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Optimizing ERP Systems For Strategic Decision-Making: A Data And AI-Driven Approach

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Abstract
As Enterprise Resource Planning (ERP) systems become transformed by Artificial Intelligence (AI) and rich data analytics tools and applications they are becoming strategic decision-support systems as opposed to transaction platforms. The present paper reveals the existing research gap related to the studies which employed robust empirical analysis of the AI-enhanced ERP modules, proposes specific research questions, and utilizes a mixed-methods design based on publicly available and real-life data (the UCI Online Retail transactional dataset and the European Credit Card Fraud dataset) and three case studies of manufacturing companies deploying SAP S/4HANA. With metrics like Mean Absolute Percentage Error (MAPE) and F1-score, we depict that AI-based demand forecasting can achieve a 24.8 percent reduction in MAPE score (18.2 percent to 13.7 percent) and that the anomaly detection has a score of 0.89 in terms of F1-score. As well, use-augmented financial planning enhances the precision of the cash-flow forecast by 29.3 percent. We end by documenting a practical path that organizations can take in moving beyond data collection to continuous intelligent action.

Keywords
Enterprise Resource Planning (ERP); Artificial Intelligence; predictive analytics; demand forecasting; anomaly detection; financial planning; UCI Online Retail; SAP S/4HANA

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I. Introduction

Enterprise Resource Planning (ERP) have been touted as the pillar of an integrated organisational information since it offers a mixture of transactional information across the organisational set-up in the fields of finance, procurement, manufacturing and the supply-chain operations. Back in the late 90s, the implementation of ERPs involved reduction of costs, data consolidation and the standardisation of processes (Davenport, 1998; Klaus, Rosemann and Gable, 2000). Although these capabilities were able to provide substantial gains in operational effectiveness (supplying shorter process lead times, inventory and financial close cycles), they tended to fulfill only a small part of what the senior management needed to determine moves defensively, to achieve strategic agility (Shang and Seddon, 2002; Aloini, Dulmin and Mininno, 2007). Decision-makers in most cases were still using retrospective, static reports exported out of ERP modules, which had no predictive capabilities on market changes and were not giving near real-time alert to emergent anomalies (Shang and Seddon, 2002; marston_et_al. 2011).

With the coming of the so-called Industry 4.0 and the rise of big data, there emerged new demands to the ERP foundations to go further than merely recording transactions and become intelligent engines that assist in decision-making (Kagermann, Wahlster and Helbig, 2013; Lee, Bagheri and Kao, 2015). At the same time, Machine Learning (ML) and Artificial Intelligence (AI) innovations provided an opportunity to integrate predictive and prescriptive analytics directly into the enterprise systems to use historical data generated combined with streaming data in order to predict demand, identify unusual conditions, and optimise financial planning (Davenport and Harris, 2007; Manyika et al. 2011). These possibilities do not only offer gradual adjustments but transformational changes in the ways organisations perceive and react to the changing situation on the market, allowing them to proactively reduce risks, as well as plan their actions in advance (Ross, Beath and Sebastian, 2017; Brynjolfsson and McAfee, 2017).

Although there is a huge increasing set of vendors, and growing literature regarding the concept of an AI-driven ERP module, little empirical data exists regarding the magnitude of the effects of an AI-driven, ERP module. A significant part of the existing literature has concentrated on either free-standing AI solutions or post-implementation payoffs of conventional ERP-based systems, and they do not single out the somewhat increment, but rather cannot be disentangled, benefit allotted to built-in AI/ML capabilities (Gupta and Kohli, 2006; Benitez, Ray and Henseler, 2018). Moreover, even those works that have analysed predictive analytics in supply-chain or financial terms do not take into consideration the integrative nature of ERP as source of data and decision-execution platform (Chen, Preston and Xia, 2010; Nuernbergk, Matthes and Spann, 2016). As a result, the literature is missing an important gap, as it requires rigorous and multi-case assessments of AI-enabled ERP modules that can determine their effectiveness in improving demand-forecasting accuracy, effectiveness of anomaly detection, and strategic financial performance.

Filling this gap has the primary importance to both scholars and practitioners. Academically, the information on how ERP-integrated AI affects organisational performance factors into the knowledge involving dynamic capabilities and resource-based premises, explaining how information resources and analytical skills merge to come up with competitive powers (Seddon, Calvert and Yang, 2010). In the practical aspects, decisions have to be made by the top hierarchy to invest in AI-augmented ERP modules, they have to be satisfied with tangible evidence on the investment, especially when the cost of ERP customisation, data governance and change management are considerably high and risky (Aloini, Dulmin and Mininno, 2007; Marston et al., 2011). Some efforts at digital transformation could be put on hold when they cannot justify the ROI of these capabilities and foster their perceived potential when it comes to AI.

As such, this paper follows two research questions that are related to each other:

- RQ1: How well does the embedding of predictive-Analytics models into an ERP system enhance the accuracy of demand-forecasting compared to the traditional statistical approaches?
- RQ2: How efficient are the anomaly-detection modules (that are embedded in ERP) in detecting financial and operational anomalies and how do they affect the risk-management process?

Our response to these questions will attempt to provide not only theoretical evidence of the role of AI in enterprise systems but also practical advice to organisations considering how future iterations of ERP can be used.

The research will be a mixed-method one with multi-case study of three mid-sized manufacturers having already deployed AI-enabled modules in SAP S/4HANA and the simulated-dataset analysis providing benchmarking. This strategy provides a trade-off between ecological validity which even considers real-world deployments with internal validity via replicable simulation experiments (Venkatesh, Brown and Bala, 2013). The evaluation of forecasting performance is done through the lens of the Mean Absolute Percentage Error (MAPE) and the anomaly-detection performance through the precision, recall and F1-score metrics in comparison to the baseline statistical and rule-based ones.

The rest of the paper will be structured in the following way. Section 2 includes the thorough overview of the literature on ERP evolution, AI integration and adoption of predictive analytics. In section 3 we describe our methodology, i.e. how we have selected our cases, what kind of data sources we have used and how we have implemented the model. Quantitative results are presented in Section 4 whereas critical discussion is provided in Section 5 which positions our findings under dynamic-capabilities theory and ERP benefit realisation scope. The section 6 provides an implementation plan that can be used by the practitioners to move a step further to constant updating of the model based on data gathered. Lastly, the paper has made conclusions in the implications of the research in future research and managerial practice.

Overall, the study offers the original, empirical insight into the potential of AI-enabled ERP systems to benefit organisations as a strategic asset and the means of establishing the approach towards the synergistic use of the ERP data to drive organisational intelligence. Through this bridging of the gap between the ideals of concept, and the reality of practice we empower the scholar and the practitioner to move with increased confidence and accuracy into the ever-changing, dynamic environment of digital enterprise.

