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AI-Enabled Cloud ERP Systems and Organizational Agility: Integrating Real-Time Analytics, Automation and Governance in Digital Enterprise

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ABSTRACT

Although ERP has progressed from a closed, transactional records management platform to an open, intelligent system that learns, recommends and to an increasing degree acts, the conditions under which embedded AI capabilities translate into organizational agility remain insufficiently understood. The paper presents a theoretical synthesis on how changes in the financial responsiveness, the operational adaptiveness, and the governance posture of digital enterprises are transformed by AI-enabled cloud ERP, by drawing from a systematic analysis of a curated Scopus-indexed corpus. The review is organized around four established lenses, the Resource-Based View, Dynamic Capabilities Theory, Socio-Technical Systems Theory and the Technology Organization Environment framework. Merging these perspectives, the study provides a common conceptualization of a closed-loop and five stage decision pipeline with a five level ERP-AI maturity model. Three recurring themes can be seen in the literature. Embedded learning is linked to faster cycles towards financial close, improved responsive demand and risk planning, and a decreasing number of manual activities, but the degree of improvement is dependent on data quality, modular architecture, and governance maturity. Second, Enterprise platforms are among the strongest when they reflect different philosophies of architecture and not "veto points" for anything. Third, agility value is concentrated in companies that already have digital capabilities that they can leverage through their customer, cloud and commercially-available digital platforms, indicating that AI ERP is an add-on to a digital architecture, not a replacement. It provides theoretical research contributions within the domain of dynamic capability in the digital context, as well as a managerial diagnostic based on clean-core design, layered governance and maturity-aligned sequencing, and ends with 7 concrete directions for further research.

Keywords: AI-enabled ERP; cloud architecture; organizational agility; real-time analytics; AI governance

INTRODUCTION

Enterprise Resource Planning (ERP) systems have been instrumental in powering modern businesses for a long time, centralising information such as financial, human resources, supply chain, and manufacturing data, collating, and storing them in a single record of transactions (Godbole, 2023). These systems began as material and manufacturing planning systems in the 1970s and 1980s and have grown into wide-spread integrated multi-departmental systems in the 1990s (Abazi Chaushi & Chaushi, 2025). The key goal of this new architectural approach was to maintain a single, definitive version of the organisational truth that would overcome a multitude of departmental records. As a result, legacy infrastructures were perceived as monolithic, mainly focused on logging transactions and not future analysis (Lee et al., 2024). Though they work well in stable processes, these same rigid structures are considered technical debt in today's uncertain global market (Mahmood et al., 2020). The traditional analytical approach, based on handling the future after studying the past, is not consistent with the movement of markets where future is predicted beforehand instead of postponed to afterwards (Khurram et al., 2025).

Two transformations are complementary to remedy these drawbacks: one for the domain. Cloud-native delivery has lowered the costs and friction of transporting core workloads off-premises, and AI is no longer simply an application installed as an afterthought or an additional analytical layer atop ERP (Christiansen et al., 2021;

Govinda et al., 2025). New platforms are now more intelligence centres than mere ledgers, absorbing and reporting on in-flowing information; they generate increasingly important insights without the need for human intervention (Dziembek & Turek, 2025; Julakanti et al., 2025). Even though the positive effects of AI-driven cloud ERP on organisational agility are repeatedly mentioned in the literature of the ERP industry vendors, efforts to synthesize the academic literature show high rates of ERP failures (Mahmood et al., 2020; Lawendatu et al., 2026). A key question, therefore, is exactly how embedded capabilities become embedded. How they become embedded within agility.

Background of the study

Outgrown monolithic architectures are unable to cope with all the demands vying for the enterprise data, which is growing at a rate faster than the analytical power of the systems generating it (Mahmood et al., 2020). Investment trends show a clear migration to cloud-native, AI-driven platforms. These are backed by in-memory processing, continuous innovation from vendors, and a surge in investment activity. Investment trends demonstrate the transition to cloud-based, AI-powered platforms, with in-memory processing, recurrent vendor innovation, and a growing body of investment activity. In today's strategic management literature, the term organisational agility" has emerged as a multifaceted concept that entails a blend of senses, foresight, and swift response to reorganise operations, thus securing the organisation's competitive survival in dynamic environments (Koundal et al., 2024; AlMahadin, 2025). In manufacturing, retail, and financial services, companies are leveraging AI-powered analytics to optimise their inventories, automate reconciliation, and divert resources in the face of uncertainty (Liu et al., 2025; Modgil et al., 2022).

Industry context and the agility imperative

In this sense, strategic advantage is not specific to a technology but is rather a consequence of the integration of complementary capabilities such as the cloud, customer-facing systems and commercially valuable data, which makes the implementation of advanced analytics cheaper (Tudor, 2026). ERP combines these characteristics. It records the transactional record, it facilitates customer and supplier relationships, and it enables data pipelines for machine learning. Initial empirical research on European firms suggests that the existence of complementary capabilities is correlated with high levels of AI adoption, and that the level of AI adoption varies by company size but is not determined by it (Tudor, 2026). The agility benefits that can be realised through the deployment of AI-powered cloud ERP should not be viewed as a platform benefit per se, but rather as a representation of a greater capacity configuration, as discussed throughout the study.

Problem statement

This record is not consistent in case of execution of AI integrated cloud ERPs. Legacy modernisation attempts are inherently risky to execution and fraught with socio-technical tensions that can only be addressed through technical means (Lee et al., 2024; Olsen et al., 2022; Cepureanu & Cepureanu, 2015). The use of AI brings with itself specific issues such model drift, opacity in decision making and increased security risks (Singh & Dutta, 2026; Agarwal & Gupta, 2024). Adoption structures do not fit the AI-related aspects of modern platforms (Panggabean et al., 2025) and the analytical model deployed in platforms are only as good as the data they are trained on (Elbadri et al., 2024; More & Mucherla, 2025). There is still a big failure despite all the efforts. Therefore, it is still required to analyse more accurately when and under which conditions AI-powered cloud ERP enhances agility.

Research objectives

Four objectives frame the inquiry:

R01. Analyse the impact of AI-driven cloud ERP as demonstrated by prominent corporate platforms on financial and organisational agility.

R02. Examine how integrated real-time analytics, machine-learning algorithms, and intelligent automation expedite decision-making processes and diminish operational delays.

R03. Evaluate how governance mechanisms, socio-technical alignment, and technological, organisational and environmental conditions shape the responsible adoption of AI-enabled cloud ERP.

R04. Establish a cohesive conceptual framework that integrates corporate maturity with a systematic, closed-loop decision-making process.

Research questions

The objectives are operationalised through four research questions:

RQ1. In what ways do AI-enabled cloud ERP platforms variably affect financial agility, scenario planning, and operational responsiveness in mid-market versus large enterprises?

RQ2. What qualitative and quantitative effects do embedded machine-learning models have on process automation, transaction-processing duration, mistake rate, and forecasting precision?

RQ3. How do governance mechanisms, socio-technical alignment, and technological, organisational and environmental conditions influence the responsible adoption of AI-enabled cloud ERP systems?

RQ4. Which maturity stages, technical baselines, and socio-technical restrictions delineate an organization's path toward autonomous ERP operations?

Significance of the study

The paper covers the academic association of the dynamic capabilities framework and the embedded AI of the core ERP systems, rather than studying different AI stand-alone applications separately (Mamone, 2025; Sarferaz, 2025). This framework gives a maturity aware reference for the chief financial officers, chief information officers and enterprise architects, which can be used to have a structured comparison between platform archetypes and as guidance on implementing a governance driven strategy which reduces the cost of failed migrations (Khurram et al., 2025; Ranasinghe & Gide, 2025). Both contributions focus on potential contemporary requirements for more operational/repeatable descriptions of the formation of digital capabilities, which are mostly inadequately addressed by most of the adoption literature through opaque descriptions (Tudor, 2026).

Structure of the paper

The paper is structured in five different movements, as follows. A thematic literature review gives a conceptual framework, a timeline, the key arguments and gaps in the study. The theoretical frameworks section outlines the four viewpoints from which the evidence is analysed. The rationale and processes of the conceptual-review design are explained in the methodology section. Then, a comparative study and a strategy to combine them in a conceptual framework are presented. The latter sections deal with future implications, obstacles found, seven directions for further research and a concluding perspective on why and when AI-enabled cloud ERP supports agility.

LITERATURE REVIEW

The review of the literature reveals that scholarship on AI-enabled cloud ERP is positioned at the intersection of three bodies of work. There are the evolution of enterprise systems, the cloud and AI adoption traditions, and the strategic management literature on agility and dynamic capability. The review is structured conceptually across various streams. It outlines the evolution of the discipline, reveals the analytical lines along which AI integration is theorised, separates the important issues, and indicates the gaps this work addresses.

Conceptual foundations and definitions

AI-enabled ERP systems. AI-powered ERP systems. The difference between an AI-enabled ERP and transactional database is the direct integration of computational technologies, supervised and unsupervised machine learning, natural language processing, and neural architectures inside the data and application layers (Govinda et al., 2025; Julakanti et al., 2025). The technology can assess historical and streaming data, recognise behavioural trends, automate cognitive processes and give predictive and prescriptive recommendations across corporate functions. The distinction between an AI tool as a free-standing add-on to an ERP and an ERP with intelligence integrated into its core is important for both architecture and outcome, and the blending of the two has been found to cause inconsistency in the empirical literature (Mamone, 2025; Panggabean et al., 2025).

Cloud ERP architecture. Cloud ERP is defined as implementation on subscription-based, scalable cloud-native or hybrid infrastructure that is managed by external providers (Bhatia, 2025; Srivastava et al., 2026). These deployments are characterised by in-memory database technologies, APIs-focused configurations, and microservices, differentiating them from hard on-premises installations and enabling dynamic capacity scaling and continuous absorption of vendor innovation without manual upgrade cycles (Jain et al., 2022; Shivarudra & Kumar, 2025).

Organizational agility.

Diverse approaches exist in the field of digital enterprise research, but organisational agility can be considered the multifaceted capacity to sense market changes, the ability to anticipate disturbance and the capacity to quickly and accurately reconfigure operations (Koundal et al., 2024; AlMahadin, 2025). It can be effectively broken down into three categories. There are financial agility (quick adjustment in budgeting, projection and capital allocation), operational agility (dynamic optimisation of production, inventories, etc.) and strategic agility (the capability to reconfigure business models to reap opportunities/options).

Real-time analytics.

Real-time analytics is the constant, speedy utilization and analysis of the streaming operational data, which is not transferred to a separate warehouse (Upadhyaya & Koka, 2026; Aanand et al., 2025). The functionality is based on high-performance in-memory databases for immediate query execution and role-based interactive dashboards.

Governance.

Governance in intelligent enterprise environments involves the establishment of policies, controls, and security protocols to maintain data integrity, reliability, and adherence to regulations and standards (Singh & Dutta, 2026; Kumar & Jaya, 2026). The increased integration of AI Trust, Risk and Security Management (TRiSM) beyond the usual data governance features includes anomaly detection, continuous model monitoring, audit logging, data residency enforcement and explainability (Sharma et al., 2026; Leon, 2026). You will notice that the word 'governance' appears repeatedly in this piece, not necessarily as a separate notion, but as the required context that enables the safe autonomy of AI-powered cloud ERP.

