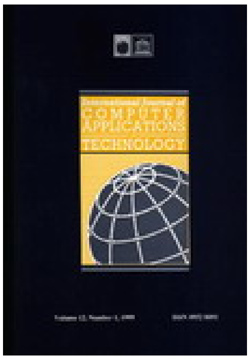

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Enhancing organisational efficiency using intelligent ERP decision

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Abstract: Enterprise Resource Planning (ERP) stands out as a viable solution, recognising its potential to elevate organisational efficiency. Organisations continue to face challenges in selecting the right ERP systems and often struggle with integrating ERP systems and Artificial Intelligence (AI) technologies. This integration issue leads to inefficient decision-making due to less responsive ERP systems. Additionally, managing the collected data and transforming it into actionable insights for informed decision-making through ERP systems remains a difficult task. Thus, the study focuses on enhancing decision-making using an intelligent ERP system. The proposed method implements a dataset obtained by surveying ERP consultants across different industry verticals worldwide. This dataset is then applied to a decision tree to generate rules, and other machine learning algorithms are tested for their performance. The results show excellent performance of decision trees, while Linear SVM, Efficient Logistic Regression, Efficient Linear SVM, and SVM Kernel are compared with this performance. The deployment shows matched cases across industry verticals and geographic regions, achieving a high accuracy of 81.5%. Additionally, the Speed of Operation, Flexibility, and Cost Efficiency are significantly improved, highlighting the importance of the intelligent ERP system in enhancing organisational efficiency.

Keywords: business benefits; intelligent resources planning; decision tree; ERP selection; intelligent systems; artificial intelligence.

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1 Introduction

In today's dynamic business landscape, organisations are constantly looking for techniques to enhance their operational efficiency and effectiveness. Enterprise Resource Planning (ERP) systems (Mayeh et al., 2016) have emerged as vital tools, offering widespread benefits and services across entire enterprises. By facilitating the sharing and transmission of information as well as data across all functional units, both outside and inside the enterprise, ERP systems play a crucial role in achieving various organisational objectives (Ebirim et al., 2024).

The advent of cloud computing has further revolutionised the deployment and operation of ERP systems. Cloud computing, characterised by its reliability, scalability, availability, and cost-effectiveness, provides significant advantages for enterprises seeking to optimise their resources (Harouni et al., 2023). Implementing cloud ERP systems enhances these benefits, despite the issues and challenges that may arise.

Moreover, the integration of Artificial Intelligence (AI) into ERP systems presents a new frontier for improving organisational efficiency. AI technologies offer unprecedented opportunities for enhancing management performance, providing leaders with advanced tools for strategic decision-making (Borges et al., 2021). However, there is a limited understanding of how to incorporate AI strategically into management practices, especially within cloud-based ERP systems (Kunduru, 2023).

To avoid ambiguity and establish a clear conceptual foundation, this study defines 'intelligent decision-making' as the systematic use of machine-learning algorithms, rule-based reasoning, and structured data analytics to support ERP implementation choices. In this context, intelligence refers not to automated decision replacement but to the enhancement of human judgement through data-driven insights, pattern recognition, and predictive modelling. Similarly, the term 'intelligent ERP' denotes an ERP environment augmented with AI-driven capabilities – such as decision trees, SVM-based classification, rule extraction using REDUCT, and big-data-enabled responsiveness – that collectively improve accuracy, consistency, and speed of organisational decision processes. These definitions distinguish the proposed Intelligent Decision Support System (IDSS) from traditional consultant-driven approaches, which often rely heavily on subjective experience and lack systematic analytical rigor.

Initially, resource planning was ineffective, and corporate executives needed a better way to manage materials, staff, and inventories. Early management relied on Material Requirements Planning (MRP) software, which was useful for inventory monitoring and preliminary purchasing, manufacturing, and delivery (Bogataj, 2019). Organisations started adopting MRP systems in the 1970s, which evolved to include more manufacturing processes and capabilities.

By the 1990s, these systems had expanded beyond basic inventory control, leading to the term Enterprise Resource Planning (ERP) coined by Gartner Group (Kenge et al., 2020). ERP systems integrate various functions within a company, enhancing overall efficiency (Wulandari et al., 2023). The latest ERP advancements involve integrating Artificial Intelligence (AI) (Jawad et al., 2024). AI enables seamless department integration, data unification, and management of extensive information. Modern ERP systems now include manufacturing, supply chain, and finance capabilities, along with features such as automation, report generation, CRM, business intelligence, as well as project management.

Historically, ERP systems have organised knowledge, generated reports, and provided real-time analysis. Today, companies seek smart technologies that can understand patterns, suggest actions, and simplify dynamic processes (Ahmed et al., 2023). The flexibility of onsite and cloud-based ERP models continues to drive the evolution of ERP systems, integrating intelligent technology to meet current and future organisational needs (Chandra et al., 2018).

The current state of the art in enhancing organisational efficiency through intelligent ERP systems involves the addition of advanced technologies like AI and machine learning. These innovations enable predictive analytics, real-time data processing, and automated decision-making, which streamline operations and improve overall productivity. Modern ERP solutions also incorporate cloud computing, offering scalability, flexibility, and reduced costs, while ensuring data security and accessibility. Additionally, the use of Internet of Things (IoT) devices within ERP systems further enhances data collection and operational insights, driving more informed and efficient business decisions (Prakash et al., 2022).

The study emphasises the significance of a structured and thoughtful approach to ERP implementation, moving beyond the conventional 'big bang' method. It underscores the need to identify specific organisational requirements and select an ERP product that aligns with these needs to ensure successful deployment. Effective day-to-day operations management is highlighted as crucial for sustaining ERP benefits. The study also recognises the invaluable role of consultants in the implementation process, addressing their expertise and the challenges they face. By understanding the dynamics between consultants and organisations, the research aims to improve ERP deployment outcomes. This study contributes to the knowledge on ERP implementation, offering valuable insights for organisations seeking to maximise ERP system potential for sustained growth and success.

The study meticulously investigates organisational processes and the necessity for ERP systems to assist in decision-making for ERP selection. By understanding these needs, the research has developed an intelligent tool that significantly aids consultants worldwide in making informed decisions regarding ERP implementation. This intelligent ERP tool leverages advanced AI algorithms to analyse various organisational factors and generate insightful recommendations. Consequently, it enhances decision-making by providing a data-driven, structured approach to ERP selection, ultimately boosting organisational efficiency. The study's findings and the developed tool are invaluable resources for consultants, enabling them to optimise ERP implementations and drive improved operational outcomes for their clients.

2 Literature survey

The existing studies delve into the transformative potential of AI in enhancing ERP systems, which are essential software tools for managing complex corporate operations, including finance, manufacturing, accounting, human resources, and supply chains. ERP systems are pivotal in improving corporate efficiency, profitability, and manageability by integrating key business processes into a unified platform. AI's integration into ERP systems promises to make them more flexible and intuitive, enabling self-learning capabilities that can anticipate future outcomes. Leading ERP firms like SAP, Workday, and Oracle are at the forefront of this innovation, developing AI applications that can be seamlessly incorporated into ERP systems to enhance the accuracy of analytics beyond human capabilities. The evolution of ERP systems (Selamoğlu, 2023) dates back to the 1960s with the advent of computer technology and inventory management software. Initially focused on manufacturing through Material Requirements Planning (MRP) systems, these evolved into MRP-II in the late 1980s. Since the 1990s, ERP systems have aimed to integrate MRP and MRP-II functionalities with finance, accounting, customer relationship management (CRM), and human resources. The issues within ERP systems are paving the way for more intelligent, responsive, and efficient enterprise management solutions.