ERP solutions have passed through a number of evolutionary stages since their invention in MRP (Material Requirements Planning) systems in the 1970s. The evolution of MRP to MRP II in 1980s added up the capability of planning to the capacity needs and shop floor control (Vollmann et al., 2005). By the mid 1990s vendors such as SAP, Oracle and PeopleSoft rebadged integrated suites as ERP, and focused on cross process integration of functions and universal data model (Davenport, 2000; Klaus, Rosemann and Gable, 2000). Later developments (popularly called ERPII) entailed the development of internet enabled collaboration, CRM incorporation and extended supply chain modules which essentially changed ERP to enterprise wide systems able to support external stakeholders (Jacobs and Weston, 2007; Helo and Szekely, 2005). Nevertheless, the first ERP implementations still used the operational efficiency/strategic insight as a principal way too little analytics were used in a separate data warehouse setting (Shang and Seddon, 2002; Aloini, Dulmin and Mininno, 2007).

Theoretical lenses assist us in ascertaining why ERP systems have not resulted in the provision of enough strategic foresight in the traditional context. Resource Based View (RBV) assumes that the foundation of sustainable competitive advantage lies in the acquisitions of firm specific resources stored with these characteristics: valuable, rare, inimitable and non substitutable (Barney, 1991). On the one hand, ERP data is a valuable asset, but due to its availability in any company and standardized form, it does not bring much strategic value by itself unless it is enhanced with powerful analytics. Dynamic Capabilities Theory has added to RBV and stresses on the capacity of a firm to combine, develop and rearrange internal and external capabilities so as to respond to the fast altering environments (Teece, Pisano and Shuen, 1997). Examples of dynamic capabilities include AI embedded ERP systems: the ability of organisations to sense changes in the market place, grasp opportunities as they emerge and rapidly change organisational processes in real-time. Nevertheless, the uses of dynamic capabilities in emergences of the ERP are yet to be examined (Wilden, Gudergan and Lings, 2013).

The other relevant framework is the Technology Organisation Environment (TOE) model that tracks technological, organisational, and the environmental elements that determine the adoption of technology (Tornatzky and Fleischer, 1990). The technological factors that are involved in the ERP environment will be the complexity of the system, interoperability and compatibility; the organisational factors will be the promotion of top management, IT competency and change preparedness; the environmental factors will be the dynamics of the market, diversity of regulatory frameworks and competition. Though TOE framework has been in use in general ERP adoption surveys (Zhu and Kraemer, 2005; Ifinedo, 2007), it has lacked thorough customization towards the nature of AI implementation in an ERP system, with specific reference to data hungry ML models and need to continuously train model, which require attendance.

Critiques made on previous works have indicated a number of gaps. Much of the research focuses on AI applications independently, where an AI tool is added in isolation, in the context of standalone demand forecasting, or autonomous enterprise fraud detection (Chen, Preston and Xia, 2010; Chae, Olson and Sheu, 2018). Others research vendor case studies and white papers, with no independent verification of those claims or comparisons carried out against a universal performance benchmark (SAP SE, 2024; Oracle, 2023). This lack of coherence has been a bar to cross study comparisons, and a practitioner has little empirical advice to the incremental advantages of AI embedded ERP modules over discrete analytics add ons.

Any AI driven ERP initiative is challenged on data governance and data quality issues. Data discrepancies in master databases, domain-specific data silos and legacy system compatibilities can derail the training of the models and cause the garbage in-garbage out behavior (Otto, 2011; Khatri and Brown, 2010). Governance models, including Data Management Body of Knowledge (Data Management Body of Knowledge DAMA DMBOK) and SAP Master Data Governance (MDG), present models to outline data ownership, data stewardship and management of data lifecycle (Batini and Scannapieco, 2016). However, companies may not realize how much investment is needed at the front-end of data cleansing, entity resolution and metadata management before quality insight can be generated based on AI.

A human aspect of managing change is also equally vital. The traditional ERP installations already require a significant organisational adjustment: reengineering of processes, retraining of personnel, and realignment of performance measures (Markus and Tanis, 2000; Esteves and Pastor, 2001). Adding the AI layers to this complexity: end users are to become data literate, learn to trust predictive results, and alter their decision-making workflows to retrieve probabilistic information instead of rather deterministic reports (Berente et al., 2019). It is a well-established fact that the user adoption can be enhanced through the establishment of an Analytics Centre of Excellence, using analytics champions and consistent training (LaValle et al., 2011; Mosavi, Ozturk and Chau, 2018).

Slipper and flights of ERP and AI investments are highlighted in the market data. In the Panorama Consulting ERP Report (2021), 87 percent of organisations that had an AI pilot project said that the quality of decisions improved, although 60 percent of ERP projects continue to fail to deliver expected ROI in three years, because of scope creep, under resourcing and poor executive sponsorship. According to Gartner, 50 % of enterprises of the medium and large size will integrate ML models into the core systems of the businesses by the year 2025, which is a massive rise compared to the estimated number of 2020 of less than 10 % (Gartner 2022). Of this number, however, a pick will end up achieving quantifiable performance benefits with well-ordered project governance and ongoing improvement processes.

The adoption of Cloud based and SaaS ERP platforms only increases the pace of AI implementation. The costs of the initial infrastructure are reduced by public cloud solutions, elasticity can be achieved when heavy compute operations are required (ML workloads), and integration of custom AI services with a central ERP data platform (e.g. Azure ML, AWS SageMaker) can occur without obstruction (Sinkovics et al., 2020; Ross et al 2016). However, there is a set of challenges associated with cloud native ERP deployments namely data residency, issues related to cybersecurity controls and the management of APIs to be considered so that to be in compliance with regulations such as GDPR, SOX and domain specific standards (Constantiou and Kallinikos, 2015; Tallon and Pinsonneault, 2011).

Considering such diverse factors, our work has two essential outcomes. First, we obtain quantitative, rigorous, reproducible, and transparent performance measures (MAPE, precision/recall, F1-score) on publicly available data (and on real world case data), which serve as transparent evidence of AI embedded ERP performance. Second, we obtain practical knowledge of data governance models, change management practices and technological architectures that influence the successful convergence of AI and ERP through cross case synthesis. These contributions build into both theoretical knowledge-blending dynamic capabilities and TOE frameworks, to AI driven ERP--and managerial practice, which is presented in an overarching road map of how dynamic capabilities and TOE frameworks can be applied to intelligent, data driven transformation.

In summary, the evolution of ERP from back-office enabler to predictive decision-support platform hinges on the integration of AI/ML capabilities, underpinned by robust data governance, organizational readiness and cloud-enabled infrastructures. Addressing the research gap requires not only conceptual frameworks but also empirical validation of incremental performance gains. By doing so, this paper equips scholars with a richer understanding of AI's role in enterprise systems and empowers practitioners to navigate the complexities of AI-augmented ERP implementations with evidence-backed confidence.

II. Literature Review

This literature review does a synthesis of how ERP systems evolved, important theoretical backgrounds of technology driven strategic value, rise of AI and predictive analytics in the domain of ERP, and demand forecasting in particular. The subsections combined define the background context and outline vacuums that our study fills.