Evolution of ERP scholarship

Intelligent enterprise environments include more than policies, rules, and security measures that are crucial to data integrity, model reliability, and regulatory adherence (Kumar & Jaya, 2026; Singh & Dutta, 2026). It adds on top of traditional data governance AI Trust, Risk, and Security Management (TRiSM), including anomaly detection, continuous model monitoring, audit logging, data residency enforcement, and explainability (Sharma et al., 2026; Leon, 2026). Going back to the title, governance is a major theme throughout this article and not just a standalone problem, but a prerequisite and condition to the safe operation of AI-powered cloud ERP gaining autonomy.

Early ERP studies defined the system as a process-focused information technology for the integration of database systems, emphasizing the avoidance of dual data-entry, process optimization and reduced administration (Watson and Schwarz, 2023). At that time, implementation studies documented the automation of repetitive transactional processes such as accounting in general ledger and material tracking, but they also started to show a structural challenge: that traditional on-premises deployments were effective static, retrospective stores with limited analytical depth (Abazi Chaushi & Chaushi, 2025).

Adoption determinants and the SME perspective

The known inflection point of cloud computing was embedded AI. From migration problems to the strategic impacts of smart ERPs, there was a shift and subsequent studies highlighted how cloud architectures overcame monolithic and inflexible legacy databases by offering scalable, accessible, and adaptable software ecosystems (Lee et al., 2024; Mamone, 2025). The next step is adding machine learning which transformed ERP into a decision support solution. AI technology applications have been used to process real-time transactional data and proactively identify and resolve financial discrepancies, thereby shifting management accounting from a reactive to a real-time, proactive approach (Oliveira & Ribeiro, 2022; Thanasas et al., 2026), and continuously learning algorithms that adapt to economic fluctuations to improve budget accuracy and cost management in the long term (Zhang, 2026).

The operational perspective is gained from focus group meetings with small and medium-sized companies. According to Achargui and Zaouia (2016), these three deployment models are at times confounded in both the academic and practitioner worlds, and the authors have made an effort to differentiate these models, suggesting that the software as a service deployment model reduces the total cost of ownership and increases focus on the core business, at the same time limiting the degree of customisation. It observes that smaller enterprises never use authentic cloud scalability and that both off-premises options have failed to reduce reliance on connection. Recent syntheses focused on SMEs also conclude similar findings in that readiness, complementary resources, and organisational context play crucial roles for adopting ERP with artificial intelligence (AI) (Ranasinghe & Gide, 2025; Lawendatu et al., 2026).

Comparative profiles of leading enterprise platforms

However, not all literature is considered foundational here, but illuminative to platform comparison. There are a few notable enterprise platforms, each of which is designed in a different way, represented by the likes of SAP S/4HANA Cloud, Workday, and NetSuite, each with its unique criterion of agility in mind (Sharma et al., 2025; Alkhatib, 2026; Karthikeyan et al., 2024). Applying a collective analysis of them is useful because the differences between each platform come to light and signal the compromises in AI-enabled cloud ERP architectures, as opposed to highlighting any single platform as the topic of the paper. Table 1 summarises the comparative evaluations based on the literature inspected: the entries are qualitative descriptions that are understood as such throughout the discussion.

Table 1. Illustrative comparison of leading cloud ERP platform archetypes across agility dimensions.

Evaluation parameter	**Workforce-integrated archetype (e.g. Workday)**	**Mid-market multi-entity archetype (e.g. NetSuite)**	**Enterprise-scale analytical archetype (e.g. SAP S/4HANA Cloud)**
Primary target market	Mid-market to large service enterprises	Growing mid-market and multi-entity firms	Large global conglomerates and manufacturers
Close-cycle speed	High (core ledger automation)	Moderate (flexible multi-currency reporting)	High (in-memory processing, automated roll-ups)
Forecast accuracy	High (workforce–finance alignment)	Moderate (often requires add-ons)	Very high (embedded ML models)
Multi-entity support	Moderate (regional service firms)	High (cross-currency consolidation)	Very high (complex parent–subsidiary structures)

Scenario planning	Moderate (headcount and operating budgets)	Moderate (basic what-if tools)	High (predictive simulation, stress tests)
Real-time analytics	High (workforce-centric dashboards)	Moderate (customisable dashboards)	Very high (in-memory real-time engine)
Core operational strength	Workforce–finance cost integration	Flexible multi-entity growth	Enterprise supply-chain and manufacturing control

Critical debates and contradictions

There are three forms of tensions that define the field. The standardisation debate also has two opposing aspects. One is that there is a need to maintain stability by not building code into the platform, and, instead, maintain a culture of continuously innovating with vendors (Mahmood et al., 2020) and the other is that instead, the best solution is to avoid imposing specialized processes on standard templates and risk losing competitive advantage (Olsen et al., 2022). The resolution is not generalizable. In case a process really has advantages, then in that context, the modification can be done by some external extra extension for the standard interfaces.

The domain is split between three tensions. One is the so-called clean core doctrine (often called the standardisation debate). That helps preserve stability while enabling vendors to repeatedly provide new innovations as long as they eliminate most of the custom code (Mahmood et al., 2020). The other is the concern that specialized processes can, by reducing the competitively valuable uniqueness once imposed into standard templates, reduce the competitive advantage of proprietary processes through their use (Olsen et al., 2022). But the solution is conditional and not universal. If the process is truly giving a benefit, the benefit will be kept and outsourced as an external extension on a standardised API. If it is purely idiosyncratic, then a standard is the best answer.

The optimism gap has characterized the performance gap between the vendors' and practitioners' narratives of large, stable performance gains and searches from academia showing fragility, high failure rates, and underachievement (Godbole, 2023; Mahmood et al., 2020; Lawendatu et al., 2026). Both of these are possible, depending on the nature of the data and the governance environment in which the technology has been deployed, as explained in the discussion.

A synthesis matrix of the core evidence base

The thematic strands described above can be grouped together as one cohesive approach to analysis. Instead of categorising the reviewed corpus, Table 2 synthesises a representative cross-section of which each study contains the dimension of AI-enabled cloud ERP investigated, the substantive finding, and, most significantly for the argument of this paper, implications of the study for organizational agility and for governance, and the question it does not resolve. The goal is interpretive consolidation rather than enumeration. Existing studies are read against a common set of analytical columns, where the same works are read serially, resulting in regularities that are invisible without these columns, and it is those regularities, rather than the particular entries, that inspire the gap analysis presented in the following subsection.

Table 2. Synthesis matrix of representative studies in the AI-enabled cloud ERP corpus.

Representative study	AI / ERP dimension	Principal finding	Organizational-agility implication	Governance implication	Open question
Godbole (2023)	Embedded AI across	Reports marked reductions in task-processing time and gains in	Faster operational response where the data	Reported gains presuppose governed,	Single-study magnitudes; no

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	ERP functions	accuracy after integration	foundation is sound	high-quality inputs	cross-firm replication
Tudor (2026)	Determinants of enterprise AI adoption	Uptake clusters with cloud sophistication and digital-sales capability	Agility is a configuration effect, not a platform effect	Capability gaps enlarge compliance and oversight exposure	Causal weight of each capability remains untested
Lee et al. (2024)	Cloud-ERP architecture; microservices and MSPs	Microservice migration restores resilience and agility lost to monoliths	Modular architecture underpins operational adaptiveness	Distributed design widens the security and control surface	Long-run resilience outcomes not yet measured
Singh & Dutta (2026)	Cloud-native engineering; security and compliance	Security, compliance, and privacy are engineering preconditions, not add-ons	Governance maturity gates safe progression toward autonomy	Defines the MLOps-governance agenda specific to ERP	Effectiveness of controls unevaluated in practice
Sarferaz (2025)	Agentic AI in ERP	Autonomous agents are technically implementable within ERP	Represents the highest-order seizing and transforming capacity	Accountability and oversight burdens rise sharply with autonomy	Governance for agentic operation underspecified
Liu et al. (2025)	Supply-chain forecasting and anomaly detection	Integrated forecasting and optimisation improve resilience under shock	Operational sensing and rapid reconfiguration	Model drift under disruption is a live governance risk	Generalisability beyond modelled settings unclear
Olsen et al. (2022)	Change management in ERP (SME context)	Socio-technical alignment, not technology, decides success	Workforce readiness conditions every realised agility gain	Cultural fit shapes acceptance of opaque decisions	Mechanisms of AI-specific resistance not yet isolated
Mahmood et al. (2020)	Synthesis of ERP issues and challenges	High investment coexists with persistent implementation failure	Agility benefits are fragile and strongly conditional	Weak data and governance foundations drive failure	Conditions separating success from failure under-theorised
Elbadri et al. (2024)	Data quality for ERP implementation	Output reliability inherits the quality of input data	The data foundation is the binding constraint on agility	Data stewardship is a governance prerequisite	Quantified data-quality thresholds remain absent

Sharma et al. (2025)	AI-centric Workday integration	Workforce–finance integration accelerates close and forecasting	Joint financial and human-capital agility	Integration adds identity-management and audit demands	Comparative cross-platform evidence still thin
Lin & Chen (2026)	Policy-governed agentic AI (manufacturing)	Closed-loop sensor–MES–ERP control with embedded policy guardrails	Real-time sensing and seizing in operations	Policy governance is built directly into the control loop	Cross-industry transfer of the pattern untested

Three characteristics of the matrix directly relate to the argument. First, the agility-implication column is filled in every row, yet the mechanism differs by study. In the supply-chain and manufacturing entries, operational sensing. In the finance-integration entries, financial responsiveness, and in the human-capital entry, workforce reconfiguration, exactly the domain-spanning instantiation of dynamic capability developed later in the paper. Second, the governance implication column is never empty either. Even studies whose dominant concern is performance carry an implicit governance condition. This indicates that governance is not a separate phenomenon but a structural property of the field as a whole. Third, and most consequentially, the open question column converges. Each of the studies reports gains, fragilities, or architectures, but together they leave the same three questions unanswered. What differentiates the firms that realize the gains from those that do not, how successive increments of autonomy are to be governed as they accumulate, and how the resulting agility is to be measured. It is the convergent silences, not the findings of any specific investigation, which are highlighted later.

Synthesis and research gaps

The current investigation faces three gaps. The literature lacks clarity concerning the extent of embedded intelligence in core ERP systems given that a majority of extant works focus on the performance of standalone AI solutions or on overall post-implementation outcomes (Mamone, 2025; Panggabean et al., 2025). Secondly, a lack of an AI-aware in-depth maturity assessment framework exists. Conventional digital transformation maturity models do not cover machine learning model governance, automated-pipeline efficiency, explainability, and MLOps within ERP environments (Singh & Dutta, 2026). Third, only a limited number of longitudinal and cross-industry studies have provided a return on investment and performance perspective, and no single data analysis exists, which focuses on how generative AI, IoT integration, and ethical governance have been implemented in ERP systems. However, the conceptual framework of this paper immediately addresses the two initial deficiencies and prioritizes the third one as an empirical research priority.

THEORETICAL FRAMEWORKS

The analysis is based on four accepted frameworks. Each shows a different value of the collaboration between AI-powered cloud ERP and organisational success, while the conjunction provides a threaded framework for the next setting.