Integrating Artificial Intelligence (AI) with Enterprise Resource Planning (ERP) systems can considerably enhance the efficiency and effectiveness of decision support systems (DSS) (Saba et al., 2021). This integration leverages big data techniques to execute an extensive range of logical functions on the vast amounts of ERP system's data. Such functions include data filtering, aggregation, and inference, which are crucial for understanding business operations and improving predictability.

ZPS (Zalando Payments GmbH) (Bandara et al., 2024), a payment facilities supplier for Zalando SE, has successfully combined ERP and big data. This integration allows the generation of real-time reports, such as factoring cash-outs with customer cash-in, which employees can access instantly. As a result, the organisation has experienced increased process efficacy, improved operational discernibility, and enhanced business development (Schoenborn, 2021). Though many establishments face challenges in managing the incorporation of ERP with big data (Nyathani et al., 2023). These challenges include handling large volumes of data, transforming collected data by ERP systems, and managing the lack of necessary technical and managerial skills.

One of the significant issues organisations encounter is the underutilisation of collected data. Studies have shown that many organisations utilise simply 12% of the data they collect, leaving a staggering 88% unused (Joshi, 2019). This data wastage can be attributed to the lack of a data-driven culture and insufficient skills required to manage and utilise big data technologies effectively (Gupta et al., 2019). Consequently, organisations struggle with ERP responsiveness which is the capability of ERP systems to respond to and process big sizes of data efficiently while handling transactions and functionalities.

Improving ERP responsiveness through AI integration can minimise data waste and enhance data utilisation. This improvement leads to several benefits, such as a better understanding of customer preferences, forecasting sales, delivering valuable business visions, in addition to refining supply chain management (Gupta et al., 2024). By making ERP systems more responsive, organisations can fully comprehend the advantages of big data as well as drive more informed, strategic decisions. This integration ultimately contributes to higher organisational efficiency and supports sustained business growth.

The deployment of an ERP system is a critical yet highly complex challenge for organisations, often marked by a surprisingly high failure rate. These systems are expensive and can significantly impact an organisation's budget, making failures during or after implementation unaffordable. Successful ERP implementation requires a strong commitment from top management, as their support is crucial throughout the process. The project demands adaptability, with frequent plan and schedule adjustments to address emerging challenges and prepare for future issues. ERP systems have become essential in the current industrial environment, yet their deployment is far from trouble-free. Organisations face numerous challenges, including system selection, finding expert consultants, and assembling a capable project team. One common issue is the lack of staff participation and interest after transitioning from previous systems to the ERP system. This poor engagement leads to information gaps between the system and actual operations, creating difficulties for top management and undermining the system's integrity and efficiency.

According to the study, one of the primary reasons for the need for ERPs is the requirement for timely and accurate decision-making in business (Grochowski, 2022). Beyond the basic function of creating, using, and saving transactional data, several other essential elements of ERPs include tools for data communication, accessing data, analysing and presenting data, and generating new data. The decision support systems highlight several characteristics that ERP systems must possess to effectively support management decision-making. Better processing of knowledge enhances the ability to handle and interpret vast information. Dealing with complex problems increases the capacity to tackle intricate issues. Reducing time and cost ensures efficiency and economic feasibility. The power of exploring encourages exploratory analyses, fostering innovation. Creating new approaches develops alternative solutions. Imagining reliability ensures hypotheses are well-supported with evidence, enhancing decision credibility (Gupta et al., 2017). Better communications improve the validity and reliability of the decision-making process. These characteristics collectively enhance ERP systems' effectiveness in supporting comprehensive and efficient decision-making within organisations.

These characteristics (Simkute et al., 2021) ensure that decision-makers are empowered with robust tools to process knowledge, address complex issues, reduce decision-making time and costs, explore alternatives, substantiate hypotheses with evidence, and enhance the overall validity and reliability of the decision-making process. Thus, the need for ERPs in organisations is critical for facilitating informed and efficient decision-making, ultimately enhancing organisational efficiency and effectiveness.

During an in-depth analysis of ERP implementation case studies, the study also examined the failures and factors contributing to them (Ahmad et al., 2015). It shows that some individuals within organisations struggle to grasp ERP intricacies and critical success factors. Key pitfalls include a lack of clarity, which creates uncertainty and stalls implementation, and inadequate training, leaving employees struggling with the new system. Poor change management can lead to resistance, while data inaccuracy can render the system unreliable. Over-customisation can result in costly and hard-to-maintain solutions, and scope creep can cause delays and budget overruns. Inadequate testing exposes the system to post-implementation issues, and poor vendor selection or insufficient resources can derail the project. These insights highlight common mistakes to avoid for successful ERP implementation.

The existing studies show research gaps in the context of ERP implementation which often centre around the need for robust decision support systems that can effectively navigate the complexities and uncertainties inherent in such projects. Traditional approaches may lack the agility and depth required to address diverse implementation challenges comprehensively. These gaps include:

1 Existing systems could not fully leverage the collective expertise of multiple ERP consultants, resulting in limited perspectives and potential blind spots in decision-making.

2 Many systems struggle to adapt to the unique requirements and operational contexts of different organisations, leading to suboptimal deployment strategies.

3 The systems offer basic decision support functionalities but lack in-depth analysis and strategic insights crucial for complex ERP implementations.

4 The systems lack clear metrics and benchmarks for assessing the success of ERP implementations, making it challenging to measure and improve performance over time.

These gaps are addressed by integrating machine learning-based intelligent expert systems, ensuring the decision support system benefits from diverse implementation knowledge and best practices. This holistic approach enhances decision-making with nuanced insights and adaptive strategies tailored to specific organisational needs. Advanced algorithms and decision-making frameworks deepen the system's analytical capabilities, allowing for sophisticated scenario analysis, risk assessment, and strategy formulation. Collaboration with ERP consultants and software development agencies ensures rigorous testing and validation in real-world scenarios, while feedback loops from stakeholders enable continuous improvement. Clear evaluation frameworks and success metrics facilitate ongoing performance assessment and optimisation, enhancing accountability and guiding organisations towards measurable outcomes.

In essence, the proposed method overcomes research gaps by leveraging advanced technologies, integrating expert knowledge, and fostering collaborative decision-making processes. By addressing these gaps, the research contributes to the development of a more robust and effective decision support system for ERP implementation, capable of driving sustainable growth and operational excellence in organisations.

3 Methodology

The proposed sophisticated intelligent decision support system focuses on the need for ERP implementation to support organisations in making well-informed decisions during deployment. The study explores various types of expert systems to enhance the system's capabilities and integration requirements. Insights gathered from a survey of multiple ERP consultants worldwide enrich the system with diverse implementation knowledge and best practices, addressing a wide range of challenges and scenarios. The proposed expert system employs advanced algorithms, including K-Nearest Neighbours, Logistic Regression, Support Vector Machines, and Decision Trees, to assess organisational requirements, select suitable ERP solutions, and devise efficient implementation strategies. Collaboration with ERP consultants ensures rigorous testing and validation in real-world scenarios. The proposed system enhances decision-making with the integration of machine learning algorithms, helping organisations improve their efficiency.