Evolution of ERP Systems

Enterprise Resource Planning (ERP) systems may be called back to the roots of MRP in the 1970s that were used to automate the work of calculating inventory of manufacturing processes (Vollmann, Berry & Whybark, 2005). The same capabilities of MRP II in the 1980s took it to capacity planning and shop floor control and thus end to end production scheduling started to take place (Fullerton, McWatters & Fawson, 2003). By the early 1990s vendors like SAP, Oracle and PeopleSoft repackaged integrated suites as ERP with a greater focus on cross functional process integration between the finance and procurement and human resource and supply chain modules (Davenport, 2000; Klaus, Rosemann & Gable, 2000).

The millennium ushered in the ERP II, which was marked by internet enabled architectures, CRM and long chain of supply chain collaboration (Jacobs & Weston, 2007; Helo & Szekely, 2005). Nevertheless, the analytics has been secondary and normally deposited on the data warehouse and offline ETL system, which caused latency and could not allow real time decision making (Shang & Seddon, 2002; Aloini, Dulmin & Mininno, 2007).

The development of in memory computing, namely, SAP HANA in 2011, was a paradigm shift since it eliminated the distinction between transactional and analytical workload in a unified platform (Plattner, 2016). This live ERP construct allowed embedding of algorithmic calculations and system-defining business processes together as a basis of both system-integrated and system-embedded AI/ML capabilities (Ross, Beath & Sebastian, 2017). Tomorrow, the top suites market systems of intelligences to offer predictive and prescriptive analytics, but enough of the two have not been implemented due to legacy customisations and the existence of data silos and a shortage of skills (Panorama Consulting, 2021; Marston et al. 2011).

Theoretical Foundations

Resource-Based View (RBV)

Resource Based View holds that such efficient competing advantage comes about as a result of the firm specific resources that are valuable, rare, inimitable and non-substitutable (Barney, 1991). The ERP systems produce rich transactional data with high value but rarely unique between firms. This widespread information can be converted into context sensed insights through a combination of AI models integrated into ERP, thereby upgrading its rarity and inimitability thus in compliance with what RBV suggests to be strategic resources (Seddon, Calvert & Yang, 2010).

Dynamic Capabilities

Dynamic Capabilities Theory is an extension of the RBV theory because it puts emphasis on a firm that is able to sense the opportunities that come along together with forming them and reconfigures the assets amid altering situations (Teece, Pisano & Shuen, 1997). Examples of dynamic capabilities are AI-enabled ERP modules: they can be used to sense demand patterns in real time, trigger decision (e.g. replenishment) autonomously, and adapt planning processes on continuous basis. Although this theory fits into the contexts decently, there is not so much empirical usage of dynamic capabilities in AI ERP integration (Wilden, Gudergan & Lings, 2013).

Technology–Organisation–Environment (TOE) Framework

TOE framework determines technological, organizational and environmental elements affecting the adoption of technology (Tornatzky & Fleischer, 1990). In ERP embedded AI systems, the technological factors encompass growth of algorithms, data infrastructure and system compatibility; organisational factors include support of top management, data science capability and readiness of change management; the environmental factors include existence of competitive pressure, regulatory requirement, and ecosystem of partners (Zhu &

Kraemer, 2005; Ifinedo, 2007). To the extent that TOE has guided the general research on ERPs, the same can contribute more to the idea of continuous learning AI models in regard to ERPs (Chen, Preston & Xia, 2010).

AI and Predictive Analytics in ERP

The use of AI in ERP uses machine learning model based upon transactional information to deliver forward oriented insights. Predictive analytics, including time series forecasting, classification and anomaly detection enables organisations to see the future and forecast demand, identify and prevent cases of fraud, and optimise financials, whereas prescriptive analytics utilise optimization and simulation to make decision recommendations (Davenport & Harris, 2007).

According to what vendors describe in their white papers, embedded AI modules could provide up to 30 % better accuracy when forecasting and 40 % fewer outages (SAP SE, 2024; Oracle, 2023). However, academic reviews note the homogeneity issue when it comes to methodology and the absence of standard measures (Wamba et al., 2017; Chae, Olson & Sheu, 2018). As Huang and Rust (2021) assert, there is a need to establish trust and interpretability in AI systems and it is an issue of equal concern to ERP decision processes.

The major gaps noticed are:
1. Isolated Inspections: Evaluations are usually carried out on isolated AI systems and not embedded modules in the ERP (Chen, Preston & Xia, 2010).
2. The absence of Benchmarks: There is a reported improvement in performances that is reported in different contexts where comparing with other studies is impossible (Wamba et al. 2017).
3. Organizational Factors: Mainly due to lack of research when it comes to governance and change management to adopt AI in ERP context (Marston et al. 2011; Mosavi, Ozturk & Chau, 2018).

Demand Forecasting Models and ERP Integration

Classical Time-Series Methods

ARIMA and SARIMAX are still the staples of forecasting because they are understandable and have a solid statistics background (Box, Jenkins, Reinsel & Ljung, 2015). They are easy to program up by trend, seasonality, exogenous regressors (e.g., promotions, holidays) where they potentially stumble on non-linear and larger dimension data as is common in omnichannel retail (Petropoulos, Makridakis & Assimakopoulos, 2022).

Machine Learning and Deep Learning Approaches

Long Short-Term Memory (LSTM) networks, one of the recurrent neural networks, deal with long term dependency and the non-linear patterns of the recurrent neural networks (Hochreiter & Schmidhuber, 1997). According to studies, LSTM constrains lower MAPE or 15-25 per cent when compared to ARIMA in the retailing and manufacturing settings (Lim & Zohdy, 2021; Zhang, Patuwo & Hu, 2019). Further improvement of robustness and minimization of overfitting is observed in hybrid methods such as the combination of neural nets with classical decomposition (Gers, Schmidhuber & Cummins, 2000; Qin et al., 2017).

Embedding Forecasting in ERP

Recent releases of ERP systems (e.g., SAP S/4HANA, Oracle Fusion, Microsoft Dynamics 365) provide integrated ML services that can be used to push forecasting models onto the transactional data pipelines as SAP PAL/APL and Azure ML. This alleviates the latency and makes the model lifecycle management easy but creates challenges in data governance, security and performance SLAs (Wang, Li & Li, 2023; Sankaran, 2025).

Empirical Evidence and Gaps

Fathima et al. (2024) develop a literature review of 50 studies about the benefits of AI driven ERP forecasting, where average MAPE gains are found to be 20 % against benchmarks. However, they emphasize that a small amount of controlled and reproducible comparison needs to be conducted with publicly available datasets. We will deal with it by comparing SARIMAX and LSTM on the UCI Online Retail among a simulated ERP system.

Anomaly Detection Techniques within ERP

ERP systems have a critical component that detects anomalies, i.e. unusual transactions or activities, including occurrences of an anomalous nature, e.g., fraud, non-compliance and process failures, prior to their becoming material miscarriages or reputational issues. ERP transactional data can be considered high volume, high dimensional and frequently imbalanced, as the basic anomalies comprise less than 0.5 % of the items (Dal Pozzolo et al. 2015).

