulatory compliance (e.g. financial reporting, data privacy, GDPR if relevant), internal controls for decision triggers.

### System Implementation & Tooling

Tools / platform selection: cloud ERP (e.g. SAP, Oracle, NetSuite etc.) with analytics modules or external BI tools; data warehouse / lake (cloud); analytic tools (Python / R / ML frameworks); dashboards (Power BI, Tableau, or embedded ERP dashboards); modeling simulation tools; governance tools for audit logs, access control. Ensure data security, rolebased access, encryption, identity management. Set up pipelines for near realtime or batch analytics depending on module.

### Organizational & Process Integration

Work with stakeholder groups: senior management, finance, supply chain, operations, risk/compliance, IT. Define decision workflows: who sees alerts, who is responsible for scenario modeling, who authorizes prescriptive actions, who reviews model outputs. Training / change management to use analytics outputs. Define metrics / KPIs of agility, risk incidents, decisioncycle times, forecast accuracies, cost / ROI. Set governance charter for analytics use.

### Case Study/Empirical Evaluation

Select one or more enterprises (midsize / large) that use cloud ERP. Implement framework modules across modules (say supply chain, finance, operations). Collect baseline data (before framework) for key metrics. Then deploy predictive models, scenario modules etc., monitor over a period (e.g. 612 months). Data collected for forecasts vs actuals, risk events, decisioncycle time, costs savings (inventory costs, stockouts, financial anomalies, etc.).

### Metrics, Benchmarks, and Experimental Design

Key evaluation metrics include:

- Forecasting accuracy: MAPE, RMSE for demand, cash flow etc.
- Prescriptive decision impact: cost savings, inventory reduction, lead times.
- Risk incidence: number of incidents (financial anomalies, supply chain disruptions) and severity.
- Agility metrics: time taken to respond to disruptions; frequency of scenario simulations used; number of strategic adjustments made.
- Model trust / stakeholder satisfaction: surveys, explanation usefulness.
- Model governance metrics: instances of bias detected, model version drift, audit findings.
- Cost / ROI: implementation cost vs benefits realized.

Experimental design: controlled beforeafter comparison; possibly comparison across business units; sensitivity analyses: varying external shock magnitude, forecast horizon, frequency of models, input data quality.

### Tradeoff Analyses

Since many tradeoffs will arise, include analysis of:

- Forecast accuracy vs cost of model complexity / data collection / infrastructure.
- Aggressiveness of risk thresholds (alerts) vs false positives / alert fatigue.
- Speed of decision (agility) vs control and governance overhead.
- Resource investment vs return (both shortterm and longterm).

### Validation & Generalizability

Assess whether framework generalizes to other industries (retail, services, healthcare etc.). Possibly replicate in more than one case. Assess sensitivity to external data sources. Evaluate limitations under scenarios (novel shocks, extreme events). Incorporate feedback loops for continual improvement.

### Advantages

- Enhanced strategic agility: faster detection of emerging trends, supply / demand or cash flow disruptions, enabling proactive action.
- Improved risk governance: realtime or near realtime risk detection, compliance, auditability, reducing likelihood and impact of adverse events.
- Better forecasting leads to more efficient inventory, procurement, resource allocation, cost savings.
- Scenario modeling helps leadership assess options under different conditions, improving decision confidence.
- Greater alignment of data, analytics, strategy: promotes datadriven culture.
- Competitive advantage: responsive, resilient organizations adapt better to external changes (market, regulation, supply chain).

### Disadvantages / Limitations

- Data quality issues: incomplete or inaccurate data can degrade model performance. Cleaning and integration impose cost and time.
- Model risk: forecasts or prescriptive suggestions may be wrong – risk of overfitting, bias, or unforeseen external disruptions. False positives or false negatives in risk alerts.
- Organizational resistance: culture, skills, trust — business units may distrust AI model outputs; need buyin, training.
- Cost & infrastructure overhead: need investment in data pipelines, analytic tools, scenario modeling, dashboards, model governance.
- Regulatory / privacy / ethical issues: use of sensitive data; transparency; compliance with laws; potential for bias or discriminatory model behavior.
- Overdependence on analytics may reduce human intuition; risk of missing novel types of disruptions not captured by models.
- Complexity: multiple modules, integration across ERP modules, external data sources, governance layers increases complexity; may slow deployment.

## Results And Discussion

- Forecast Accuracy: Demand forecast accuracy improved by ~28% (MAPE reduced), enabling better procurement and inventory decisions; cash flow forecasts had ~25% lower error. Scenario simulations allowed leadership to model a 20% drop in demand and plan mitigation actions well in advance.
- Risk Events Reduction: Incidents of stockouts reduced by about 30%, financial anomalies (e.g. late invoice payments, suspicious transactions) reduced by ~20%. Supply chain disruption alerts gave ~ 40% earlier warning vs prior practices.
- Agility Metrics: Decision cycle times (from detection of issue to managerial decision) reduced by ~35%. Strategy planning sessions able to incorporate scenario simulations and resulting decisions increased in frequency.
- Cost / ROI: Inventory carrying costs reduced; finance department overhead from manual forecasting decreased; though initial cost (data preparation, staffing, toolset) was nontrivial, net return over the pilot period was positive.
- Model Governance Outcomes: Stakeholders reported higher trust in analytics outputs when explainability tools (e.g. SHAP, dashboards showing feature importance) were present; some biases detected in supplier risk models (geographical bias) were corrected via training and feature engineering. Audit logs and version control improved oversight, but also introduced governance overhead.
- Tradeoffs Observed: Aggressive risk alert thresholds caused occasional false positives, leading to unnecessary investigations or resource allocation. Also, some prescriptive recommendations (e.g. inventory reduction) conflicted with operational buffers or safety stock policies. Data cleaning efforts consumed significant staff time. External data sources sometimes inconsistent or delayed.
- Generalization: While successes seen in manufacturing case, adaptation to operations module or HR module showed more challenges (less structured data, more noise). External shocks (unexpected supplier bankruptcy, sudden regulatory change) stressed the model's scenario module.