3.1 Data collection

A survey of ERP consultants and consulting firms deeply involved in ERP implementation processes worldwide was conducted. To achieve the research goals, the study focused on meticulously constructing a series of methodically structured questionnaires to form the primary dataset. To reach a wide audience, the study included individual ERP consultants as well as representatives from consulting firms supporting ERP journeys. The figure shows the steps for data collection.

Figure 1 Proposed method for efficient decision-making in intelligent ERP system (see online version for colours)

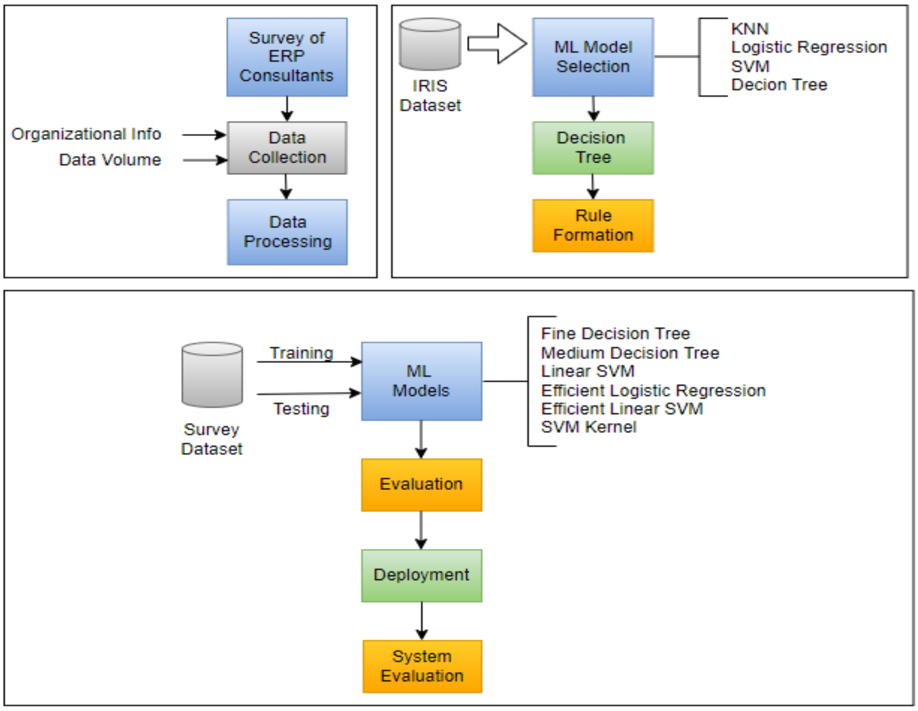
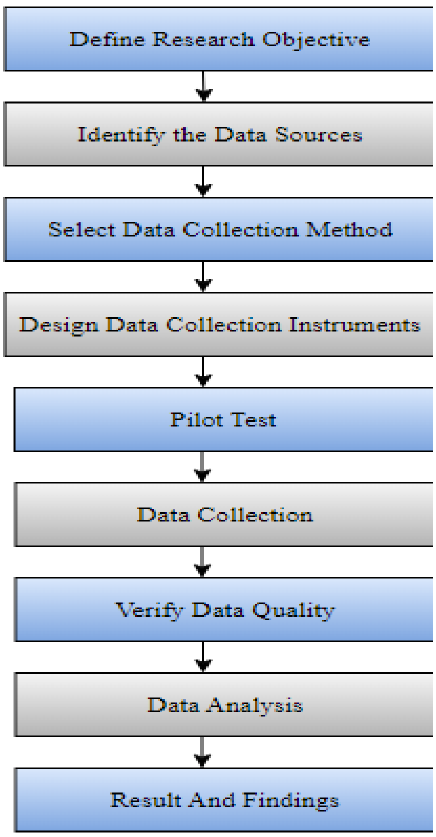


Figure 2 Steps of data collection (see online version for colours)



This dataset collected a broad spectrum of information from organisations to investigate the need for ERP implementation. These questionnaires were structured into two distinct categories. The first set focused on understanding the operational scope of consulting organisations, including their core business activities and service offerings. The second set delved into data management aspects, exploring the extent and nature of data handled or anticipated by these organisations. The separate questionnaires helped to collect distinct information needs and respondent profiles, maximising the relevance and comparability of the collected data. This structured approach, supported by predefined answer choices, facilitated meaningful analysis across responses.

The preparation of these questionnaires benefited significantly from the authors' diverse industry domain expertise, which was complemented by insights gained during personal interview sessions. Each questionnaire was accompanied by a carefully drafted introductory letter to ensure clarity and precision in communication, essential given the varied dissemination methods, including postal mail and electronic channels. Personal interactions with consultants further enriched the data collection process, providing opportunities for in-depth discussions and supplementary insights. This approach enhances the comprehensiveness and depth of the gathered feedback, ensuring that the survey data provides valuable insights into the decision-making processes surrounding ERP implementations across various organisational contexts.

3.1.1 Questionnaires

These two questionnaires comprise a total of 69 questions, gathering comprehensive information about business operations, product or service methods, and reporting, as well as the overall organisational knowledge. Tables 1 and 2 present sample multiple-choice questions from both questionnaires, designed to collect information about organisational and data volume.

Table 1 Sample questionnaire for organisational data

Q. No.	*Question*	*Options*
1	What is your software Budget to ERP in % of Turnover?	- Less than 5% - 5% to 10% - 10% to 15%
2	What are the reports you are getting from the existing system?	- Consolidated - Separate - Disintegrated
3	What is the frequency of generating these reports?	- Weekly - Monthly - Quarterly - Yearly
4	Are the reports online / offline?	- Online - Offline
5	Are there running many parallel systems in your company where similar reports are compiled?	- Yes - No

Table 2 Sample questionnaire for data volume info

Q. No.	*Questions*	*Opt 1*	*Opt 2*	*Opt 3*	*Opt 4*
1	How many Customers do you have?	Less than 50	50 to 250	250 to 500	More than 500
2	How many Vendors do you have?	Less than 50	50 to 250	250 to 500	More than 500
3	How many Subcontractors do you have?	Less than 50	50 to 250	250 to 500	More than 500
4	What is the percentage of Inventory carrying cost?	Less than 5%	5%	10%	More than 20%

3.2 Data processing

The dataset comprises responses to 69 questions, with around 100 responses. These responses are cleaned and tabulated. Furthermore, each question is assigned an identifier to facilitate further rule generation. Coding each question with unique acronyms streamlines the rule-generation process by making it easier to identify and retrieve questions from the database. This approach improved the organisation and clarity of rule representation, allowing for more efficient and accurate rule creation. The systematic tracking of questions enhanced overall management.

Table 3 lists the abbreviations assigned to each question, facilitating their identification and management within the rules database.

Based on these abbreviations, responses are tabulated as shown in Table 4.