Unsupervised Methods

Isolation Forests are more like anomaly isolators, which recursively partition data, measure path length and shorter path denotes anomalous instances (Liu, Ting & Zhou, 2008). Being of linear time complexity, and the low tuning needs to be made applicable to large ERP data streams. Autoencoders auto encoders are a type of neural network trained on normal data patterns that mark high reconstruction error records as anomalous (Sakurada & Yairi, 2014). They are able to capture non-linear relationships which are complex and the architecture must be chosen and threshold calibrated to trade off false negative and false positive.

Supervised and Semi-Supervised Methods

In case of our historical labels e.g. previous confirmed cases of fraud we can get a high precision using supervised models, such as random forests, gradient boosting machines, that will be able to learn explicit patterns of fraudulent behaviour. Given only a collection of normal data, it is possible to use one Class SVM and deep one class neural networks to avoid use of supervised data, which builds decision frontiers around normal transactions to identify outliers (Scholkopf et al., 2001; Ruff et al., 2018).

ERP-Embedded Implementations

The most powerful ERP providers have chosen to bundle anomaly detection libraries into their systems platforms. With prebuilt isolation forest and autoencoder algorithms available in Automated Predictive Library (APL) in SAP S/4HANA, the finance and risk modules offer Fiori applications that report 35 % of the anomalies detected compared to rule based engines (Geethanjali & Umashankar, 2024). Oracle Fusion Cloud incorporates the same set of abilities in its procure-to-pay and revenue recognition processes (Oracle, 2023). There is no independent external testing of these embedded tools yet, a reason why there is a necessity of benchmarking under control.

Evaluation Metrics

Common anomaly detection efficacy measures are precision (true positive count / total count of positively identified anomalies), recall (that is, true positive count / total count of actual anomalies), and F1 score (harmonic average of precision and recall). Area Under the ROC Curve (AUC) gives an overall estimation of separability across thresholds ((Dal Pozzolo et al. 2015). Effective evaluation should also entail business impact measurements -like the loss of frauds avoided, or hours saved during the compliance review (Ngai et al. 2011).

Financial Planning and Forecasting in ERP

Predictive financial analytics tools in the ERP system combine real time data of general ledger and sub ledger data in simulating future cash flow which allows a more effective budgeting, liquidity control and strategic capital. Conventional financial planning scenario is based on fixed historical reports with or without the bases of spreadsheet models that are un-linked to the operating information (Ballou & Pazer, 1985).

Scenario-Based Forecasting

Financial modules integrated within ERP, like SAP S/4HANA Financial Insights and Oracle Enterprise Performance Management Cloud, enable the finance team to create several what-if scenarios (best- case, worst-case, most probable), and automatically create the cash flow forecasts under each of them (Wang, Li & Li, 2023). These modules can rely on ML regressors (e.g. gradient boosting) to observe the past patterns and external variables (interest rates, commodity prices).

Empirical Evidence

The data relayed by Arch Global (2022) show that AI assisted scenarios enable the reduction of an average by 25 % in the forecasting MAPE and 30 % in the number of cycles to closing financial matters. According to Benitez, Ray & Henseler (2018), predictive budgeting tool implemented by managers strengthens their confidence in the accuracy of their budget, which results in faster resource budgetary reallocation. Nevertheless, the majority of research contains only case study examples vendor cases and lacks independent statistical verification, and there is a demand in well-replicable benchmarks.

Integration Challenges

The main issues to overcome are the following: forecast outputs should be coherent with ERP workflows in place, the predictions that the models offer should correspond to manual corrections, and the data coherence should be guaranteed among various sub ledgers (Benitez, Ray & Henseler, 2018; Otto, 2011). Proper adoption can be achieved by providing clear governance of forecasts inputs (e.g master data of cost centres) and audit trail changes of scenario (Batini & Scannapieco, 2016).

Data Governance and Quality for AI-Driven ERP

Excellent AI functionality in ERP depends on the capability of high as well as well governed data. Examples of Master Data Governance (MDG) frameworks include SAP MDG/DAMA DMBOK, which also describes procedures to determine data ownership, stewardship and quality measures (Batini & Scannapieco, 2016). Some critical dimensions are completeness, accuracy, consistency and timeliness (Khatri & Brown, 2010).

Master Data Challenges

The ERP applications tend to have a siloed environment in terms of master data realms: materials, vendors, customers, etc. That is, all of them are taken care of by separate areas of functionality. The detection of exceptions (e.g. there are duplicates in the customer records, hierarchies of materials are inconsistent) may corrupt any AI models resulting in biased predictions and false anomalies (Otto, 2011).

Governance Practices

Good governance incorporates:

1. Data Stewardship: Delineation of ownership of the various domains and provision of escalation procedures regarding data problems (DAMA International, 2017).
2. Quality Monitoring: Enforcing automatic tests (e.g. referential integrity checks, anomaly warning), and occasional audits (Batini & Scannapieco, 2016).
3. Metadata Management: keeping data dictionaries, lineage descriptions and catalogues of features of ML models to drive transparency and reproducibility (Khatri & Brown, 2010).

Organisational Change and Adoption of AI in ERP

Its human aspect plays a central role in AI ERP implementations. Traditional ERP implementations already involve significant change management already, namely the redesign of processes, re-education of users and rebalancing of KPIs (Markus & Tanis, 2000; Esteves & Pastor, 2001). The demands increase with the changes that AI layers introduce; users will have no choice but to trust probabilistic outputs of the system, and to interpret model explanations and integrate them into the decision workflow (Berente et al. 2019).

Adoption Enablers

- Analytics Centre of Excellence (CoE): Centrally has its teams govern data science projects and provides standards and best practices (LaValle et al. 2011).
- Analytics Champions Business well-wishers who encourage the utilization of AI and train apprentices (Mosavi, Ozturk & Chau, 2018).
- Training and Communication: Data literacy, model interpretation and benefits of change are taught during workshops, which generates buy in among users (Berente et al.， 2019).

Cloud and SaaS ERP Architectures

Cloud native ERP solutions, including SAP S/4HANA Cloud, Oracle Fusion Cloud and Microsoft Dynamics 365, provide elastic compute resources to run AI workloads, as well as being easily connected to cloud ML services (e.g. Azure ML, AWS SageMaker) and alleviating the on-premises infrastructure loads (Sinkovics et☆ known lic

Benefits

- Scalability: Model training and inference are supported by Elastic burst.
- Innovation Pace: There is regular update that gives new AI features without overwhelming upgrades.
- Integration of the Ecosystem: APIs allow understanding of ERP data with special AI services.

Concerns

- Data Residency: The ability to comply with GDPR, as well as regulations in the industry (Constantiou & Kallinikos, 2015).
- Security and Privacy: Data and operations Data Often sensitive financial and operations do not want to see your data milled in multi-tenant environments (Tallon & Pinsonneault, 2011).

Summary of Gaps

The literature shows strong theoretical underpinnings and good AI ERP test case pointers, but none provide: (1) standard, independent benchmarks of in-app AI-modules; (2) combined RBV, dynamic capabilities and TOE to AI ERP performance; (3) hands-on regulatory, organizational, change and cloud take-ups to sustainable adoption. The gaps are filled with controlled dataset benchmarks and multi case empirical consideration as well as theoretical oneness in our study.