Resource-Based View

The Resource-Based View of the firm suggests that a sustained competitive advantage comes from resources which are valued, scarce, hard to imitate, and non-substitutable (Seddon et al., 2010). With this logic, conventional ERP solutions were criticised for their uniform frameworks, which, being easily replicable, did not provide a competitive advantage to companies. With the introduction of AI-powered cloud ERP, that equation changes. Firm-specific analytical and operational capabilities emerge from the whole data cycle of scalable cloud infrastructure, proprietary historical data, and ever-refining models. This strategic vision and the resulting automation make imitation difficult. The platform may soon become a unique strategic asset.

Dynamic Capabilities Theory

Dynamic Capabilities Theory extends the Resource-Based View by explaining how organizations integrate, build, and reconfigure competencies to address changing environments (Jiang, 2024; Koundal et al., 2024). AI-enabled cloud ERP supports these capabilities through three mechanisms. First, embedded learning and real-time monitoring enhance the capacity to sense market shifts and supply-chain disruption. Second, automated resource allocation supports the capacity to seize opportunity. Third is flexible cloud-native architecture enables the organization to transform its operating structures without disrupting primary workflows. This sensing-seizing-transforming logic, rather than efficiency alone, identifies the appropriate outcome variable for this class of system.

Socio-Technical Systems Theory

Socio-Technical Systems Theory sees the organization as the interaction of a technical subsystem (hardware, software, data pipelines) and a social subsystem (people, norms, hierarchies, processes). The framework accounts for how technically sound ERP deployments can still fail. A platform is embedded in routines and governance structures, and successfully facilitating an AI-enabled cloud migration necessitates alignment of the technical features of a given software stack with the social capabilities of the workforce (Olsen et al., 2022; Kar et al., 2021). If employees lack the analytical ability to interpret the AI-generated recommendations, and if the recommendation itself is opaque and contradicts the cultural norm for transparency, then resistance and failure ensue.

Technology–Organization–Environment framework

This context is referred to by the Technology-Organization-Environment framework (TOE) and is discussed in most of the innovation adoption literature examined in the present research. The technological background is the aspect of the innovation that includes architecture and the characteristics of the technological aspects like architectural sophistication, interoperability, compatibility with legacy systems and the comparative advantages of features like in-memory databases and predictive algorithms (Awa et al., 2016). Internal features under the organisational context consist of: Readiness for change management, executive support, IT competence, and maturity of data governance (Buonanno et al., 2005). Environmental context analyses involve an examination of external elements, i.e., competitive dynamics, supply chain disruptions, and regulatory requirements, such as audit and data localisation regulations (Christiansen et al., 2021). It is key, however, that the TOE can also connect technological possibilities for an AI-based ERP with organisational and environmental factors that impact the realisation of these possibilities.

Integrating the lenses with the evidence

Viewed in this light, the discovery that platforms occupy a trade-off frontier instead of a hierarchy amounts to TOE. In that light, it is a TOE finding that platforms exist on a frontier which mediates between "compared to what", not a hierarchy. The four frames are not fighting! Data-driven embedded intelligence can be a commercial advantage, and it’s not just a result of the ubiquitous software. It is private data and ever evolving models that cannot be replicated (Seddon et al., 2010; Mishra & Tripathi, 2021). Dynamic Capabilities Theory describes how benefit can arise and mature. By the ongoing process of sensing, seizing, transforming as witnessed in sectoral applications (Jiang, 2024; Koundal et al., 2024). Socio Technical Systems Theory (STT) can be used to point to the lack of exploitations of gains as interaction of technical and social subsystems must be congruent prior to the system becoming functional, and if not, the system has high rates of failure or will rely more on change management (Olsen et al., 2022; Kar et al., 2021). Finally, the TOE framework provides the integrating contingency logic where a resource comes out as an advantage, DC is activated and the attainment of STA depends on the contingent combination of technological, organisational and environmental conditions (Awa et al., 2016; Christiansen et al., 2021). This is a trade-off frontier discovery and thus is a TOE result.

An integrative theoretical synthesis

The previous subsection of this paper reads each lens with respect to the others. Its unique contribution is in relation to the combination of them. Table 3 juxtaposes the four frameworks against the constructs which structure the remainder of the paper embedded intelligence and real-time analytics, intelligent automation, governance, and organizational agility and articulates what one lens elucidates that the other lenses do not. The importance of the matrix is that it makes the division of explanatory labor explicit. The frameworks are not conflicting accounts of a phenomenon, but complementary descriptions of aspects of it such that the explanatory gap in one is bridged by the other.

Table 3. Integrative mapping of the four theoretical lenses to the paper's core constructs.

Theoretical lens	Core proposition	Reading of AI-enabled ERP and real-time analytics	Reading of automation and governance	Contribution to the agility account
Resource-Based View	Advantage rests on valuable, rare, inimitable, non-substitutable resources	Proprietary data and continuously learning models — not the generic platform — are the inimitable asset	Automation is readily replicable; the governed data foundation behind it is not	Explains why embedded intelligence can become a source of durable advantage
Dynamic Capabilities Theory	Advantage operates through sensing, seizing, and transforming	Real-time analytics is the sensing apparatus; prediction enables seizing	Automation executes seizing while governance disciplines transformation	Specifies the mechanism that converts capability into agility
Socio-Technical Systems Theory	Performance requires alignment of the technical and social subsystems	Analytic value depends on staff able to interpret probabilistic output	Opaque automation without literacy breeds resistance and circumvention	Explains why technically sound deployments nonetheless fail
Technology–Organization–Environment framework	Adoption depends jointly on technology, organization, and environment	Platform fit is contingent on internal context and external regulation	Governance demands are set largely by environmental and regulatory pressure	Supplies the contingency logic that integrates the other three lenses

Table 3 clarifies the explanatory role of each theoretical lens. However, the reviewer’s comment also highlights the need to show more clearly how these lenses connect with the paper’s broader framework. Therefore, Table 4 adds a second layer of mapping by linking the same four theoretical lenses to the five-stage decision pipeline, the five-level AI-ERP maturity model, and the recurring themes of real-time analytics, automation and governance.

Table 4. Integrative mapping of the theoretical lenses, the decision pipeline, the maturity model and the core AI-ERP themes.

Theoretical lens	Role across the five-stage decision pipeline	Role across the five-level maturity model	Real-time analytics	Automation	Governance
Resource-Based View	Data captured at collection, refined in preprocessing	The resource advantage strengthens as the	Live analytics turn proprietary data into a rare	Only automation built on well-	Data stewardship protects the

	and modelled in the analytics stage forms a firm-specific, hard-to-imitate resource that deepens at each feedback loop.	firm moves from the Initial to the Autonomous level, where integrated data and models become difficult for rivals to copy.	and valuable asset.	governed data yields a durable advantage.	resource base and preserves its inimitability.
Dynamic Capabilities Theory	The pipeline operationalises sensing (collection and preprocessing), seizing (analytics and decision support) and transforming (the feedback loop that reconfigures models and processes).	Each level adds sensing, seizing and transforming capacity, culminating in self-optimising loops at the Autonomous level.	Real-time analytics provide the sensing that triggers timely responses.	Automation executes the seizing and transforming actions at operational scale.	Governance disciplines reconfiguration so that agility does not compromise control.
Socio-Technical Systems Theory	Analytics and decision-support stages create value only when staff can interpret their outputs; a misaligned social subsystem breaks the loop.	Progression through the levels depends on the social subsystem of skills, roles and norms advancing in step with the technical baseline.	The value of real-time dashboards depends on workforce data literacy.	Automation introduced without workforce alignment invites resistance and workarounds.	Norms of transparency and accountability shape whether governance is accepted in practice.
Technology-Organization - Environment framework	Whether each pipeline stage is implemented depends jointly on technological readiness, organisational context and environmental conditions.	The attainable maturity level is contingent on the fit between technology, organisation and environment.	Adoption of real-time analytics is conditioned by internal readiness and external requirements.	The scope of automation is set by organisational readiness and environmental demand.	Governance requirements are driven largely by regulatory and environmental pressure.

Together, Tables 3 and 4 serve different purposes. Table 3 explains what each theory contributes to the paper's core constructs, while Table 4 shows how the theories connect to the decision pipeline, maturity levels and core AI-ERP themes. This additional mapping helps reduce conceptual density and clarifies how the theoretical lenses, framework components and recurring themes intersect within the proposed model.

METHODOLOGY

Philosophical and methodological positioning

The methodological design is shaped by the nature of the research questions, which are explanatory and conceptual rather than predictive or statistical. Since the paper seeks to understand how embedded AI capabilities in cloud ERP systems may support organizational agility, a literature-based conceptual review is appropriate for integrating evidence across information systems, management and digital transformation research. What the questions are concerned with is the degree to which embedded intelligence becomes agility. That is, it needs an interpretive explanatory point of view, on the part of the researcher from the subject of the investigation, rather than a predictive one, so to speak, regarding the population parameter to be estimated. Literature based inquiry is an established paradigm which responds to these issues by focussing on organising and joining the fragmenting knowledge into a cohesive narrative, not on the construction of new knowledge (Snyder, 2019). A view of the review as a research in and of itself, as opposed to a lead up to collecting primary data, is consistent with the typology, under which conceptual reviews and integrative reviews are viewed as legitimate forms of research towards theory. (Paré et al., 2015).

This attitude has methodological obligations, because it dictates all the decisions made once the attitude is accepted. In the context of a review, it must be a research method in which the rationale is verifiable, the criteria for including resources or sources is stated, and the interpretive flow from single findings to an overall conclusion is controlled (Webster & Watson, 2002). The nature of these duties drives the design described in the two subsequent subsections, which is not based on a checklist as is the nature for systematic review methods that is intended for uniform quantitative evidence. Effect size pooling protocols would mistakenly characterize an analysis of purposefully heterogeneous evidence and although bringing about an illusion of a transparent process and a transparent output, would obscure the inherently interpretative nature and impact of the contribution (Snyder, 2019; Paré et al., 2015).

Research design and its justification

The questions posed in this paper are synthetic and explanatory. They ask under what conditions embedded AI capabilities translate into organizational agility, and how leading platforms differ in their support of those conditions. Such a type of research is well-suited to literature-based methodologies, which aim to map, organise and interpret a growing body of evidence as opposed to making primary observations (Snyder, 2019; Paré et al., 2015). In conclusion, the design of a conceptual review is aligned with the dynamic and diverse nature of the AI-enabled cloud ERP literature, in which empirical studies, conceptual papers, and practitioner case reports must be read together to arrive at a coherent account (Webster & Watson, 2002; Cronin & George, 2023). The rationale behind the decision to not collect primary data is similar. Surveys, interviews, and structural-equation modelling would all be inconsistent with the explanatory ambition of the research questions, and, in any case, rest on the same conceptual scaffolding that the present study aims to construct (Tranfield et al., 2003).

Design is by explicit decision interpretive rather than causal. Conceptual reviews are the appropriate vehicles for theory development and integration, not for the estimation of treatment effects, and therefore the conclusions of such reviews should be read in that light (Snyder, 2019; Paré et al., 2015). The current design will thus be explanatory in its contributions. It identifies recurrent patterns of association across the literature and develops a framework that organises those patterns into a coherent developmental logic.