Table 3 Abbreviations used for each question

Que #	*Attribute*	*Que #*	*Attribute*	*Que #*	*Attribute*
1	ICBG	24	OS	47	MMNEMP
2	SUBMP	25	RDBMS	48	INVAGE
3	MULLOC	26	BOM	49	STRRCD
4	MULCUR	27	COMERP	50	STRISS
5	MULLAN	28	LEDERP	51	STRRET
6	MISCOL	29	ERPBEN	52	PNTTRF
7	BUSARA	30	NCUST	53	DOCTRF
8	MFGTYP	31	NVEND	54	STREMP
9	NEMPS	32	NSCON	55	PPAGE
10	REVENU	33	NLOCS	56	NPROD
11	SFTBDG	34	DPERS	57	MANDEP
12	SYSTEM	35	SDAGE	58	PROORD
13	REPORT	36	NSORD	59	SUBCON
14	REPFRQ	37	VSORD	60	MATMAS
15	REPNAT	38	SDNEMP	61	ACTMAT
16	REPUSE	39	MMAGE	62	NBOM

Table 3 Abbreviations used for each question (continued)

Que #	*Attribute*	*Que #*	*Attribute*	*Que #*	*Attribute*
17	REPPAR	40	SCHMON	63	BOMLEV
18	REPEMP	41	LNGAGR	64	BOMMAT
19	MISFEQ	42	LNPSCH	65	PPNEMP
20	REPACC	43	REQDEP	66	FIAGE
21	REPDEC	44	ENQSUP	67	INVICE
22	INDPRO	45	OFFSUP	68	INVCAR
23	COMFAC	46	POSUP	69	FINEMP

Table 4 Sample tabulation of the responses received

Queation Number / Questionnaire set #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	28	29	30
1	2	1	1	2	2	4	4	8	4	5	3	6	4	4	1	4	1	3	4	5	1	6	3	3	2	1	1	1	6
2	2	1	1	1	1	4	3	6	5	5	0	6	4	2	1	4	1	2	4	4	1	7	3	3	2	1	1	1	4
3	2	2	1	2	2	4	4	8	3	4	3	6	4	4	1	4	1	3	4	5	1	6	3	3	2	1	1	1	3
4	1	2	2	2	2	0	8	8	4	5	2	6	3	1	1	2	1	3	4	0	2	6	2	3	2	1	1	1	6
5	1	1	1	1	2	4	1	8	5	5	2	6	4	2	1	4	1	4	4	5	2	6	3	7	2	2	1	1	3
6	2	1	1	1	1	2	8	8	4	5	0	5	3	1	1	4	2	4	4	4	1	7	3	3	2	1	1	1	6
7	1	0	2	2	2	0	8	8	1	4	2	5	3	1	1	4	1	5	4	6	1	0	3	5	2	2	1	1	3
8	2	1	1	2	2	2	1	11	3	5	0	5	4	2	1	4	1	4	4	5	1	7	2	4	1	1	0	0	5
9	1	1	1	2	2	4	15	3	4	5	1	6	0	1	1	5	1	3	4	5	0	8	3	7	2	0	1	1	0
10	1	0	2	2	2	0	10	3	1	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	2	2	0
11	1	0	2	2	2	0	10	5	2	2	0	6	4	2	1	4	2	4	4	5	1	0	0	3	2	1	0	0	3
12	1	0	1	2	2	4	9	1	1	5	1	6	4	1	1	4	2	2	3	6	1	7	2	4	0	1	0	0	6
13	1	1	2	2	2	0	1	7	2	5	0	6	4	1	1	4	2	4	1	6	1	7	3	3	1	1	0	0	6
14	1	1	2	2	2	0	14	7	1	2	0	0	2	1	2	3	2	4	0	4	1	3	1	2	1	1	0	0	0
15	2	0	2	2	2	0	4	7	2	5	2	6	4	1	1	4	1	4	2	6	1	7	2	3	2	1	1	1	4
16	1	0	2	2	2	0	5	8	1	3	0	6	4	1	2	3	2	5	2	4	2	0	1	2	0	1	0	0	2
17	1	0	0	0	0	0	13	8	1	4	1	6	0	2	1	5	1	5	0	6	1	2	0	0	0	1	0	0	0
18	0	1	1	2	2	2	12	4	5	4	1	3	2	1	1	2	2	0	5	5	2	6	2	4	1	0	0	0	1

3.2.1 *Rule generation*

The study conducts rule generation on the dataset by focusing on selected attributes using the decision tree algorithm. Rule generation using decision trees is an effective technique in machine learning and data analysis. Decision trees, widely used for classification and regression, can be converted into a set of clear, human-readable rules. These rules offer valuable insights into the factors influencing specific outcomes and help uncover actionable patterns by examining the tree's branches. This makes it easier to understand and explain the data's underlying logic. Such rule-based models are beneficial for predictive analysis and guiding business strategies, policy decisions, and other areas where transparency and interpretability are crucial.

The study analyses K-Nearest Neighbours, Logistic Regression, Support Vector Machines, and Decision Trees to compare their performance. The Iris dataset, a classic for classification tasks with 150 samples, each having four features and one target class label, is used for evaluation. The scikit-learn library in Python is employed to implement these algorithms and facilitate their comparison.

- *K-Nearest Neighbours*: It is a non-parametric method used for classification and regression tasks (Kramer, 2013). In *k*-nearest neighbours, the prediction for a new sample is based on the *k*-nearest neighbours in the training set. The Euclidean distance (Brownlee, 2020) $d(x, xi)$ is given by,

$$d\left(x, x_i\right) = \sqrt{\sum_{j=1}^{n}\left(x_j - x_{ij}\right)^2} \tag{1}$$

- *Logistic Regression*: It is a linear model used for binary classification tasks. (Jain et al., 2020) Logistic regression predicts the probability of an event occurring by fitting a logistic function to the data. The equation shows the logistic regression. The probability of predictor variables x is expressed as,

$$P\left(y = 1 \middle| x\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}} \tag{2}$$

- *Support Vector Machines*: It is a linear model used for classification tasks. Support vector machines attempt to locate the hyperplane that divides the distinct classes by the maximum margin (Jiang et al., 2021). The decision function of weight vector ω and feature vector x is calculated as,

$$f\left(x\right) = \omega . x + b \tag{3}$$

The accuracy of all tested machine learning algorithms is around 0.96, with decision trees performing comparably to other methods. Among the models, Support Vector Machines achieved the highest accuracy of 0.97. Logistic Regression and K-nearest neighbours both had an accuracy of 0.96. *Decision Trees* also had an accuracy of 0.96, particularly with a maximum depth of 3 or more. After determining that the decision tree model was suitable, the authors focused on selecting the optimal method for its preparation. Decision trees are favoured for their ease of interpretation, capability to handle both categorical and numerical data, and ability to manage missing values.

3.2.2 Technical architecture and algorithmic details

Naive Bayes Algorithm

The Naive Bayes algorithm is a probabilistic classifier grounded in Bayes' Theorem, which states that the posterior probability of a class given observed features is proportional to the product of the class prior and the likelihood of observing those features under that class. Formally, for a feature vector $X = (X_1, X_2, \ldots, X_n)$ and class Y, Bayes' Theorem gives:

$$P(Y|X) = [P(Y) \cdot P(X|Y)] / P(X)$$

Under the Naive conditional independence assumption, the likelihood decomposes as:

$$P(X|Y) = \prod P(X_i|Y).$$

This simplification enables efficient computation even in high-dimensional spaces and forms the mathematical basis of all Naive Bayes variants.