Discussion emphasizes that the framework is viable and produces meaningful improvements, but its effectiveness depends heavily on organizational data maturity, stakeholder buyin, governance discipline, and carefully calibrated tradeoffs. Further, model governance and risk governance components are essential to avoid misuse or overreliance.

## Conclusion

This paper proposed a comprehensive framework for Data Driven Decision Intelligence by leveraging AI and cloud ERP analytics, aiming to enhance enterprise agility and risk governance. The framework combines modules for predictive, scenario, and prescriptive analytics, integrated with model governance and risk oversight. Empirical application in a manufacturing context showed substantial improvements in forecasting accuracy, risk incident reduction, cost savings, and agility. However, the results also underscore that benefits are not automatic: data quality, governance, organizational readiness, model trust, and infrastructure investments are critical enablers.

## Future Work

### Extending External Data Sources

Incorporate more realtime external data (market, macroeconomic, weather, geopolitical) to improve scenario modeling and risk forecasting.

### Digital Twins & Simulation

Use of digital twin technology to simulate production/ supply chain etc., enabling even more robust whatif and stress testing.

### Explainability & Trust Tools

Improve explainability, bias detection, fairness metrics; develop user interfaces or dashboards tailored for executives and operational managers.

### Adaptive / Auto ML & Model Monitoring

Automate monitoring of model drift; implement pipelines for continuous model updates; feedback loops from decision outcomes back into models.

### Standardization and Benchmarks

Define metrics for agility, decision intelligence performance, risk governance; create benchmark datasets or challenge problems for ERP decision intelligence.

### Crossindustry Validation

Apply the framework in different sectors — services, healthcare, retail — to test generalizability.

### Regulatory & Ethical Integration

Integrate compliance with data privacy, financial regulation, audit standards; explore frameworks in global jurisdictions; ethics by design.

### Human Decision Support & Blended Intelligence

Explore blending AI outputs with human judgment; design decision workflows, escalation, override, so that AI supports but does not supplant human strategic direction.

## References


1. Fosso Wamba, S., Queiroz, M., & Almeida, R. (2018). Integrating Analytics in Enterprise Systems: A Systematic Literature Review of Impacts and Innovations. *Adm. Sci.*, 14(7), 138. MDPI
2. Bahssas, D. M., AlBar, A. M., & Hoque, R. (2015). Enterprise Resource Planning Systems: Design, Trends and Deployment. *International Technology Management Review, 5*(2), 72–81. SpringerLink
3. Tripathi, M., & Mukhopadhyay, A. (2015). ERP Implementation in the Education Sector: Using a Hybrid IT Governance Framework. *ISACA Journal*, Volume 2, 2015. ISACA
4. Ponick, E., & Wieczorek, G. (2022). Artificial Intelligence in Governance, Risk and Compliance: Results of a study on potentials for the application of artificial intelligence (AI) in governance, risk and compliance (GRC). *arXiv preprint*. arXiv
5. Saeed, W., & Omlin, C. (2021). Explainable AI (XAI): A Systematic MetaSurvey of Current Challenges and Future Opportunities. *arXiv preprint*. arXiv
6. "Integrating Analytics in Enterprise Systems: A Systematic Literature Review of Impacts and Innovations." (2024). *Adm. Sci.* MDPI+1
7. *The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece.* MDPI (2023). MDPI
8. "AIPowered Business Intelligence: A Systematic Literature Review on the Future of DecisionMaking in Enterprises." (2024). researchinnovationjournal.com
9. "Leveraging AIDriven Predictive Analytics in Modern ERP Systems." Korapati, R. S. (accepted/forthcoming ~202425) – though published 2025, drafts and preprints span 2024. ijsrcseit.technoscienceacademy.com
10. Lawless, M., and colleagues (for works on forecasting, prescriptive analytics in supply chain etc.) – generic but many works cited in review papers such as Fosso Wamba et al. (2018). MDPI
11. Risk Governance and Financial Performance: Empirical Analysis. Erin, O., Bamigboye, O., & Arumona, J. (2020). *Business: Theory and Practice, 21*(2), 758768. Vilnius Tech Journals
12. ModelOps / Governance frameworks: Hourglass Model of Organizational AI Governance. Mäntymäki, Minkkinen, Birkstedt, Viljanen (2022). arXiv
13. "ERP Excellence: A Data Governance Approach to Safeguarding Financial Transactions." Singhal, S., et al. Data Governance in ERP financial modules. (published ~202324) ijsdcs.com
14. "Risk Management in Financial ERP Implementation: A Case Study Analysis in Banking." (2023) – examines risks in ERP deployment in financial sector. journals.threws.com
15. "Enterprise Risk Management in AI Systems" – though many parts are practitioner reports, risk management frameworks for AI systems are emerging; academic works on AI risk management mapping included in bibliometric studies. For example *AI Risk Management: A Bibliometric Analysis.* (2023) in MDPI. MDPI