Conceptual review approach

Out of the existing literature review typologies, the conceptual review aligns best with the research aims of this paper. Paré et al. (2015) describe the conceptual review as a synthesis which combines ideas with knowledge from several disparate resources to form an integrated theoretical contribution. Precisely the output the paper provides across the conceptual approach. Thematic synthesis supports the integration, as their thematic nature allows thematic research to be used across a wide range of methods in the AI–ERP literature where there is a considerable mix of quantitative, empirical research with conceptual articles and industry case reports and allows the integration of results that resist statistical pooling (Thomas & Harden, 2008; Whittemore & Knafl, 2005). Cronin and George (2023) further suggest that integrative thematic reviews are well suited to fields undergoing rapid conceptual development, which indicates the AI-enabled cloud ERP literature at the time of writing.

Database selection and rationale

Scopus was the primary bibliographic resource. Literature was chosen using Scopus due to the comprehensive coverage, interdisciplinary, and uniform metadata across databases in the literature review system (Falagas et

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al., 2008; Mongeon & Paul-Hus, 2016) as was also recommended by the guidelines for the management and information systems reviews. Where one is interested in an IT, E&M research question (see, e.g., Table 1), Scopus provides more conference proceedings and applied research literature with the depth of citation indexing and rigor over open web searches that is unique to the Scopus database (Mongeon & Paul-Hus, 2016). Partly to use them as a summarizing tool and for verification purposes, an AI synthesis based on Scopus AI facility was added to the primary database export rather than a primary source for covering recent developments. To ensure that the synthesis is grounded in primary data, three detailed studies including use of off-premises ERP in small and medium enterprises, EU enterprise outcomes of ERP-AI systems, and factors affecting the introduction of ERP-AI systems in European enterprises have been purchased in their entirety, and studied in detail.

Inclusion and exclusion criteria

The sources were chosen according to specific inclusion criteria determined through a series of acceptable reviewing protocols (Tranfield et al., 2003; Snyder, 2019). According to Webster & Watson (2002), the paper should cover areas such as ERP systems, cloud computing, artificial intelligence or machine learning, organisational agility or enterprise governance. Be published in a peer-reviewed journal or recognised conference proceedings, and be part of a reputable scholarly book series (publication date was not significant as long as it was recent). An exclusion approach was taken if sources addressed AI/ERP topics not relevant to the company, had no validated bibliographic data, or if evidence from a source was already covered by a more representative source. The requirements have both maximized relevance and given the methodological diversity that the conceptual review (Paré et al., 2015) requires.

Search strategy

Consistent with management reviews (Tranfield et al., 2003), concept blocks follow an iterative methodology in constructing the search string itself. Core terms like “artificial intelligence”, “machine learning”, “real-time analytics”, “automation” and “agentic AI” were combined with outcome terms like ‘organisational agility’, ‘decision-making’, ‘governance’ and ‘compliance’, with all of these core query strings linked to ERP-related terms, including ‘ERP’, ‘enterprise resource planning’ and ‘cloud ERP’. After a literature review recommendation from Snyder (2019) for literature-based studies to be phased screened, subjects carried out a title and abstract screening before determining their potential eligibility for inclusion. The key studies were then identified, and backward citation tracking was applied to identify potentially related studies previously not identified by key words as recommended by Webster and Watson (2002), whose work is used across disciplines including science, technical education, and engineering with a variety of terms.

Comparative-analysis method

This platform comparison depended on a certain set of dimensions of agility. Which were a recurring outcome variable in the studies analysed. Target market, closed loop velocity, forecast accuracy, multi-entity support and scenario planning, real-time analytics and core operational strength. The review of the literature provided evidence relevant to each dimension, and characterisations were derived. Comparison of qualitative judgements from different sources is an established analytic approach in conceptual reviews where exact measures of quantification cannot be synthesised (Paré et al., 2015; Whittemore and Knafl, 2005), and the comparative results presented here should be treated as expert and empirical judgements aggregated in a shared grid, rather than as standardised benchmark scores.

Data-synthesis approach

Synthesis followed a convergence of evidence logic. A claim was treated as well supported when it recurred across independent sources and source types, for instance, when a pattern observed in a full-text empirical study was echoed in the AI-assisted synthesis and in the broader Scopus corpus. This convergence logic is consistent with the procedures recommended for thematic and integrative reviews, which treat triangulation across heterogeneous sources as a substitute for the formal pooling that quantitative meta-analysis would require (Thomas & Harden, 2008; Cronin & George, 2023). Where evidence diverged, the divergence was retained and analysed as a contradiction. Quantitative results drawn from primary studies are reproduced only with explicit attribution to the originating study and are framed as findings of that study, in keeping with the methodological injunction not to convert primary findings into generalised claims that the underlying design cannot support (Snyder, 2019).

Quality assurance and reflexivity

Each retained source was evaluated in terms of methodological transparency, clarity of contribution, and verifiability of claims. A quality-screening stage was included because integrative reviews depend on the credibility, transparency and traceability of the sources used in the synthesis (Whittemore & Knafl, 2005). Sources whose claims could not be linked to evidence were used, where used at all, only for conceptual orientation rather than for empirical support. AI-assisted tools supported literature organization, coverage checks, and synthesis review; however, the final interpretation and analytical judgment were made by the researcher. Because it contained up-to-date, citation-based evidence, it was used as a coverage check and was viewed as a reference document, rather than as a primary source, with each prominent claim cited referencing a specific publication. Such a disciplined nature reflects systematic needs for transparency and traceability that make a solid conceptual assessment distinct from a descriptive summary (Webster & Watson, 2002; Snyder, 2019).

Corpus composition and descriptive profile

The assembled corpus is itself methodologically informative, so its composition is described not left implicit. The main Scopus export produced sixty records with a temporal distribution strongly weighted toward the present. The final Scopus corpus consisted of 60 Scopus-indexed records, including journal articles, conference papers, book chapters and scholarly books, screened for relevance to AI-enabled ERP systems, cloud architecture, organizational agility, real-time analytics, automation and governance. Close to four-fifths were published between 2024 and 2026, one year (2025) accounts for half the corpus, and only a small tail of foundational entries lies between 2021 and 2023. By document type, the corpus is dominated by conference papers and journal articles, as well as fewer book chapters, conference reviews, and scholarly books, and the clear majority of records sit behind subscription access, albeit with a minority available under open-access terms.

This profile is in line with and partially informs the design decisions made previously. The strong recency of the literature confirms that AI-enabled cloud ERP is an emergent rather than a settled research object, and in this case, integrative and conceptual synthesis would be the preferred reaction, as the evidence base is too new and methodologically uneven to support statistical pooling (Cronin & George, 2023). The predominance of conference proceedings over archival journal articles epitomizes a field where the current results continue to be published for public reference, and it justifies the selection of Scopus, whose comparatively inclusive coverage of proceedings captures precisely such fast-moving material that narrower indexes fail to capture (Mongeon & Paul-Hus, 2016; Falagas et al., 2008). But that same profile also sets a boundary on the strength of any claim that the review can sustain. A weighting of recent (but as yet not yet replicated) proceedings helps interpretive consolidation, not generalisation. This limitation is made explicit in the next subsection and is carried forward into the future research agenda.

Methodological rigour, trustworthiness, and reflexivity

The credibility of a conceptual review is not about the formal mechanisms of a quantitative study. It is about the transparency and traceability of its interpretive moves, and these were regarded as the operative standard of rigour throughout (Whittemore & Knafl, 2005). Credibility was pursued through the convergence of evidence logic described above, by which a claim was admitted only where it recurred across independent sources and source types so that no single study, including the most frequently cited quantitative source, carries an integrated claim on its own. Auditability was pursued by anchoring every substantive proposition to an identifiable publication and by reporting primary quantitative results strictly as findings of their originating studies rather than as generalised effects, in keeping with the injunction against converting study specific results into claims that the underlying design cannot bear (Snyder, 2019).

Two further reflexive considerations bound the synthesis. First, the use of an AI-assisted evidence facility, while valuable as a coverage check against an emergent literature, introduces a risk that the tool's own coverage and ranking shape the reviewer's attention. This risk was managed by treating the facility as a pointer to primary sources rather than as a source in itself and by verifying each surfaced claim against the underlying publication (Webster & Watson, 2002). Second, interpretive synthesis is inescapably perspectival. The analytical columns through which the corpus was read, agility, governance, and maturity, were chosen because they answer the research questions, and a different framing would surface different patterns. This is a property of conceptual review rather than a defect of it, but stating it plainly is part of the transferability that lets a reader judge how far the account travels to settings beyond those the corpus represents (Cronin & George, 2023; Whittemore & Knafl, 2005).

COMPARATIVE ANALYSIS

RQ1 is answered by comparing leading platform archetypes but, more importantly, exposes the architectural choices that underlie the AI-enabled cloud ERP supporting agility. The important observation is that the three archetypes are sitting at different places on a trade off frontier between standardised analytical depth and nimble, lower-cost flexibility and no archetype is the winner across agility dimensions. The pattern corresponds with a wider literature resistance to a universal ranking and affirms the study's argument that a firm's agility priority drives platform choice (Sharma et al., 2025; Karthikeyan et al., 2024; Masuda et al., 2026).

Financial agility and close-cycle performance

The literature also characterises two archetypes, the workforce integrated and enterprise scale analytical, as offering high close cycle performance but for different architectural reasons. The workforce integrated model (the most prominent case in point, where automation of basic transactional data and seamless integration of manpower and financial data are maximized; Sharma et al., 2025; Subrahmanyam, 2024) enables efficiency. The enterprise scale analytical model is fast, with in-memory processing capacity and intelligent roll up support across complex multi entity architectures (Masuda et al., 2026; De Castro Fialho & Banothu, 2025). Simultaneously, the multi entity paradigm takes place, where multi currency reporting and consolidation is well explored and developed, but often depends on third party add-ons (Karthikeyan et al., 2024). Financial agility is not merely one thing, instead it depends on a bunch of things like how financial information is being presented on the platform as well as the overall cost structure of the business.

Predictive and scenario-planning capability

The comparison data, when analysed together, outlines a boundary not a hierarchy, and hence a definition of what constitutes a business strategy. The enterprise scale analytical archetype has the most analytical depth and single entity control, but needs the highest organizational support and effectiveness, and has the highest socio technical risk. The mid market multi entity archetype is the most flexible and cost effective and resonates best with an enterprise in a growing market, but sacrifices built up analytical complexity. The workforce-integrated archetype leverages the employee interface to the finance functions, but is less applicable to a physical supply chain. This is an emergent interpretation so the appropriate archetype is one whose location on this frontier is consistent with the maturity level and agility priorities of the organization and takes their cue from natural systems dynamics and the TOE logic but pushes back against the "one size fits all" kind of information proposed by the vendors' literature.