As a generative classifier, Naive Bayes estimates the joint distribution

$$P(X, Y) = P(Y) \prod P(X_i|Y)$$

and infers the posterior by normalising across all classes. Depending on the nature of the feature space, different likelihood models are used. In Gaussian Naive Bayes, each continuous feature is assumed to follow a normal distribution with class-specific parameters $(\mu_{yi}, \sigma_{yi}^2)$, yielding:

$$P(X_i = x \mid Y = y) = (1 / \sqrt{(2\pi\sigma_{yi}^2)}) \cdot \exp(-(x - \mu_{yi})^2 / (2\sigma_{yi}^2))$$

The Bernoulli and Multinomial models instead rely on discrete probability mass functions suitable for binary and count-based data. These mathematical preliminaries allow the algorithm to maintain analytical tractability, making Naive Bayes a robust and efficient classifier.

Decision Tree Algorithm

Decision trees construct hierarchical decision boundaries by recursively partitioning the feature space. Given a dataset D, the algorithm selects a feature and splitting criterion that maximises homogeneity within subsets. This choice is based on impurity measures defined mathematically over class distributions. In classification trees, the two most common impurity functions are entropy and Gini impurity:

$$Entropy(D) = -\sum P(c) \log_2 P(c),$$

$$Gini(D) = 1 - \sum P(c)^2,$$

where $P(c)$ is the probability of class c in dataset D. A split S on feature f is evaluated using Information Gain:

$$IG(D, S) = Entropy(D) - \sum (|D_i| / |D|)\, Entropy(D_i),$$

where D_i are child nodes induced by the split.

The recursive partitioning continues until a stopping criterion is met or until all samples in a node belong to the same class. For regression trees, impurity is measured using variance or mean squared error. Mathematically, the objective is to minimise:

$$MSE(D) = (1/|D|) \sum (y_i - \hat{y})^2$$

Although a fully grown decision tree minimises impurity, it risks overfitting. Pruning methods address this by minimising the cost-complexity functional:

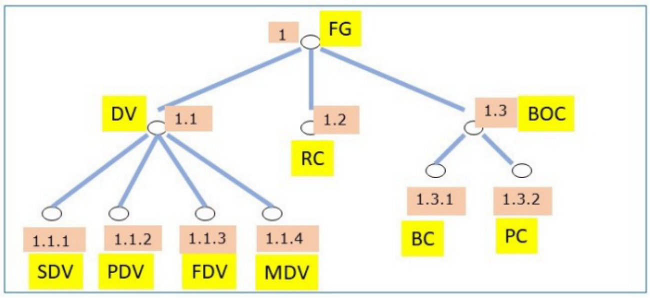
$$C(T) = R(T) + \alpha|T|,$$

where $R(T)$ is the empirical risk, $|T|$ is the number of leaves, and $\alpha \geq 0$ controls model complexity. These mathematical formulations provide a theoretical basis for tree construction, guiding the algorithm toward interpretable yet effective decision boundaries.

3.2.3 Decision trees

Decision trees are a tree-like structure where every node shows a test on an attribute (Gupta et al., 2017), every branch denotes the test outcome, along with each leaf node representing a class label or a numerical value as shown in Figure 3. Creating a decision tree includes selecting the best attribute for splitting the data using metrics like Gini impurity or entropy, splitting the dataset based on this attribute, and recursively repeating the process for each subset. This continues until a stopping criterion is met, such as reaching a uniform class in a node or a predefined depth.

Figure 3 Decision tree (see online version for colours)



- *Entropy*: Entropy quantifies the level of impurity or uncertainty in the dataset, with p_i representing the probability of an instance being assigned to a specific class.

$$Entropy = -\sum_{i=1}^{n} p_i \log_2(p_i) \tag{4}$$

The preparation of decision trees involves assessing their effectiveness using intermediate factors such as Data Volume, Reporting Complexity, and Business Operation Complexity. Table 5 displays the calculated entropy, which measures the impurity of the dataset.

Table 5 Entropy calculations

Node	*Meaning*	*Attribute*	*Entropy*
1.1	Data Volume	DV	0.33
1.2	Reporting Complexity	RC	0.213
1.3	Business Operations Complexity	BOC	0.011

Furthermore, in decision tree construction, the process begins by calculating the Gini Index, Information Gain, and Gain Ratio for all attributes. The attribute with the best Gain Ratio, or the highest Gini Index or Information Gain, is then selected based on the defined priorities. This chosen attribute is used to split the dataset, and the process is recursively repeated for each resulting subset until a stopping criterion is met. To compare the Gini Index with other methods for decision trees, the study utilised the scikit-learn library in Python to implement the various techniques.

Gini Index: The Gini Index measures impurity in decision trees by calculating the probability of misclassifying a randomly selected element based on the label distribution. A lower Gini Index value indicates greater data purity. For a dataset D with k classes and p_i as the proportion of the dataset belonging to class i, it is given by the equation:

$$Gini(D) = 1 - \sum_{i=1}^{k} (p_i)^2 \tag{5}$$

- *Information Gain*: It measures the reduction in entropy acquired by splitting on a particular attribute. It evaluates how well an attribute separates the data into distinct classes. After splitting by an attribute, the information gain IG for subset D_i of dataset D given by:

$$IG = Entropy(D) - \sum_{i=1}^{n} \frac{D_i}{D} * Entropy(Di) \tag{6}$$

- *Gain Ratio*: The gain ratio is defined as the information gain divided by the intrinsic information of the attribute. The gain ratio is used to deal with the bias of information gain against attributes encompassing several distinct values. Gain ratio GR is a modification of information gain considering the Intrinsic information I of each attribute as shown in the equations below.

$$I = -\sum_{i=1}^{n} \frac{Di}{D} * \log_2 \frac{Di}{D} \tag{7}$$

$$GR = \frac{IG}{I} \tag{8}$$

Following this analysis, a decision tree was developed. For each node on the decision tree, a set of questions contributing to the result was identified. The REDUCT algorithm was used to determine the CORE attributes from all contributing attributes for each node. In the context of the decision tree, core attributes are the essential features necessary for maintaining classification accuracy, while REDUCT refers to the minimal subset of attributes that can still provide the same decision-making power as the full set. The REDUCT algorithm is used to identify these core attributes, streamlining the decision-making process by focusing only on the most impactful features. Specifically, for attributes affecting the volume in the Order to Cash process, the CORE attributes were identified, as shown in Table 6.

Rules are formed using these CORE attributes, with additional rules developed at each stage using the REDUCT method. Sample rules for other key decision parameters are provided below. Overall, a total of 152 rules are developed through decision tree traversal, with the number of rules attributed to each node. Table 7 shows rules for each Decision Tree node.