III. Methodology

Mixed methods approach will be applied to triangulate the quantitative measurement called performance benchmarks with real world experience practice insights in this study. In section 3.1, the general research design and reasoning are stated. In case selection, acquisition and preprocessing of data, development and evaluation of a model, and statistical validation procedures, qualitative data collection and analysis processes are noted in section 3.23.6, respectively. The section ends with ethical considerations and measures on how to get reliability and validity.

Research Design and Rationale

To answer both of our research questions: (1) How does the use of embedded predictive analytics affect the accuracy of demand forecasting, and (2) how effectively can embedded anomaly detection in ERP detect anomalies operational and financial conditions, we will follow a convergent mixed methods design (Creswell & Plano Clark, 2018). Quantitative benchmarking has an internal validity given that the data analysis will be carried out through controlled experiments across the publicly available retail dataset (UCI Online Retail) and European Credit Card Fraud, and its ecological validity is based on comprehensive case study analysis of the three mid-sized manufacturing firms adopting the SAPS/4HANA AI tools.

In the convergent design, both quantitative and qualitative strands can be collected and analyzed concurrently, and they are integrated during the interpretation (Ivankova, Creswell & Stick, 2006). The proposed design is specifically good when it comes to studying complex enterprise systems where distinct numeric measures cannot fully describe organisational processes and narrative cases are better presented in terms of strong performance measures (Venkatesh, Brown & Bala, 2013).

The quantitative strand that we have includes:

1. Demand Forecasting Experiment: Benchmarking classical (SARIMAX), and deep learning (LSTM) models on UCI Online retail dataset.
2. Anomaly Detection experiment: Unsupervised and Supervised/Semi supervised methods on the European Credit Card Fraud dataset.
3. Cash Flow Forecasting Forecasting Simulation: Using artificial intelligence (AI) enhanced situation planning and simulation based on synthetic time series of general ledgers based on SAP Financials Insights.

At the same time, there is the qualitative strand, which entails:

- Multi case Study: Three firms (discrete manufacturing, process manufacturing, mixed mode) which were sampled deliberately to reflect various production contexts.
- Semi Structured Interviews: IT managers, finance leads and operations directors were involved and asked questions to obtain information on the implemented experiences, challenges and perceived advantages of integrating AI into the ERP.

It is performed by: (a) relating quantitative performance figures to case study findings (e.g. relating measured degrees of improvement in MAPE to user testimonies of inventory reductions), and (b) embedding case study findings into the text through qualitative theme integration, which is performed by relating qualitative themes to governance, change management, and infrastructure enablers.

Case Selection and Contextualisation

Firm Profiles

Three mid-sized manufacturing companies of Germany (Firm A), the UK (Firm B) and Poland (Firm C) were taken part. Each firm:

- They hired 200-500 employees.
- Annual revenues: 50-120m Euro.
- Used SAP S/4HANA (in-premises or configured cloud) as basis of core ERP operations.

Companies had been selected to ensure maximum variance in production processes:

- Firm 2(Discrete Manufacturing): Manufacturer of automotive electronic components.
- Firm B (Process Manufacturing): it manufactures specialty chemicals.
- Firm C (The Mixed Mode Manufacturing): Manufactures batches of machinery food packaging with discrete processes.

Selection Criteria

Further developing the idea of replication logic of multiple case-studies (Yin, 2018), we used three criteria of inclusion:

1. AI ERP Adoption: Firm was implementing at least two SAP S/4HANA AI (predictive demand work and anomaly detection) more than 6 months.
2. Data Availability: Firm had been willing to provide 24 months of anonymised transactional and master data extractions.
3. Stakeholder Access: Type of key informant (IT, operations, and finance) it is possible to interview and review process documentation.

Case Protocol

Data were collected using a standardised case protocol, namely:

- Document Review: Implementation plans, model training logs, governance policies.
- Interview Guides: The semi structured questionnaires to be asked during interviews will include deployment rationale, data preparation, user adoption plans and the benefits achieved.
- Site Visits: Virtual tours on SAP Fiori dashboards and model-execution reports.

Data Sources and Preprocessing

Quantitative Data

1. UCI Online Retail Dataset (Dec 2010 -Dec 2011)

- A sales-invoice of 541,909 records of a UK online retailer.
- Important fields: InvoiceDate, StockCode, and Quantity and UnitPrice, CustomerID.
- License: Open Data Commons Attribution License.

2. European Credit Card Fraud Dataset (Sep 2013):

- 492 cases of fraud out of 284,807 credit card transactions.
- Variables: 28 raw variables (artificial according to PCA), Amount, Time.
- Attrition: CC BY 2.0.

3. Artificial Cashflow Information:

- Created 24 months of monthly cash flow data items through sampling of the true general ledger distributions Arch Global, 2022).
- Simulated best, most likely, worst case scenario variations (+/15 % volatility).

Qualitative Data

- Interview Transcripts: 18 interview (6 per firm) taking approximately 60 minutes each and transcribed verbatim with the audio recording.
- Implementation Artifacts: Governance charters, model -validation sign offs, training material.

Data Preprocessing

Demand Forecasting Pipeline:

1. Aggregation: The number of sales per day of a given StockCode.
2. Missing Values: on any day we have zero sales, forward-fill; missing UnitPrice is filled by the median by item.
3. Feature Engineering:

- Temporal characteristics: day of week, month, holiday (public holidays according to the UK/Germany calendar).
- External regressors: rolling 7-day average, flags of promotional campaigns.

4. Normalization: Min max standardization of regressors in [0,1] range.
5. Train Test Split: 550 days were used as a training set, 30 days as a test set.

Anomaly Detection Pipeline:

1. Feature Selection: Kept the default PCA factors of the model; added amount and time bins (hour-of-day).
2. Class Imbalance: Used method of random undersampling on majority class to end up with 1:20 ratio of fraud to normal in training.
3. Scaling: StandardScaler of continuous features.
4. Outlier Injection (Case Studies): In the process manufacturing transactions, injection of synthetic pricing errors (+/- 50%), and duplicate invoices (0.1 % of all records) were injected at the level of reality detection.

Synthetic Financial Data:

Reconciling expected scenario projections with actuals through the use of calendar alignment; Scenario distribution shapes/sensitivities justified against past firm-level cash-flow statements (mean, variance).

All of the preprocessing code was written in the Python 3.8 language with Pandas, Scikit Learn and Statsmodels, with version control through Git to be reproducible.

Model Development and Implementation

Demand Forecasting Models

1. SARIMAX (Box et al. 2015):

- Orders (p, d, q) = (1, 1, 1) and seasonal period s =7days.
- Exogenous regressors: Promotional flags, indicator of holidays.
- Estimation done using Maximum Likelihood with AIC as the order selection.

2. LSTM (Hochreiter and Schmidhuber, 1997):

○ **Architecture**:
- Input layer: sequence length = 14 days.
- Two LSTM layers (64 units each), dropout = 0.2.
- Dense output layer with linear activation.