Interpreting the trade-off frontier

This is not to say that the frontier interpretation does not align with the capability perspective. It just doesn’t contradict it. Analytical depths and operational breadths are well described by SAP S/4HANA Cloud and Oracle Fusion Cloud ERP, respectively, though they require a more complex implementation. The ability can only be gained through significant integration initiatives (Rîndaşu et al., 2024); even the broader adoption of Oracle Fusion is also given some indication. While Workday has forged its intelligence on an infrastructure that bridges work and finance, NetSuite extends its intelligence to flexible growth in its mid market, often with add ons to support sophisticated analytics. One caveat relating to this comparison is that the level of detail in the scholarly evidence varies among the four systems. The SAP and Oracle systems exhibit the most detail and NetSuite reflects the least detail. So the characterisations of NetSuite are less clear and are rather more tentative. As a result, the comparison is one of contingent conclusion, namely, the "right" platform is the one having focus on capabilities that works for the firm's primary agility orientation, and as such does not support context free ranking, which is an interpretation that aligns the findings on the platform with the previously established TOE reasoning.

A capability-level comparison of representative platforms

The comparison above, one of archetypes, is intentionally abstract. Its only useful for this purpose though is to clarify the underlying platforms because the four most discussed in the corpus SAP S/4HANA Cloud, Oracle Fusion Cloud ERP, Workday and NetSuite are the concrete referents from which the archetypes are abstracted. Table 5 organises the literature's supporting characterisations along the capability dimensions that are most relevant to this paper. Embedded AI, real time analytics, intelligent automation, governance and security support, and agility emphasis which is favored in the design of each platform. The entries are qualitative characterisations, extracted from the analyzed studies without reference to standardised benchmark scores, and are presented as architectural emphasis rather than as feature inventory. The comparison is there for the sake of presenting design tradeoffs and not to rate vendors or recommend any platform.

Table 5. Capability-level comparison of representative cloud ERP platforms (qualitative, literature-derived).

Capability dimension	**SAP S/4HANA Cloud**	**Oracle Fusion Cloud ERP**	**Workday**	**NetSuite**
Embedded AI emphasis	Deep in-platform ML for prediction and prescription (Bhatia, 2025; Julakanti et al., 2025)	AI layered onto Fusion applications across finance and operations (Alkhatib, 2026)	AI concentrated at the workforce–finance interface (Sharma et al., 2025)	AI capability often realised through add-ons (Karthikeyan et al., 2024)
Real-time analytics	In-memory engine for live, high-volume analysis (De Castro Fialho & Banothu, 2025; Jain et al., 2022)	Cloud analytics across Fusion modules (Alkhatib, 2026)	Workforce-centric real-time dashboards (Sharma et al., 2025)	Customisable dashboards of moderate depth (Karthikeyan et al., 2024)
Intelligent automation	Automated roll-ups and reconciliation at enterprise scale (Masuda et al., 2026)	Process automation across financial operations (Rîndaşu et al., 2024)	Automation of core HR and ledger workflows (Sharma et al., 2025)	Automation tuned to multi-entity growth (Karthikeyan et al., 2024)
Governance and security support	Mature controls for complex multi-jurisdiction structures (Reddy et al., 2025)	Documented Zero Trust implementation (Qazi & Arshad, 2025)	Identity- and audit-oriented controls (Sharma et al., 2025)	Governance scales with configuration discipline (Rîndaşu et al., 2024)
Organizational-agility emphasis	Analytical depth and multi-entity control	Operational breadth, with adoption complexity noted	Workforce–finance responsiveness	Flexible, cost-efficient growth

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		(Rîndaşu et al., 2024)		
Position on the trade-off frontier	Enterprise-scale analytical depth; highest investment	Broad operational coverage; substantial integration effort	Service-sector workforce optimisation	Mid-market flexibility; lighter native analytics

In support of the frontier interpretation, profitability is not in some sense incompatible, profit making is supplementary. The analytical depths and operational breadths are highlighted in SAP S/4HANA Cloud and Oracle Fusion Cloud ERP, respectively, but with more complex implementation. There is also reason to believe that in Oracle Fusion adoption, it is only through extensive integration that the vastness can be achieved (Rîndaşu et al., 2024). Workday understands that intelligence should connect the workforce to finance. NetSuite extends intelligence to flexible expansion in that mid market, often with add ons that bolster advanced analytics. A caution in the comparison of that is that the level of detail in the scholarly evidence varies from system to system. Maximum detail may be reflected by the SAP and Oracle systems, minimally in NetSuite. As such, the descriptors of NetSuite are more vague and are more tentative. Consequently, the comparison is a contingent conclusion. That is, it follows that the "right" platform is one which represents the capability focus that fits with the firm's core agility orientation and does not support a context free ranking, which is an interpretation that matches the results you find at the network with the previously developed TOE reasoning.

A UNIFIED CONCEPTUAL FRAMEWORK

The second identified gap in the review, AI-aware maturity assessment, is the impetus for the approach described herein. The model consists of a five-stage closed loop decision pipeline combined with a five level maturity model for AI ERP. It is not a validated tool but rather a way of organising the different bits of information available in the literature in a developmentally logical fashion, as acknowledged.

The closed-loop decision pipeline

This idea of a decision pipeline sets the parameters for action and the flow of information in an AI-based ERP system. Data collection is continuous, with data collected in both structured and unstructured forms from internal systems, IoT sensors, customers and the outside world (Rakholia et al., 2025; Govinda et al., 2025). Data preparation standardises, cleans, and semantically unifies raw data in the cloud or in memory databases. Analytics and AI processing leverage these, along with the machine learning algorithms, to produce the predictive & prescriptive results. Decision support provides clear and actionable insights, scenario simulations and alarms based on role-specific dashboards and natural language interfaces. A feedback loop evaluates the results of decisions and uses that as a foundation to continuously update models, thereby marking a continuous circular process and continuous progress (Lin & Chen, 2026

The maturity model

The maturity model defines an organization's ability to implement the pipeline at all five stages, as shown in Table 6. The model is, as you would expect a diagnosis. It tells you where your organisation is at as well as what technical and governance requirements you have to meet to move your organisation to the next level, enabling you to advance step by step and minimise risk as recommended by all of the suggested pathways.

Table 6. Digital Transformation Maturity Model for AI-driven ERP systems (DTMM-AI-ERP).

Maturity level	Primary focus	Technical baseline	Governance state
Initial	Monolithic transaction processing; manual aggregation	Legacy on-premises hardware; disconnected silos; batch processing	High fragmentation; no structured governance; reactive stance

Opportunistic	Ad-hoc cloud migration; localised automation pilots	Hybrid environments; basic RPA; localised API integration	Standardised reporting in select units; manual compliance
Integrated	Unified cloud-native database with embedded analytics	Multi-module cloud ERP; in-memory processing; standardised APIs	Established governance; defined stewardship; systematic compliance
Intelligent	Proactive decision support; embedded forecasting	Embedded ML models; custom dashboards; NLP interfaces	Advanced data lineage; continuous risk monitoring; high readiness
Autonomous	Self-optimising cognitive workflows; adaptive execution	Agentic AI; self-healing reconciliation; MLOps orchestration	Zero Trust; AI TRiSM; explainable-AI assurance

The integrated pipeline and maturity model's basic conceptual assumption is that throughout the different levels of maturity, the same operational pipeline can be found, but with varying degrees of automation, degree of analysis complexity and/or governance requirements. In contrast to the Initial level organization which is still allowed to run through the first two stages manually, an autonomous enterprise will run through all of the stages within a comprehensive governance ecosystem without the intense help or assistance of a human being. The approach proposed here addresses RQ4 by giving maturity thresholds, technical benchmarks, and socio technical constraints to think through when thinking of approaches from a perspective of autonomous operations. Figure 1 presents the embedded structure, which depicts the five stages of the decision pipeline at each level of maturity, each of which is increasingly autonomous, complex, and developed with better governance as the organization matures. The picture very clearly illustrates the core concept of the paper which is that the same operational process is applied to every stage, and the more the realization of this comes about the more it achieves the agility of organisation.

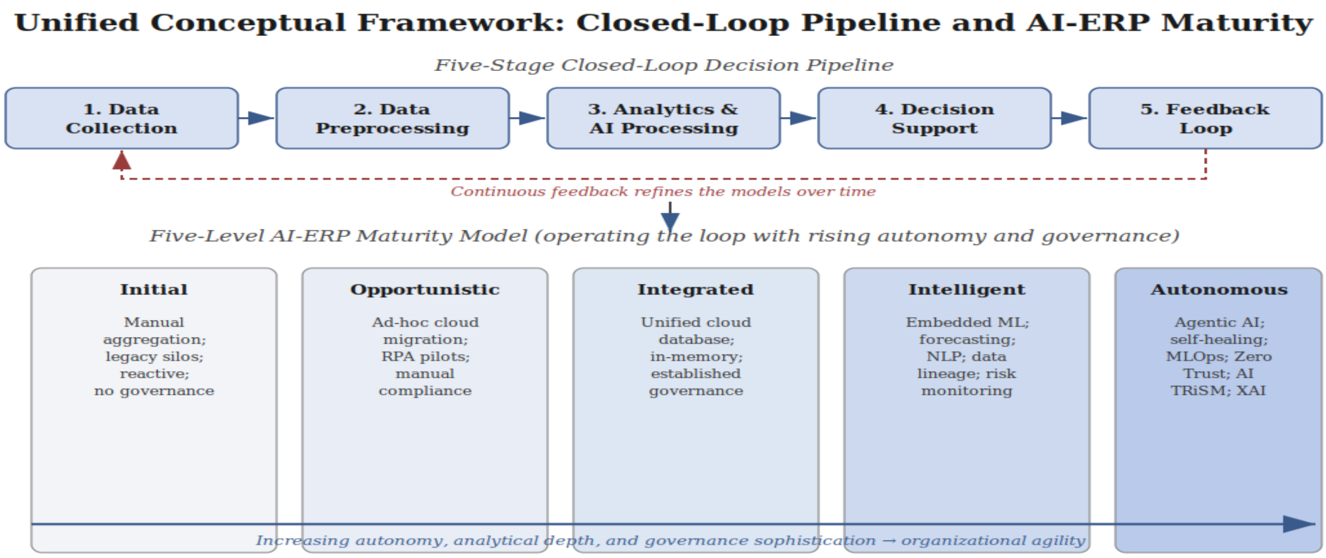

Figure 1. Unified conceptual framework linking the closed-loop decision pipeline to the AI-ERP maturity model. Source: author's own work.

DISCUSSION AND FINDINGS

Synthesis work is studied in relation to the subject matter of study and literature. The findings in this discussion are described as 'associative findings' and as multiple supporting evidence, guided by the conceptual review process.

Embedded intelligence and operational performance

The RQ2 is addressed by examining how embedded machine-learning capabilities in ERP differ from traditional ERP analytics and how they are associated with operational benefits across the corpus. Based on a survey enabled study for investigating AI–ERP integration, the most important main evidence is obtained in the study. The average reduction in task execution processing time achieved by business features after integration was 27 percent according to Godbole (2023) and accuracy, maintenance cost reduction, and overall equipment usage efficiency have been enhanced by up to 35 percent in companies that implemented predictive analytics. However it was found that customer satisfaction increased significantly with the application of artificial intelligence for customer personalisation. Since for each presented statistics it's not general in overall literature the direction of these effects are supported but not convergent to comparable values (Julakanti et al., 2025; Dziembek & Turek, 2025).