Table 6 Core attributes for rule generation

Rule #.	*No. of Customers*	*No. of Sales Orders*	*Value of Sales Order*	*No. of Employees in Sales*	*Sales Data Volume*
1	More than 500	More than 200	50 Lakh to 1 Cr	10 to 25	High
2	More than 500	More than 200	25 Lakh to 50 L	More than 25	High
3	More than 500	100 to 200	25 Lakh to 50 L	More than 25	High
4	More than 500	More than 200	5 Lakh to 25 L	5 to 10	Medium
5	More than 500	100 to 200	25 Lakh to 50 L	10 to 25	Medium
6	More than 500	Less than 50	Less than 5 L	More than 25	Medium
7	250 to 500	50 to 100	25 Lakh to 50 L	10 to 25	Medium

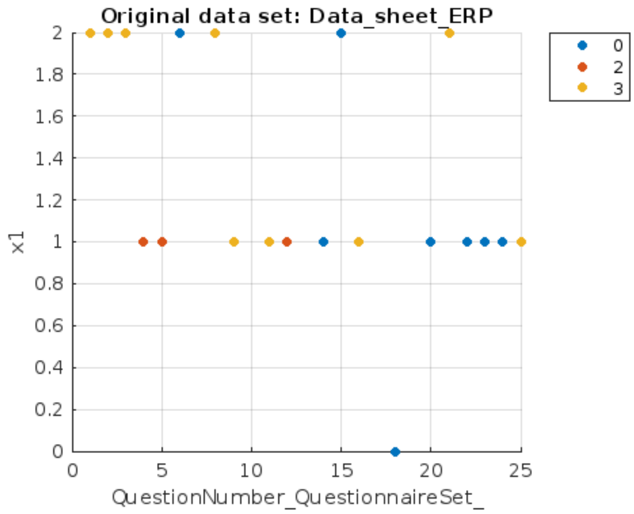
Table 7 Decision tree nodes with the number of rules for each node

Node	*Meaning*	*Attribute*	*# of rules Contributing the decision*
1	Goal (Need ERP)	FG	18
1.1	Data Volume	DV	27
1.1.1	Sales Data Volume	SDV	13
1.1.2	Materials Data Volume	MDV	16
1.1.3	Production Data Volume	PDV	15
1.1.4	Finance Data Volume	FDV	9
1.2	Reporting Complexity	RC	13
1.3	Business Operations Complexity	BOC	4
1.3.1	Business Complexity	BC	20
1.3.2	Product Complexity	PC	17

3.3 Machine learning models

After forming rules with the decision tree, the machine learning (ML) models were trained on the organisation's primary dataset to identify the best-performing algorithm for intelligent ERP decisions. The performance ML models like Fine Decision Tree, Linear SVM, Efficient Logistic Regression, Kernel SVM, Naive Bayesian and Ensembled model in the form of the boosted tree are compared on a primary dataset of the survey. The scikit-learn library in Python is employed to implement these algorithms and facilitate their comparison. To train the models, the dataset is split into 80% for training and 20% for testing. Furthermore, to prevent overfitting, the study employed 5-fold cross-validation. Figure 4 shows predictor variable response in the dataset for different questions.

Figure 4 Representation of predictor variable ($x1$) (see online version for colours)



3.3.1 Performance evaluation

The models performed well on the survey dataset, and their effectiveness was evaluated based on accuracy, prediction speed, and training time across all 69 attributes. Table 8 details the performance of each machine learning model. The Fine Decision Tree and Medium Decision Tree models achieved the highest accuracy of 60%, while the Medium Decision Tree model had the fastest prediction speed, processing 1300 observations per second. Conversely, the Efficient Logistic Regression model was the fastest in terms of execution time but had a relatively low accuracy of 35%. Overall, the Fine Decision Tree model emerged as the best-performing model, balancing high accuracy with a smaller model size.

Table 8 Accuracy comparison

Model	*Validation accuracy*	*Prediction speed (obs/sec)*	*Training time (sec)*	*Model size (kb)*	*No. of features used*
Fine Decision Tree	60%	240	4.14	12 kb	69/69
Medium Decision Tree	60%	1300	5.24	12 kb	69/69
Linear SVM	35%	450	2.28	39 kb	69/69
Efficient Logistic Regression	35%	460	1.42	51 kb	69/69
Efficient Linear SVM	35%	320	2.32	51 kb	69/69
SVM Kernel	35%	440	4.04	109 kb	69/69

Figure 5 illustrates a graphical representation of the compared ML models in terms of accuracy, speed, and training time.

Figure 5 Performance evaluation of ML models (see online version for colours)

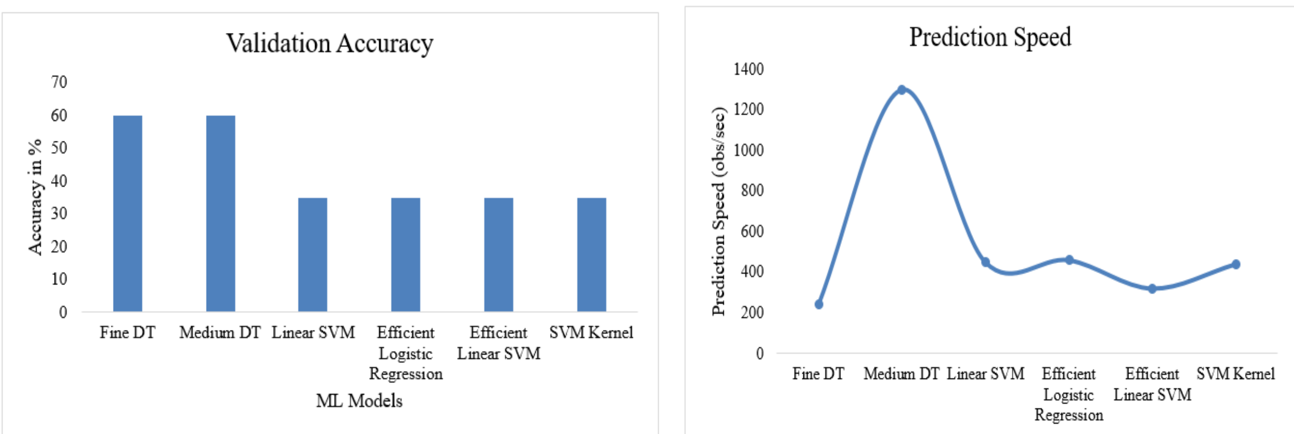
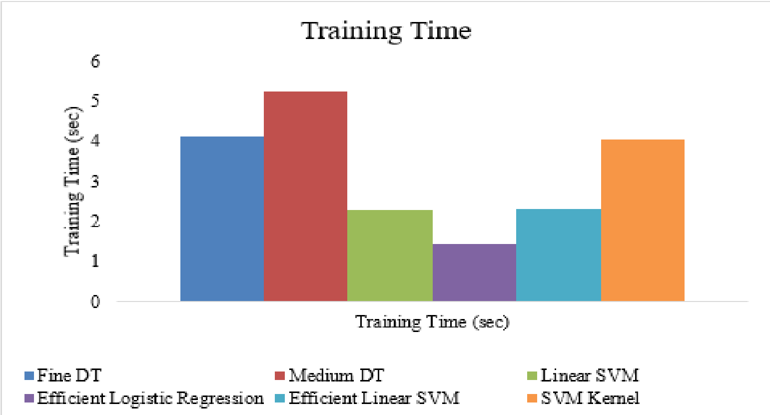


Figure 5 Performance evaluation of ML models (see online version for colours) (continued)



4 Deployment

The proposed system is designed to provide clear guidance on ERP implementation decisions, indicating whether the implementation is likely to be successful or not. To ensure ease of interpretation, the output is formatted in a user-friendly manner, avoiding complex technical jargon. The report incorporates a business framework context to enhance its usability for decision-making and analysis. The authors also explored the potential use of this report for simulating further business and critical decisions. The standard deployment process for the system is outlined below. The deployment process involves key steps: Preparation, Testing, and Final Deployment.