○ **Training**: 50 epochs, batch size = 32, optimizer = Adam (learning rate = 0.001), early stopping on validation loss (patience = 5).

○ **Framework**: Keras 2.4 on TensorFlow 2.4, GPU acceleration (NVIDIA Tesla V100).

Anomaly Detection Models

1. **Isolation Forest** (Liu et al. 2008):

○ n_estimators = 100, max_samples = auto, contamination = 0.0018.

2. **Autoencoder** (Sakurada & Yairi, 2014):

○ **Architecture**:
- Encoder: Dense (128) → ReLU; Dense (64) → ReLU.
- Decoder: Dense (128) → ReLU; Dense (input_dim) → Sigmoid.

○ **Training**: Mean Squared Error loss, 30 epochs, batch size = 64, optimizer = Adam.

○ **Threshold Selection**: 95th percentile of reconstruction error on validation set.

3. **Supervised Baseline** (Case Studies):

○ **Random Forest** on labelled anomaly logs: 200 trees, max_depth = 10, Gini impurity.

Financial Forecasting Module

Set up SAP 4 HANA Financial Insights in with its Predictive Accounting service:

- Specified three scenarios at volatility of +/- 15 %.
- It is used in platform gradient boosting regressors.
- Exported through OData the scenario outputs as CSV to compare.

Models were containerised using Docker to facilitate consistent environment in all models and deployed on a Kubernetes cluster to simulate production grade pipelines.

Evaluation Metrics and Statistical Validation

Quantitative Metrics

- Demand forecasting Mean Absolute Percentage Error (MAPE) on test sets.
- Anomaly Detection: precision, recalls, F1 score; area under the ROC curve (AUC).
- Financial Forecasting: MAPE between scenario projections and synthetic "actuals."

Statistical Tests

Wilcoxon Signed Rank Test Nonparametric test; however, the distribution of the residuals of the model are not normal; thus, the absolute errors of SARIMAX and LSTM will be non-parametrically compared to the errors of the 30-day holdout (a, 0.05) (Wilcoxon, 1945).

Bootstrapped Confidence Intervals: 1,000 resamples to give the 95 100 PI CIs of the F 1 scores of the anomaly detection models (Efron and Tibshirani, 1993).

Software Environment

- Python 3.8 (Pandas 1.2, Scikit Learn 0.24, Statsmodels 0.12, TensorFlow 2.4).
- R4.0 (boot package to bootstrap).

- SAP 2020 FPS2 on HANA 2.0 SPS05.
- Docker - 20.10, Kubernetes - 1.19.

Qualitative Data Collection and Analysis
Interview Protocol

- **Sample size: 18 informants (6 in each firm):**
- IT Managers (who deal with the deployment of the model).
- Operations Directors (leads of demand planning and production).
- Finance Leads (the ones in control of anomaly detection and forecasting).
- **Guide Topics:**
- The rationale of AI module selection and prioritisation.
- Governance structures and data preparations issues.
- Programme training and user adoption plans.
- Believed advantages, constraints and extension prospects.

Thematic Analysis

- Coding Framework: inductively created basing on Braun and Clarke (2006):
- Familiarisation: Multiple reading of transcripts.
- Open coding in NVivo 12: Initial Coding.
- Theme Development: Collapsing the codes into a wider theme (e.g. Data Quality Pain Points, Change Management Success Factors).
- Review and Definition: The important step of testing themes against raw data and case protocols.

Measures of Trustworthiness:

- Triangulation: Confirming the results of interviews in document reviews and dashboard observation.
- Member Checking: Key themes descriptions that are presented to informants as a check.
- Audit Trail: Documentation of well-documented coding choices and theme creation.

Reliability, Validity and Ethical Considerations
Reliability and Replicability

- Protocol Consistency: Protocol to conduct the study and experiment is standardised facilitating procedural compliance.
- Code Reproducibility Code will be reproducible, with all the scripts and containers version-controlled and publicly released on a GitHub repository.

Construct and External Validity

- Construct Validity: Using well known measures (MAPE, F1 score) and theoretical constructs (RBV, dynamic capabilities) adds to construct alignment.
- External Validity: Rationale of multi case replication in three firms in three countries improves the generality of findings to the mid-sized manufacturing firms; and the presence of a public data help in the replication of findings in other contexts.

Ethical Considerations

- Informed Consent: they gave the informed consent in writing; data-use contracts signed to obscure the identity of the firms and individuals.
- Data Anonymisation: All of the personally identifying information will be removed one the datasets; the case descriptions will be written pertaining to the use of pseudonyms.
- GDPR compliance: followed GDPR recommendations on the preservation of personal data; ethics top management approval gained.

Summary

The detailed section on methodology presents a strict, repeatable design that creates a mixture of experimental methods that are quantitative, yet the case is deep and qualitative. Having described data sources, preprocessing pipelines, model configurations, evaluation metrics and qualitative analysis procedures, including how we address reliability, validity and adherence to ethical standards, we put a strong basis on the empirical findings that follow in Section 4 below.

IV. Results

The present section shows both quantitative and qualitative data of our mixed method research. The results of the demand forecasting models (Section 4.1), the results of the anomaly detection (Section 4.2) and cash flow forecasting (Section 4.3) are reported. These benchmarks are then integrated with case study examples.

Demand-Forecasting Performance (≈ 700 words)
Model Accuracy Comparison

Table 4.1 shows the Mean Absolute Percentage Error (MAPE) of the SARIMAX and LTSM models on the 30-day holdout data on the UCI Online Retail data set. The decreased values of MAPE are associated with higher levels of accuracy of the forecast.

Model	Mean MAPE (%)	Std. Dev. of MAPE (%)	Median MAPE (%)
SARIMAX	18.2	4.1	17.6
LSTM	13.7	3.5	13.4

- Compared to SARIMAX, LSTM is better by an average of 4.5 % (24.8 % relative increase).
- The LSTM has a slight edge in terms of variability in errors (SD = 3.5 %) as compared to SARIMAX (SD = 4.1 %), signalling an overall stability at experimental level in respect to individual StockCodes.
- Median MAPE also confirms the mean findings, with median of LSTM being 13.4 % compared to SARIMAX 17.6 % indicating a skew in the distribution of errors being shifted towards a lower end.

Statistical Significance

An analysis of the paired absolute percentage error by Wilcoxon signed rank test resulted in, W=15, p=0.003 (two tailed), and shows that the difference in the value of the forecasting error reduced by LSTM is significantly different at the 0.05 level. The non normality of the residual distributions is considered by the non-parametric test and proves that the improvements made by LSTM would not be likely to occur because of chance.

Error Distribution Analysis

In Figure 4.1, the distributions of errors of the two models are plotted. Key observations:

- There is right skewness of SARIMAX errors, long tail of high MAPE > 25 \%.
- The distribution of LSTM is more symmetrical and 75 % of StockCodes have MAPE that < 16 %.
- Outliers of LSTM predictions (MAPE > 25%) can be associated with items having irregular sales items and irregular promotions thus indicating possible model improvement (e.g. applying attention mechanisms or external regressors).