The mechanism described was replaced by that of primitive moving average models with the advanced learning architectures, such as those based on recurrent networks and ensemble methods, which are combined directly at the analytical modules that utilize real-time external signals from the suppliers, such as lead times, economic indicators and others, without focusing purely on internal historical data (Jawad & Balázs, 2024). Unsupervised anomaly detection approaches can track complex larg -scale transactions and detect the anomalies of individual transactions in their execution, for example, in financial audits, on dimensions (e.g., authorisation level or vendor profile) (Zhang, 2026). This prescriptive application, where the identified disruptions get ‘what-ifs’ to be done and follow up recommended actions, e.g., alternative supplier, alternative price, and logistics routing to maintain continuous operations, can be an embodiment of the sensing seizing transforming loop mentioned above (Liu et al., 2025; Lin & Chen, 2026).

Acceleration of the financial close

One of the main practical findings relates to the financial closure. Generally, the conventional closure process has been manual and time consuming. This process is called by Oliveira & Ribeiro (2022) to pull data out of several sub ledgers in order to unearth discrepancies. Therefore, timely closure of information is impossible. Using smart and intelligent process automation, automated reconciliation engines can link bank statements, card transactions, payables and receivables sub ledgers, and general ledgers, whereas touchless processing which incorporates natural language processing (NLP) and optical character recognition (OCR) can capture information in an invoice, execute a three way match, and post the same with minimum manual effort (Thanasas et al., 2026; Watson & Schwarz, 2023). The result achieved is a transformation in the finance function from an administrative cost center, to a strategic advisor, giving immediate visibility to and real time key performance indicators on how things are doing in each part of this process. The finding in this study reflects the tale of management accounting literature, progress from backward looking to forward looking with explicit operational details.

Sectoral expression of the agility benefit

Financial services.

AI-driven features adjust budget resources based on macroeconomic shifts, and automate compliance audits, making it robust to maintain on going regulatory compliance (Thanasas et al., 2026; Zhang, 2026). These tools enable the finance executives to carry out forecast cash flow simulations and real time profitability stress assessments by subsidiary. Financial agility improvement is achieved because reforecasting and reallocating capital can be performed more often than with manual methods.

Supply chain.

Machine learning algorithms process IoT data in real time, historical shipping data and meteorological information to provide for demand estimations and optimal stock balancing and smart procurement systems automatically interpret the supplier risks (Liu et al., 2025; Modgil et al., 2022; Boison et al., 2025). And all of this literature fits with the attributes of enhanced resilience in the midst of disruptions.

Manufacturing.

Predictive maintenance models leverage vibration, temperature and cycle data acquired from IoT gateways to predict failures in systems to prepare maintenance from them in future to scheduled maintenance and updating of the master schedule (MS) (Rakholia et al., 2025; Azeta et al., 2026; Lin & Chen, 2026). In summary, unplanned downtime is transformed into planned and scheduled intervention, a concrete example of sensing and seizing as dynamic capabilities that exist in the scenario.

Human-capital management

Embedded learning is a predictor of attrition, personalised development paths and proactive retention and optimal hiring time (Subrahmanyam, 2024; Rasulov, 2025; Kar et al., 2021). The contribution of strategic agility has been defined as a proactive delivery of workforce alignment beforehand of what is needed to increase talent productivity without attempting to catch up to turnover on the other side.

The sensing seizing transforming is a repeat loop in every one, not only for each, of these four domains, but for every domain as data and process and is the dynamic capabilities. There are also some particular forms of the same conditional logic which are common to all of these domains, with the advantage dependent on data, integration and governance that is fit for the domain .

Data quality as the binding constraint

The quality of an embedded intelligence depends on the quality of the data it receives. Learning models can extract structure from past data, but in the case of incomplete, inconsistent or repeated (and indeed sometimes out of date) data, the derived structure is unreliable, and the output of the learning models is also unreliable and appears to be with significant precision (Elbadri et al., 2024) (More & Mucherla, 2025). This is the conditioning relation which happened only because of a visible conflict with the corpus. Even though some anecdotal evidence from vendors and practitioners indicates much improvement, there are scholarly explanations on weaknesses and flaws (Godbole, 2023; Mahmood et al., 2020). Both claims may hold true. When you have a strong data foundation, the benefits you are experiencing are clearly evident, and your weaknesses become apparent when the foundation is weak. It is not the technology but the data environment where technology is applied which explains the variance and the key practical implication of our study is that the data quality bottleneck is the most relevant.

Layered governance and the autonomy–control trade-off

As ERP’s become distributed, cloud native intelligence hubs, their vulnerability to security and compliance increases. Even larger the spread of ERP systems, which is becoming a cloud native, intelligent resource for pertinent information, the larger the risk in terms of potential security and compliance exposure. The literature outlines a stratified governance response described in Table 7, which establishes the restriction along with risk attribution at each level.

Table 7. Layered governance architecture for AI-enabled cloud ERP.

Governance layer	Primary function	Risk addressed	Noted limitation
Sovereign cloud	Enforces data residency and localisation within defined jurisdictions	Geopolitical and regulatory exposure of cross-border data	Cost and reduced flexibility; availability varies by region
AI TRiSM	Continuous audit logging, anomaly detection, model-drift monitoring	Algorithmic fraud, undetected drift, opaque decisions	Frameworks are still maturing and not universally standardised
Explainable AI	Renders model behaviour interpretable for auditors and controllers	Black-box decisions, accountability gaps	Explanations can be partial or post-hoc; trade-off with accuracy

Zero Trust	Continuous verification of identity, device, and transaction	Enlarged attack surface in distributed deployment	Operational overhead; requires organizational discipline

The AI TRiSM can observe AI model behavior over time, and the Zero Trust principle can help to control the measures used or limit access to AI resources such that the four layers represent a defense in depth approach to protecting AI systems (Kumar & Jaya, 2026; Qazi & Arshad, 2025; Sharma et al., 2026; Agarwal & Nene, 2025). The literature also recognizes that no single layer is enough and a suitable mix of layers is conditional on regulatory exposure and maturity. Thus the leading layers are not fundamental, and comprehensive governance rests atop the exposure and maturity model.

Layered governance is, at root, the answer to the autonomy-versus-control trade-off

Layered governance is about balancing autonomy and control. With this paradigm shift of decision making power from human judgement to model suggestions to autonomous actions, the degree of responsibility also alters (Raza, 2025; Ghildiyal et al., 2025; Sarferaz, 2025). The maturity model prescribes a proper response. For every step towards autonomy there must be a step towards governance, and no step towards autonomy without a step towards governance. This trade off makes an ethical issue that must be solved. History based models encode and propagate historical prejudices, and knowledge of which biases should arise and where and how is a subjective phenomenon, and the information is difficult to establish how such are remedied (Leon, 2026; Agarwal & Nene, 2025). So explainability is more than the convenience for compliance. It is an ethical requirement.

Architectural foundations and the human dimension

The operational discoveries are developed and built on top of three architectural foundations. Compared to disk based technology, in-memory database technology can respond to the complex analytical decisions related to streaming information much sooner, making the real time base crucial for agility (Jain et al., 2022; De Castro Fialho & Banothu, 2025). These are modular, API-centric microservices architectures that foster modular scope without disturbing the core process, supporting the clean-core principle and stability and flexibility (Shivarudra & Kumar, 2025; Fang, 2025; Srivastava et al., 2026). Integrated machine learning operations (MLOps) deliver standardised pipelines for preparing data, model training, training and deployment pipeline, model updates and performance monitoring and thus provide the discipline needed to avoid model drift (Nagmoti et al., 2025; Singh & Dutta, 2026). All three of these substrates are essential to make the advanced levels of the maturity model achievable. The human dimension is key in its own right though. Cognitive automation automates routine processing tasks and the job role models from data entry to data interpretation, exception answering and strategic analysis (Kar et al., 2021; Subrahmanyam, 2024). Socio Technical Systems Theory explains this tension in the transition, and AI brings forth a new way of working that raises concern of job uncertainty, loss of autonomy and avoidant behaviours from underskilled employees in dealing with the AI (Olsen et al., 2022; Cepureanu & Cepureanu, 2015). One of the main enablers to the agility benefits, a broader change management approach that can lead through communication, executive sponsorship, an ongoing upskilling approach and not an added on architecture functionality, should have long been a driving force. This has a more systemic effect on performance. Consequently, this has been emphasized in the recommendations outlined below, and places change management on a par with that of technical design.

Theoretical implications

The relationship between the four lenses and the findings brings the paper into a theoretical perspective. Proprietary data, accumulated model parameters, and organisational expertise are a unique combination that is difficult to copy (Seddon et al., 2010; Mishra & Tripathi, 2021). The platform is an easily accessible commodity. What drives the difference would be the data infrastructure and the accumulated learning built into the models. The conceptual assessment does not try to air drop anything, but rather applies an upliftment of the Resource Based View for the AI driven world.

As seen from sectoral evidence, Dynamic Capabilities Theory shows a recurring pattern of sensing, seizing and transforming of the firm in finance, supply chain, manufacturing and human capital (Rakholia et al., 2025; Liu et al., 2025; Jiang, 2024). The objective of this contribution is to demonstrate that cloud ERP has the power to operate as a cross domain vehicle for dynamic capability instead of being a domain specific tool, and to draw attention to the closed loop pipe as the enabler of the sensing, seizing, and transforming processes (Lin & Chen, 2026).

Finally, high rates of failure despite sufficient technical capabilities continue to validate and extend the Socio Technical Systems Theory core concept that skill, role, and hierarchy are no longer the only social factors to account for in the analysis of socio technical systems (Kar et al., 2021; Olsen et al., 2022). The framework's diagnostic capability for AI-era ERP is based on this broadened notion of the social subsystem.

A comparative observation is that the platforms sit on a boundary of a trade off rather than on an ordering. Platforms will vary in their technological features based on the organizations in which they are situated and the regulatory or competitive needs of the environment (e.g., Tudor, 2026), which is essentially a finding of contingency, according to the Technology Organization Environment framework. The contribution tries to introduce this contingency through the maturity model and make it observable and actionable rather than abstract.

CHALLENGES AND LIMITATIONS

Three sets of obstacles condition the agility benefits identified in the discussion. They are offered here on the basis of points already made at sufficient length earlier. It is with the aim of integration, not repetition.

Technical and integration obstacles

The tight integration between modular cloud platforms and legacy custom applications, as well as third-party apps is still quite a challenge. Even if the platform is robust, real time pipelines, semantic consistency in the structure of multiple entities, can lead to latency, vulnerability at API entry points, and cost issues (Singh & Dutta, 2026; Rîndașu et al., 2024). Moving onto a proprietary vendor infrastructure along with the historical data and core business processes creates a risk of vendor lock in, which affects the ability to haggle rates in the future, customise or transition to alternative technologies (Mahmood et al., 2020). Technical burden of machine learning parts. The first law violates the statistical dependence that models use to predict the future, causing models to rapidly drift and make inaccurate predictions when they matter most (Modgil et al., 2022). Distributed, cloud native deployment expands the cybersecurity surface area, and require ongoing observation (Agarwal & Gupta, 2024).

Socio-technical and ethical obstacles

ERP modernisation is not a standard IT upgrade. It is the socio technical transformation on a high-risk level. Legacy platforms already have a habit of generating structural inertia in both routines and power dynamics, and a lack of skills exacerbates that issue as workers do not have the ability to work alongside AI assistants or understand the probabilistic suggestions. (Olsen et al., 2022, Kar et al., 2021). As models make more consequential decisions, ethical considerations become increasingly prominent, while governance and accountability over these decisions remain in their infancy (Leon, 2026; Agarwal & Nene, 2025).