After completing the rule generation, the authors tested the rules by traversing through the algorithm using samples from various industry verticals to represent different levels of complexity. The results were highly positive, confirming the effectiveness of the ERP implementation recommendations. Encouraged by these results, the authors engaged with several software development agencies, receiving strong interest in the joint development of the product. Once developed, the tool will be tested across diverse industry verticals to ensure its robustness and applicability. During testing, the prototype was used to evaluate ERP implementation decisions across various industries. The authors ensured a broad range of parameters to create diverse samples, including different industry verticals and important geographies.

4.1 Evaluation of proposed system

- *Success Rate*: The success rate during testing indicates the proportion of test cases that met the expected or desired outcomes that reflect how well the ERP implementation tool performed across different industry types and geographic regions. Table 9 provides a detailed view of the industries covered during the testing phase. The industries covered include automobile, auto OEM, manufacturing, electronic component manufacturing, pharma, hospitality, and port and public transport, as well as other industries. The results presented below detail the matching cases within each industry vertical across various geographical regions. Furthermore, the overall success rate in each geographic section is indicated by the proportion of matching samples relative to the total cases

Figure 6 Deployment process (see online version for colours)

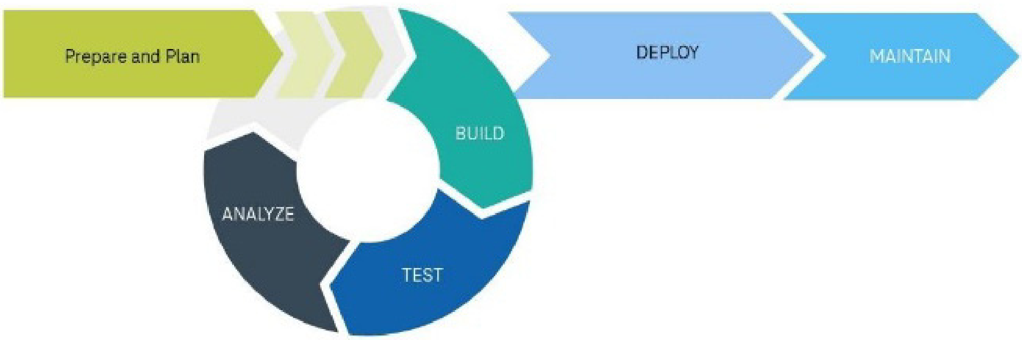


Table 9 Tabulation of prototype test results

Geography	Industry Vertical								Total		
	Automobile	Auto -OEM	Manufacturing	ECM	Pharma	Hospitality	Port and Public Transport	Others	Matching samples	Total samples	Matching%
EU	1	1	1	0	-	-	2	0	5	8	63
APAC	-	-	-	-	2	-	-	1	3	4	75
SA	1	-	3	-	-	-	-	-	4	4	100
NA	1	1	2	-	4	-	-	-	8	8	100
UK	-	-	-	-	-	1	-	1	2	3	67
Total	3	2	6	0	6	1	2	2	22	27	82

The results indicate cases with matching results as compared to the total number of samples for that specific industry type and geography combination. The success rates for the SA and NA regions are 100%, followed by the APAC, UK, and EU regions with success rates of 75%, 66.7%, and 62.5%, respectively. The test results demonstrate an 81.5% success rate, with 22 out of 27 test cases showing matching results. One key insight from the exercise was the identification of a case where the tool produced a negative result for the German agriculture industry. This highlighted the need for improvements in the questionnaire to address non-standard industries more effectively. Consequently, the feedback from this exercise will be used to enhance the tool and ensure it accommodates a broader range of industry types. Figure 7 shows the distribution of match cases based on industry verticals and geography.

- *Speed of operation*: The proposed ERP system expressively augments functioning efficiency by assimilating numerous functions into a single platform. By consolidating all data and streamlining communication processes, the system facilitates quicker decision-making, reduces operational delays, and increases the overall speed of operations. Consequently, organisations can perform tasks more efficiently, leading to faster decision-making and improved business performance.
- *Flexibility*: The flexibility of the ERP system is crucial for effective decision-making and operational efficiency. The system enhances resource utility, reduces quality costs, and improves vendor performance, customer satisfaction, and information accuracy. Its adaptability allows it to cater to diverse industry needs, thanks to modular components designed for seamless integration. Modern intelligent ERP systems can be easily tailored to fit specific company requirements, minimising disruptions and enabling gradual functionality expansions. Ensuring that interfaces are consistent, user-friendly, and customisable, including for mobile devices, further boosts productivity and aligns with employee needs. This flexibility is vital for optimising decision-making and achieving a higher return on investment.
- *Cost*: The cost evaluation for the proposed ERP system demonstrates its significant impact on reducing operational expenses. By utilising real-time data, the ERP system minimises delays and defects, leading to more efficient management of operations. This efficiency translates into reduced manual work, lower processing costs, and shorter decision-making times. The cost comparison analysis before and after ERP system installation, detailed in Table 10, shows the financial benefits of the system. This analysis highlights an effective implementation of the ERP system leading to substantial cost savings and improve overall company performance.

Figure 7 Distribution of match cases based on geography and industry verticals (see online version for colours)

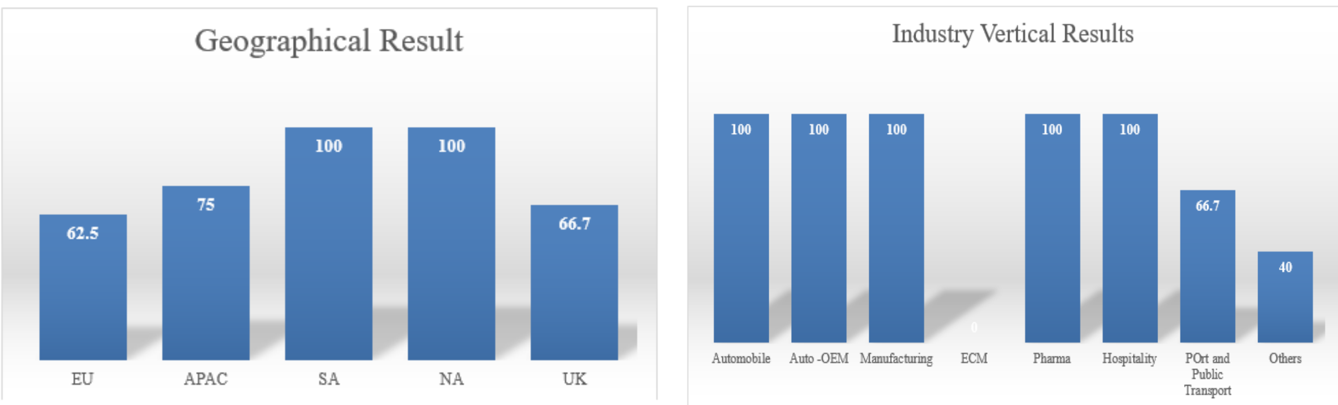
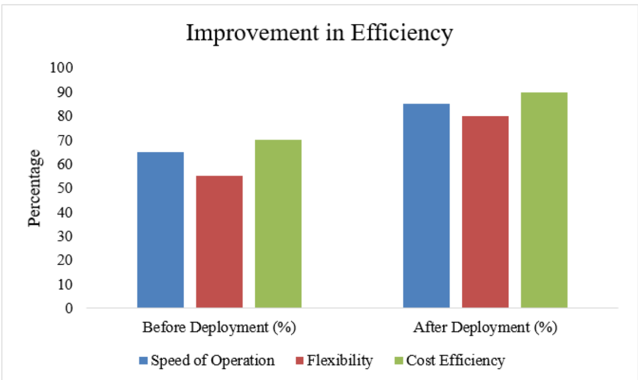