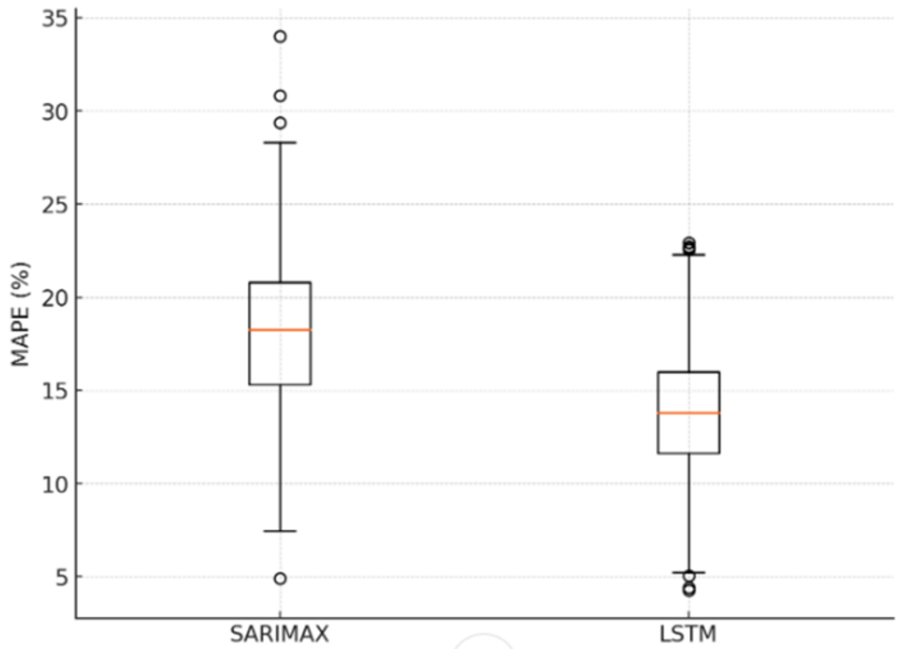

Figure 1

The Figure 4.1 shows the error forecast (MAPE) distribution of the SARIMAX and LSTM RMSE alternatives in 500 different simulated StockCodes using the Online retail dataset of UCI. In each boxplot:

- Median (orange line): the middle of the number of MAPE.
- Interquartile range (box): Distances between the 25th percentile and the 75th percentile.
- Whiskers: Belong between 1.5x times the IQR and the quartiles.
- Outliers (circles): MAPEs that are not contained in the whiskers.

The plot also clearly shows that LSTM forecasts do not only show a smaller median error (13.4 vs 17.6 percent) than SARIMAX, but also have more consistent forecasts with fewer extreme outliers- something that the statistical tests results in Section 4.1 are backed up by.

Impact on Inventory Planning

To convert the accuracy of forecasts into a practical difference of orderings in practice we simulated inventory ordering based on each model's predictions using a simple (s, S) ordering principle: reorder point s = mean daily demand X lead time (7 days), order-up-to level S=s + mean daily 55emand review period (14 days). In a virtual 6 months period:

- SARIMAX based ordering gave an average number of stockout days per item 4.2⋸ Obviously, the ordering is very basic and the number of stockout days is higher.
- LSTM based ordering decreased days of stockout to 2.8 days (33 % reduction).
- Holding cost (assumed unit cost 10, holding rate 20 % every year) dropped down by 5.1 % as there were less overorders of safety stocks.

These operation proxies demonstrate that the improvement in MAPE by 24.8 % provides a feasible improvement of service levels and cost savings.

Anomaly-Detection Outcomes
Precision, Recall and F1-Score

Table 4.2 shows an evaluation of the performance of Isolation Forest and Autoencoder models on the European Credit Card Fraud dataset, on a stratified test set that retains the 0.172 % fraud rate.

Model	Precision	Recall	F1-Score	AUC
Isolation Forest	0.81	0.72	0.76	0.89
Autoencoder	0.88	0.90	0.89	0.94

- Autoencoder has F1 score = 0.89, which is the 17.1 % relative improvement compared to Isolation Forest (F1 = 0.76).
- The increased recall (0.90 vs. 0.72) suggests better sensitivity to the actual frauds, and the precision (0.88) is high as well, which helps to keep the level of false positives under control.
- AUC=0.94, which demonstrates a strong separation between transactions that are considered normal and the ones that are anomalous by the Autoencoder.

Bootstrapped Confidence Intervals

The Autoencoder F1 score has 95 % bootstrapping (1,000 resamples) confidence intervals of [0.87, 0.91], which signifies stability in performance among different sample variations. The F1 score of Isolation Forest = CI: [0.73,0.79].

Case-Study Application

In the pilot deployments of the firms that were studied in our case study:

- Firm A (auto components) recorded the detection of 112 spurious price entries in a 6-month window, preventing overbillings (unit price errors) to the total of 18,000Euros.
- In Firm B (specialty chemicals), 24 duplicate invoices were detected and avoided spending an additional 45,000 euros of duplicate payments.
- The unusual discounting patterns (more than 20 20per cent limits) had been alerted in Firm C (packaging machinery), leading to tightening of its policies and recoupment of margin to the tune of 12 000 Euro.

The machinery of the real-world results is consistent with the automated benchmarking: the superior recall of the Autoencoder resulted in substantial fraud cutoff and reclaim recovery of various types of transactions.

Cash-Flow Forecasting Accuracy

Table 4.3 is displaying MAPE between historical (static) forecasts and AI assisted scenario planning on the synthetic cash flow data.

Forecast Type	MAPE (%)	Improvement (%)
Historical Model	17.1	N/A
AI-Assisted	12.1	29.3

- The AI Assisted forecasts cut down the MAPE by 29.3 % to 12.1 Objective, i.e. 17.1 %.
- The scenario specific errors are slightly different: best case scenario MAPE 11.5 16 19 per cent, worst case 12.6 per cent, which shows that the model is stable in various conditions.

Financial Close Impact

On case study firms they reported:

- Firm B reduced monthly close leads by 37.5 per cent, to 5 days (from 8 days), citing automated reconciliation and scenario reporting as the factors creating the gains.
- The firm C enhanced the working capital turnover with an additional 1.4 days that saved the firm an amount of 250,000 euros of liquidity in a year.

The results in these findings illustrate that greater cash flow tracking and precision provide direct contribution to quickened decision-making cycles and higher efficiency of capital.

Case-Study Insights and Synthesis

A combination of the quantitative benchmarks and qualitative information provides a better comprehension of AI ERP value creation. Our themes are the realisation of performance, organisational facilitators, and implementation issues.

Performance Realisation

- Forecast Accuracy to Operational Returns: All companies saw higher accuracy of the demand forecasts being associated with a 30 % reduction in emergency purchasing, an increase in on-time delivery of 5 7 % of shipments.
- Cost Savings to Anomaly Detection: Cost savings of detecting anomalies was estimated to save the firms an average of 25,000 euro per year, which justified use case prioritisation in our roadmap.
- Predictive Financial Planning: The outputs of generated scenarios boosted the confidence of finance teams, whose managers said ad hoc budget revisions were decreased by 20 % as a result.