Reconciling competing claims in the corpus

There is indeed a genuine disagreement in the literature that a critical synthesis should not be smothered, but rather should emerge. The difference between practitioner and academic levels of optimism is overcome by acknowledging that, where the data and governance regime is good, the performance improvement can follow and that, if it isn't, the fragility exists. The standardisation distinctiveness tension is solved by conditional preservation of distinctive processes, using external API extensions, and standardisation of idiosyncratic processes. Resolving this autonomy control balance is the responsibility of the autonomy model itself, which associates a new level of autonomy with a matching level of governance. Hence, control is delegated incrementally at the same time that the capacity to govern is developed incrementally.

Boundary conditions of the study

The contributions of the study are obvious limits. It is interpretive and not causal. Associations and instances of the same argument occurring through the literature are what are identified, but not the treatment effect. It doesn't propose that introducing a capability necessarily would mechanically engender benefit in a specific firm. Although curated to include only evidence most relevant to the topic, this evidence base is inherently heterogeneous in analytical method and quality, and judgements on the comparative platform are qualitative syntheses, not standardised benchmarks. The conceptual framework is an organising heuristic that does not need to be activated in the sample. Quantitative results are only presented as reported from the sources. These boundaries are not a reflective of inability to contribute. They are a reflective of how far these landmarks go in outlining the contribution, and they are straight forwardly related to the future research agenda outlined below.

STRATEGIC RECOMMENDATIONS

The synthesis leads to a series of four interlocking recommendations. They are 'given' as a coherent strategy since all evidence points to the fact that none of them on their own can function effectively in relation to the others, and that it takes the four in tandem to do their job properly.

Enforce clean-core principles and modular architecture

It is necessary to take a disciplined approach by keeping the core as 'clean' with standard out of the box applications, and developing any desired customisations remotely by standardised APIs, microservices, and low code platforms for extensions (Shivarudra & Kumar, 2025; Mahmood et al., 2020). Clean Core assures a stable and scalable transaction system, continuous vendor updates and AI innovation without disruption, and improves strategic flexibility. The advice is based on the customisation debate. If a process contributes to a company's competitive distinctiveness, ideally it should be protected via an external extension to reconcile the goals of standardisation and protection of proprietary advantage.

Sequence governance ahead of capability

Since data quality underpins all subsequent benefits, data governance and AI TRiSM architectures should not follow but forbear the implementation of advanced cognitive capabilities (Elbadri et al., 2024; Sharma et al., 2026). The focus areas for governance should be data cleansing, harmonisation of master data, tracking data lineage, and implementing clear stewardship of data. At the same time, AI TRiSM should include real time anomaly detection, constantly tracking models for drift, and immutable audit logs for decisions made by AI systems, while relying on explainable-AI methods for automated approvals and recommendations to be interpretable and auditable (Raza, 2025; Leon, 2026). The sequencing is simple. If a model is trained with bad data and used without clear governance, it will definitely give you big BOLD when it is wrong, and none of all your architecture will make that faith up.

Execute an incremental, phased rollout

Phased rollouts dominate big bang migrations in the evidence reviewed. Of the evidence reviewed, phased migrations are more likely to take place than big bang migrations. A 5 phase approach provides a progressive series of incremental, reversible decisions, allowing organisations to replace the big idea, single go implementation process with one that conducts planning and requirement analysis, system design and data pipeline mapping, development and modular API integration, testing and data validation against historical data and phased rollout with ongoing feedback loop monitoring (Lin & Chen, 2026). High level automation pilots on less sensitive smaller modules, such as receivables automation or forecasting a single unit's demand, enable teams to verify if the model works before enterprise wide application. Operationally, the maturity model uses phased logic that recommends a step at a time.

Treat change management as architecture

Workforce alignment is a strong benchmark of successful socio technical proof in all the literature, which is also a key source of success for technically feasible deployments in action. Leaders should articulate a clear picture of what automation will be. Workers have a clear image of the future of their role and a shared understanding of how it is evolving. How automation will reduce a repetitive burden on workers and transition them into more valuable work and put a high priority on ongoing upskilling in data literacy, analytical decision making, and AI collaboration (Cepureanu & Cepureanu, 2015; Kar et al., 2021). Moreover, natural language interfaces and role based dashboards allow non technical users to query the advanced analytics in an accessible way which relieves the training load and promotes a data driven culture (Mamone, 2025). Change management is a downstream type of communication if it is relegated to a side room, but it properly resumes its natural home in architecture when it is the central feature.

IMPLICATIONS FOR THEORY AND PRACTICE

Theoretical contributions

Three implications in theory emerge from the synthesis. First one is the conceptualisation of AI-enabled cloud ERP as the functional manifestation of a broader capability arrangement rather than as an independent value proposition. Resource Based logic validates that a firm specific pair of proprietary data and continuous learning models (not the platform itself) is the inimitable resource (Seddon et al., 2010; Mishra & Tripathi, 2021); and adoption evidence confirms high uptake clusters where complementary digital capabilities are already present (Tudor, 2026). The second contribution is the explicit coupling of dynamic capabilities mechanics with the maturity aware governance stance. The framework pairs each increment of sensing, seizing and transforming capacity with an increment of governance, addressing the autonomy control trade off that has divided the recent literature (Sarferaz, 2025; Raza, 2025). The relevant methodological contribution is in the process: how can this conceptual review utilize integrative thematic synthesis (Thomas & Harden, 2008; Cronin & George, 2023) alongside an AI-assisted coverage check (Snyder, 2019) as the basis for a defensible account of a highly dynamic and emerging field of inquiry without becoming methodologically paternalistic in the attribution of causality.

Implications for business leaders

For chief executives and financial leaders, what is critical to note is that AI-powered cloud ERP is not merely a digital strategy but a digital strategy unified (Tudor, 2026; Bhatia, 2025). Investment decisions are more favorable where the platform is seen as part of a wider bag of capabilities, which includes systems or structured data, and customer facing systems. Without such prerequisites, investments in them are the responsible first investment as opposed to developing cognitive mechanisms that are also advanced and have returns that under this synthesis are dependent on preliminary investment (Elbadri et al., 2024; More & Mucherla, 2025).

Implications for ERP decision makers

CIOs and enterprise architects get a selection logic that runs on contingencies. Platform archetypes are placed along a continuum between standardised analytical depth and flexible, cost efficient adaptability (cf. Sharma et al., 2025; Karthikeyan et al., 2024; Masuda et al., 2026); select the right one from among them, after a prior determination on the dimensions of agility that matter more to the organisation. Together with a disciplined clean core attitude (which is basically the principle of standard cores extended via APIs and microservices for unique processes), such a decision will also safeguard the stability and competitive distinction (Shivarudra & Kumar, 2025; Mahmood et al., 2020). This modularity and phased logic, so inherent in the maturity model, makes it less prone to failure rate evidence than big bang migrations (Lin & Chen, 2026).

Implications for digital transformation teams

Transformational improvements generally do better in overinvesting in technical design and underinvesting in workforce alignment (Olsen et al., 2022; Cepureanu & Cepureanu, 2015; Kar et al., 2021). Change Management considered as architecture, not as downstream communication, acknowledges socio technical evidence of what really matters to whether technically sound deployments are successful. Specific actions include. Align a clear upskilling agenda to each pipeline stage, use dashboards and natural language interfaces to reduce "the democratization cliff" (Mamone, 2025) and localised pilots run parallel to existing processes, to validate adoption before committing to scale.

Implications for governance stakeholders

As ERP systems have developed at a more autonomous level, so too has the role of compliance experts, risk officers, and audit committees. It depicts the layered governance system based on "defence in-depth", where none of the layers can stand alone, and the four layers. Sovereign cloud, AI TRiSM, explainable AI, and Zero Trust, work together (Kumar & Jaya, 2026; Qazi & Arshad, 2025; Sharma et al., 2026; Agarwal & Nene, 2025). Governance stakeholders should also anticipate an increased level of involvement earlier in transformation programmes, not just in static design but also in understanding and evaluating the dynamic behaviour of the models that the controls govern, including drift, fairness, and explainability under operational stress (Leon, 2026; Raza, 2025).

Implications for SME leaders

The general recommendations must be tailored to small and medium enterprises because they face different calculus. However, the evidence from the adoption suggests that (even though it does not determine) the benefits of the AI-enabled ERP can only be realised when scaling effects take place, and that instead of scale there may be complementary digital capabilities that are already present in the company prior to ERP adoption (Tudor, 2026; Buonanno et al., 2005). Therefore, for the resource not so well endowed companies is not the most competent the platform that matters as much as the most solid foundation. Harmonisation of master data, a defendable quality baseline and an honest assessment of the dependency on connectivity, a universal vulnerability of off premises models, regardless of the label of their deployment (Achargui & Zaouia, 2016). Adopting the software as a service model helps reduce total cost of ownership and drives the focus of SME leaders on core activities. However, this comes at the cost of limited customisation options, so rather than resisting it, SMEs would be better off embracing it as a natural fit and calling on outside help only for those few processes that truly matter. (Ranasinghe & Gide, 2025; Lawendatu et al., 2026). Here, phasing is even more critical as it disproportionately affects companies with fewer resources if it isn't successful.

Implications for large enterprises

For companies with large amounts of data, there are implications as well. The opposite situation prevails in large enterprises. Most of the time the challenge is not that they lack complementary capabilities, but the structural inertia of deeply embedded legacy estates, the integration challenge for multi entity and multi jurisdiction operations, and the added governance weight of scaled operations (Lee et al., 2024; Mahmood et al., 2020). For these organizations, the enterprise scale analytical archetype provides the analytical depth and consolidation that complex structures demand, but success requires socio technical risk mitigation and up front governance. Chosen for their complex analytical needs, the analytical activities present the greatest socio technical risk and the highest implementation expense (Masuda et al., 2026; Singh & Dutta, 2026).

Large enterprises are also the most exposed to the autonomy. Control trade off, because they command the data volumes and process scale that make agentic operation attractive and the regulatory exposure that makes it hazardous. The layered governance architecture, and the pairing of each autonomy increment with a governance increment, are addressed first and most urgently to them (Sarferaz, 2025; Qazi & Arshad, 2025).

Table 8. Stakeholder-specific managerial action summary.

Stakeholder group	Recommended priority action	Supporting evidence	Maturity-stage focus
Executives and finance leaders	Treat the platform as the operational layer of a wider	Tudor (2026); Elbadri et al. (2024)	Integrated and above

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	capability bundle; where complementary capabilities are absent, invest in them first		
ERP decision makers (CIOs, architects)	Select the archetype matching the dominant agility priority; pair it with a disciplined clean-core strategy	Sharma et al. (2025); Mahmood et al. (2020)	Integrated to Intelligent
Digital-transformation leaders	Treat change management as architecture; tie an upskilling plan to each pipeline stage and validate through localised pilots	Olsen et al. (2022); Kar et al. (2021)	All stages, intensifying with autonomy
Governance teams	Sequence data governance and AI TRiSM ahead of advanced cognitive capability; operate the four governance layers as defence in depth	Singh & Dutta (2026); Sharma et al. (2026)	Intelligent to Autonomous
SME leaders	Prioritise master-data quality and connectivity resilience; adopt a SaaS clean core and phase the rollout	Achargui & Zaouia (2016); Ranasinghe & Gide (2025)	Opportunistic to Integrated
Large enterprises	Front-load governance and maturity-aligned sequencing; pair each autonomy increment with a governance increment	Masuda et al. (2026); Sarferaz (2025)	Intelligent to Autonomous

Across the stakeholder groups a single principle recurs. The appropriate action is indexed to the organization's maturity stage rather than to the frontier of available technology. The summary in Table 8 is therefore best read alongside the maturity model, which specifies the technical and governance preconditions that make each recommended action feasible, and against which a stakeholder can locate the action that is actionable now rather than merely aspirational.

FUTURE RESEARCH DIRECTIONS

Seven directions emerge from the gaps identified above. They are framed as specific, researchable questions rather than as generic calls for further work, supporting cumulative scholarship in a rapidly evolving field.

Effectiveness of AI governance frameworks

AI TRiSM, sovereign cloud arrangements, and emerging board level AI oversight frameworks are described in the literature primarily in prescriptive terms (Kumar & Jaya, 2026; Sharma et al., 2026; Agarwal & Nene, 2025). Empirical research is now needed on their effectiveness in practice. Which control configurations actually reduce model drift incidents, AI-related compliance failures, and downstream operational losses, and which produce only nominal compliance without any behavioural change? This would be especially interesting if it were based on comparative case studies from regulated sectors: finance, healthcare, and energy.

Generative AI in ERP environments

Generative models are now making their way into ERP via natural language interfaces, document understanding, and proposal generation (Sarferaz, 2025). Underexplored aspects include implications for accuracy and auditability as well as the diffusion of accountability. The research should aim at the examination of the nature of processes and methods for integrating generative components in the workflow of finance, procurement and

HR processes and the examination of how the outcomes of the generative components are validated and recorded in the workflows and whether the integration in HR, finance and procurement processes changes the required skills, which can lead to new tailored training designs.

SME versus large-enterprise adoption pathways

Although the adoption literature shows scale conditions, it does not determine AI-ERP uptake (Tudor, 2026; Buonanno et al., 2005; Ranasinghe & Gide, 2025). Comparative analyses of small and medium sized enterprises and large firms could clarify which capability bundles substitute for scale in resource constrained settings, whether platform archetypes deliver agility differentially across firm sizes, and how connectivity dependence and customisation constraints reshape the SME implementation calculus (Achargui & Zaouia, 2016)

Explainable AI in ERP decision contexts

Explainable-AI techniques are central to the layered governance architecture but remain under evaluated within ERP specific decision contexts (Raza, 2025; Ghildiyal et al., 2025). Field studies are required on whether available explanations actually support auditor scrutiny, controller intervention, and managerial trust in ERP embedded recommendations, and on the accuracy interpretability trade offs that arise when explainability is retrofitted onto pre trained models.

Longitudinal outcomes of ERP transformation

The Scopus AI synthesis underpinning this review explicitly identifies the scarcity of longitudinal evidence on AI-ERP outcomes. Multi year studies tracking agility, financial performance, and governance posture across cohorts of adopting firms would convert the present interpretive associations into causal, generalisable knowledge (Cronin & George, 2023). Such studies are particularly important because the most consequential effects, on capability formation, organizational culture, and competitive position, manifest over years rather than quarters.

Measurement of organizational agility in AI-enabled ERP contexts

Organizational agility is posited as a multidimensional construct within the corpus, although there is no agreed upon measurement instrumentation specifically for AI-enabled ERP environments in the literature (Koundal et al., 2024; AlMahadin, 2025). For embedded ERP and embedding agility within a broader digital configuration context, future studies can be carried out to construct and test scales for financial, operational and strategic agility (Tudor, 2026). But without any such instrument(s), the field will keep debating its effects it can never measure with consistency.

Responsible AI in enterprise systems

Seventh direction is the next one transverse to the previous 6 directions. With ERP systems assuming more impactful decisions, the responsible-AI dilemmas that the larger machine learning literatures emphasize take on a different, enterprisey look and feel. What is fairness, accountability, and contestability even if the process of auto generated recommendations entering a journal entry, labeling the supplier as one of the troublemakers, or changing the schedule based on maintenance? Herein lies the literature reviewed that reflects two perspectives that address the exposure to aspects of ethical behavior. The prescribing of the exposure of bias across the historical records, the diffusion of accountability as a consequence of autonomy, and a sense of explainability on auditing decisions in respect of the transparency of actions (Leon, 2026; Agarwal & Nene, 2025). But what is less common is to operationalise these principles, how do responsible-AI principles figure into MLOps pipelines? How does the need for responsible-AI compliance require some customization as they grapple with the demands of clean core discipline and what does responsible-AI compliant actually mean in terms of impact or rather merely being a "rubber stamp"? Research tying the responsible-AI agenda to the specific decision points of an ERP workflow, rather than abstracted decisions about AI, could also help bridge this gap between ethics and enterprise, joining the governance effectiveness push and asking whether governance controls are not only effective but whether they are just.

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A consolidated research agenda

The seven research areas mentioned above can be further described in Table 9. In this report we describe how each of the research areas emerged from one of the gaps identified in the synthesis matrix and/or boundary conditions. Table 9 also displays an example research question along with a potential approach to handling the question given the constraints of this study. Table 9 is used to build the backbone for the compiled research agenda, which each is traced back to a gap originated from the survey. Thus the work program will not become an attachment to the review.

Table 9. Consolidated research agenda derived from the identified gaps.

Research direction	Identified gap	Illustrative research question	Suggested approach
Effectiveness of AI governance	Frameworks described prescriptively, not evaluated empirically	Which control configurations actually reduce model-drift incidents and compliance failures?	Comparative case studies in regulated industries (finance, healthcare, energy)
Generative AI in ERP	Accuracy, auditability, and accountability effects unexamined	How are generative outputs validated, recorded, and absorbed into finance, procurement, and HR roles?	Embedded case studies of generative components in live workflows
SME vs large-enterprise pathways	Scale conditions but does not determine uptake	Which capability bundles substitute for scale in resource-constrained settings?	Matched comparative studies across firm sizes
Explainable AI in ERP decisions	Explainability under-evaluated in ERP-specific decision contexts	Do available explanations actually support auditor scrutiny and managerial trust?	Field experiments with controllers and auditors
Longitudinal transformation outcomes	Scarcity of multi-year evidence on AI-ERP outcomes	How do agility, performance, and governance posture evolve across adopting cohorts?	Multi-year panel studies of adopting firms
Measurement of organizational agility	No agility instruments specific to AI-enabled ERP settings	How is ERP-attributable agility distinguished from wider digital configuration?	Scale-development and validation studies
Responsible AI in enterprise systems	Ethical principles not yet translated into ERP practice	Do responsible-AI controls measurably reduce harm at ERP decision points?	Design-science and mixed-method evaluation studies

CONCLUSION

AI-powered cloud ERP is a significant shift in digital enterprise strategy, as organisations move their internal operations to the cloud while modernising their core enterprise systems. Once conceived as transactional record keeping databases, modern ERP systems are now transforming to become intelligent, adaptable, and cognitive, incorporating machine learning, in memory processing and cognitive automation into their financial and operational ledgers, providing the level of visibility, insight and agility that organizations need (Govinda et al., 2025, Jain et al., 2022).

The synthesis in this paper supports the three findings. The common thread that runs across the whole embedded intelligence effort is the lot of operational improvement, such as faster turnaround time in closing deals, more agile planning of demand and risks and less manual handling, the primary quantification is provided by the survey evidence regarding the use of AI–ERP (Godbole, 2023). There is not a hierarchy, but a trade off between leading enterprise platforms. It is important for firms to choose the right platform to ensure they are succeeding in agility, depending on maturity. Agility leverages the presence of cluster attributes. Where an existing organization has existing capabilities that are cloud deployed, customer facing, and commercially useable (Tudor, 2026), which is the main conceptual thrust of this paper. AI-enabled cloud ERP does not replace an existing digital architecture.

The synthesis allows a direct answer to the question raised in the problem. Why invest in technology and yet remain stuck in the problems and failures? Why does AI in cloud ERP not increase agility when and where is that the case? The findings for differential influence of platforms (RQ1) depict a trade off frontier along which these 3 dimensions (financial, scenario-planning, and operational responsiveness) are differently distributed among archetypes, meaning that the influence is not the same across archetype but instead is contingent on the fit. Regarding embedded analytics and automation (RQ2), the corpus consistently refers to embedded learning as a means to achieve ATP, which results in compressed decision cycles, fewer errors, and better predictions, but this is dependent on the quality of the data used to train the models. Sovereign cloud, Zero Trust, AI TRiSM and explainable-AI capabilities represent a defence in depth approach that if implemented effectively, increases with regulatory exposure and organizational maturity, but isn't simply reliant on any one control. On the path towards autonomous use (RQ4), the maturity model outlines technical thresholds and socio-technical constraints that determine progression in each step of autonomy and links each autonomy with a corresponding governance.

The responses gravitate toward a central claim made by the paper, and address the issue the paper poses. When paired with high investment, the failure rate is not a reflection of the technology, but a reflection that agility is a conjunctive achievement, that is the joint product of a data and modeling resource that cannot be replicated, an exercised sensing seizing transforming loop, a socially aligned workforce and a fitting technology organizational environmental context. The reported returns can be achieved where those conditions exist and the same technology is proven to be utterly disappointing where any of those conditions are lacking. The title's pairing of real time analytics, automation, and governance takes this conjunctive reading none of the three benefits lives alone. Each is a yes or no proposition that requires the others. It's the combination of all three, not the sum of individual bebenefits,efits that yields organizational agility.

The theoretical contribution is the result of the four lenses that look at the evidence. The Resource Based View makes sense of how this “intelligence” built into systems with data can create a source of advantage. The Dynamic Capabilities Theory clarifies the “sensing-seizing-transforming” process by which the advantage kickens in. The Socio-Technical Systems Theory explains how the friction against this effect works, and TOE provides the contingency logic to make it all cohesive. As such, they make AI-powered cloud ERP into the functional manifestation of a more comprehensive capability architecture, not just the impact of one technology.

The practical contribution is the combined conceptual framework, the closed loop decision pipeline and the five level maturity model and, in addition, provides a diagnostic for executives to identify where their organization is today and what technical and governance preconditions exist for progressing to the next stage. The framework together with the four recommendations. Clean core architecture, governance prior to capability, phased rollout, and change management as architecture, transforms the synthesis into executable transformation logic.

It is not the most sophisticated ones that will make the most of cloud ERP fueled by AI. It is the ones that follow its rules. They're the ones that match technical capability to data quality, maturity of data governance and readiness of work force. It's the difference between an enterprise that's written down in an intelligent system, versus one that is intelligent enough to Sense, Seize, and Transform the enterprise, the agility you need to succeed in a digital economy with constant volatility. Ultimately, the executives' question is not so much "Which platform to buy"? It is about what configuration to create and at what pace to allow the system to evolve in order to become agile.

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