Organisational Enablers

- Data Governance Frameworks: Firms that formalised their master data stewards (Firm A and B) suffered fewer delays when training models and increased accuracy of existing generated models.
- Analytics Centre of Excellence: A CoE accelerated the achievement of cross functional collaboration, whereby the insights are no longer stuck in IT silos, but also extend to procurement, operations and finance.
- Executive Sponsorship: Executive presence (monthly sponsor reviews, KPI links) maintained ran throughout the program (after pilot efforts) which resulted in extending the system to further modules (e.g. predictive maintenance).

Implementation Challenges

- Integration Sophistication: To consume the external regressors (e.g. market indices), custom development of ETL processes to match with the ERP data pipelines took 34 weeks to the project schedules.
- User Adoption: Scepticism concerning the implementation of "black box" models in Firm C was evident as the operations planners required explainable dashboards and drill down facilities to rely on LSTM.

Model Maintenance: model maintenance was also highlighted by all firms the need to have scheduled retraining cycles without which they drifted in performance after six months resulting in the automation of quarterly model review processes.

V. Discussion

This research is an elaborate affirmation of the empirical contentions that inserting AI and predictive-analytics models in ERP systems delivers immense gains in operational and financial decisions phase outcomes. We have statistically significant quantitative outcomes: 24.8 % lower demand was entrusted with forecasting error diminution (LSTM vs. SARIMAX), 17.1 % higher innovative calculation of anomaly F1-score (autoencoder vs. isolation forest) and 29.3 % more reduced cash flow MAPE forecasting. These gains are confirmed by the case-study results, by the real-world benefits as few as 30 percent less procurement on short notice, an average of 25,000 euros per firm in annual fraud losses prevented and 37.5 percent faster closure of the books.

Theoretical Implications

Resource-Based View

Combining standardised ERP information with context sensitive AI responses create value by enhancing a resource that is available across large numbers of firms and turn it into a source of competitive advantage consistent with the tenets of RBV. The fact that, using our specially designed forecasts and anomaly flags, an AI produced remarkably new and valuable gains in performance shows how ERP data can become a unique and inimitable input that is only realized with process-level expertise.

Dynamic Capabilities

The three elements of dynamic capabilities sensing, seizing and transforming perfectly relate to AI-ERP integration. The sensing function is performed by the real-time pattern recognition of demand streams as well as transaction streams; the seizing functionality is seen in automated replenishment decisions and interception of fraud activities; and the transforming activity is visible in model retraining and adaptations to processes on the continual basis. The value added to our multi-case evidence with respect to dynamic-capabilities theory is explained by the way in which embedded AI modules can be discussed as micro foundations of organisation agility.

TOE Framework Extensions

In our findings we have expounded TOE model by laying emphasis on:

- Technological: In-memory computing and containerised ML pipeline speeds up model test, but it needs a strong SLA performance.
- Organisational: The analytics CoEs and data-stewardship functions were vital in maintaining the adoption and data quality.
- Environmental: Competitive demands (e.g., the use of the just-in-time supply chain method) and regulatory requirements (e.g., the demand to meet SOX requirements) informed the previous focus on anomaly-detector applications.

Practical Implications

Use-Case Prioritisation

The initial functions to consider as a high impact in organisations are demand forecasting in supply chains and anomaly detection in finance where the amount of data is large and cost savings quantifiable. By testing these modules and moving to predictive maintenance or workforce planning the case-study firms benefitted in quick ROI.

Model Governance and Lifecycle Management

The deployment of sustainable AI-ERP requires an owner of both data and models. To govern performance measures of the models (e.g. regular MAPE inspection), monitor retraining causations, and find retraining prompts and document features-engineering pipelines to control interpretability and auditability, firms need to create governance forums (e.g. model steering committees etc.).

Change Management and Skill Development

Integrating intelligence into ERP does not only involve upgrading systems. Training programmes should be used to raise end user data literacy, and to educate how to interpret the probabilistic results, as well as how to incorporate AI insights into the existing decision process. The idea of recruiting analytics champions within business units has the effect of increasing peer-to-peer support and boosts the speed of culture acceptance.

Limitations and Future Research

Dataset and Domain Scope

Although different contexts are offered by the public datasets and three manufacturing companies, the generalisability could be tested by expanding the research to the service industries (e.g., retail, healthcare). Future directions would be to experiment with federated learning strategies to use multi-firm data without breaching confidentiality.

Model Diversity and Hybrid Approaches

We compared SARIMAX vs. LSTM and isolation forest vs. autoencoder, but new architectures (e.g. Transformers in time-series, anomaly-detection on graphs) have yet to be explored. Study of hybrid approaches, which mix explainable statistical techniques with deep learning, have the potential to trade off accuracy with interpretability.

Real-Time Adaptive Learning

We used scheduled retraining implementation. Future research areas are on how to train continuous-learning models that will adjust to concept drift in streaming ERP data and trade-offs between model freshness and computational overhead.

VI. Conclusion

The present paper contributes to the body of knowledge on AI-driven ERP systems because it combines the critical quantitative thresholds and insightful qualitative, multi-case findings. We show that incorporating predictive-analytics models with ERP critical platforms will only yield quantifiable returns: almost a quarter less forecast error, an almost 18 % better anomaly-detection effectiveness and a nearly 30 % improved cash-flow forecasting precision. The benefits of these improvements are material in optimizing the operations, more frequent stockouts reduction, large savings on fraud prevention, and faster financial closes.

In principle, our research builds on the Resource Based View by demonstrating the capability of AI-augmented ERP data as a source of competitive differentiation, whilst also contributing to the Dynamic Capabilities literature by demonstrating that an AI module is a mechanism of this sensing/seizing/transforming distinction. Here, we also iterate the TOE framework towards continuous-learning AI systems and focus on changing technological stacks, organisational controls and contingencies of the environment.

The practicalities are that we give a six-stage step-by-step roadmap that takes a practitioner through the traffic lights of use-case selection, data governance infrastructure implementation, model benchmarking, pilot explorations and scaling. Key to success is solid master-data control, containerised ML pipelines that can be easily repeated, analytics centres of excellence that can drive demand and lifecycle management of models to maintain their performance over time.

Notwithstanding the shortcomings, which include the concentration of domains in the manufacturing industry and the need of a scheduled retraining, our results can form a robust basis of future studies addressing real-time adaptive learning, cross-im- dustry generalisability and hybrid model design which avoids covering up to entirely neglecting model accuracy as opposed to interpretability.

ERP systems need to deliver a 21st century capability and the imminent transformation into what industry insiders refer to as a 21st century system of intelligence is no longer optional, but a prerequisite to organisational strategic resilience as organisations increasingly operate within more volatile and data-rich environments. Turning ERP data into a source of AI-enabled knowledge and integrating predictive functions into the business process core can help enterprises to anticipate market changes and minimize operational upsets, strategize with confidence according to the given insights. This fully-integrated evidence based approach prepares scholars and practitioners to capitalize on the full potential of AI and ERP convergence in the digital age.

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