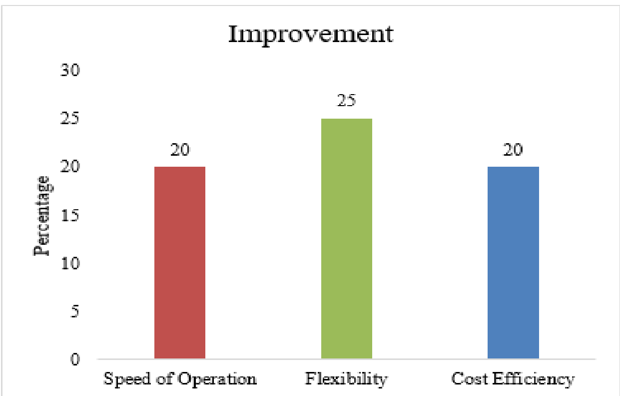
Table 10 shows an increase in performance of organisational efficiency in terms of speed of operation, flexibility and cost. The results demonstrate a notable enhancement in key performance metrics following the implementation of the proposed decision-making system. Specifically, the speed of operation improved by 20%, indicating that processes are now executed more swiftly. Similarly, cost efficiency saw a 20% increase, reflecting a reduction in operational expenses. Flexibility, a critical factor in adapting to various business needs, increased by 25%, showing that the system can better accommodate diverse requirements and changes. Overall, these improvements as shown in Figure 8, highlight the effectiveness of the system in optimising organisational performance.

Table 10 Improvement in organisational efficiency

Metric	*Before deployment (%)*	*After deployment (%)*	*Improvement (%)*
Speed of Operation	65	85	+20
Flexibility	55	80	+25
Cost Efficiency	70	90	+20

Figure 8 Improvement in efficiency (see online version for colours)





5 Discussion

The study is centred on developing an advanced decision-making system tailored for organisational use, to achieve superior global performance. The primary focus is on enhancing the effectiveness of decision-making processes by integrating a range of machine learning algorithms into the system. These algorithms, including models such as Decision Trees, Support Vector Machines, and others, are used to evaluate and refine the system's predictive accuracy and reliability.

A key feature of the proposed system is its incorporation of a comprehensive survey dataset that includes responses from a diverse global audience. This extensive dataset is crucial for expanding the system's applicability across different organisational contexts and geographical regions. By leveraging a wide array of data, the system gains the capability to offer more generalised and relevant insights, making it adaptable to various industrial and regional needs.

In the comparative analysis, the Decision Tree model has emerged as the most effective machine learning approach for this system. This model's ability to structure data into clear, understandable decision rules allows for improved interpretation and actionable insights. The superior performance of the Decision Tree model highlights its efficiency in processing and analysing complex datasets, providing organisations with a reliable tool for making informed decisions about ERP system implementation.

The system's benefits are evident in its impact on organisational operations. By implementing the proposed decision-making system, organisations can expect notable improvements in operational efficiency. Specifically, the system enhances the speed of operations and reduces costs, contributing to overall cost efficiency. This is achieved by streamlining processes and minimising delays through effective data analysis and decision support.

A critical measure of the system's effectiveness is its success rate. The study reports a high success rate of 81%, indicating that the system consistently delivers accurate and valuable insights. This high success rate is indicative of the system's reliability and its ability to provide meaningful recommendations for ERP system implementation. It signifies that the system is capable of effectively supporting organisations in making well-informed decisions, thereby enhancing their operational efficiency and optimising their ERP strategies.

1) *Inclusion of Prototype Testing Results*: The paper includes an expanded evaluation section where the Intelligent Decision Support System (IDSS) was tested across *multiple industry verticals and geographic regions*. A total of *27 real-world test scenarios* – covering automobile, manufacturing, pharmaceuticals, electronic component manufacturing, hospitality, transport, and others – were executed to validate the accuracy of the system's recommendations. The results demonstrate an *81.5% match rate*, clearly indicating the practical effectiveness of the proposed method in real organisational settings.

2) *Addition of Deployment Performance Metrics*: To reflect the operational benefits of the system, we have included a detailed performance comparison showing improvements in *speed of operation (20%)*, *flexibility*

(25%), and *cost efficiency (20%)* after applying the decision-making framework. These metrics serve as a simulated environment demonstrating efficiency gains attributable to the proposed system.

Together, these additions provide both *real-world evidence* and *simulation-based performance insights*, thereby strengthening the empirical contribution of the work as recommended.

6 Conclusion

The authors, drawing on extensive experience in organisational management and decision support systems, conducted a comprehensive study of operational modules and decision-making processes within organisations. This investigation provided valuable insights into how various components interact and impact overall efficiency. By examining the existing processes used by consultants to determine ERP requirements, the study underscores a commitment to understanding real-world practices and challenges.

This study enhances organisational efficiency through intelligent ERP decision-making using AI algorithms such as Logistic Regression, Support Vector Machines, and Decision Trees. The developed system achieved an impressive success rate of 82% approximately, with 22 out of 27 test cases showing matching results. Key deployment steps include preparation, testing, and final deployment.

The creation of the Intelligent Decision Support System (IDSS) represents a significant advancement in decision-making tools for ERP implementation. Leveraging modern technologies and data-driven approaches, the IDSS is highly sophisticated and adaptable, potentially revolutionising how organisations approach ERP implementation and enhancing overall effectiveness.

A notable aspect of the IDSS is its potential for commercialisation, as evidenced by interest from multiple industries, highlighting its market viability and practical relevance. The expert system emulates human decision-making expertise, offering timely advice, diagnoses, or recommendations in complex domains such as healthcare, finance, and engineering. By encapsulating ERP experts' knowledge and reasoning, the system aids in problem-solving, error reduction, and efficiency improvement. It also supports training, decision-making, and task automation, ultimately boosting productivity and ensuring high-quality outcomes.

In conclusion, this research makes a commendable contribution to decision-making support for ERP implementation. Through a thorough study and the development of the IDSS, this work significantly advances organisational management and the broader business landscape. Organisations stand to benefit from valuable tools and insights that optimise their ERP implementations and decision-making processes.

7 Future scope

The study represents a significant advancement in ERP decision support systems. Despite achieving a promising success rate, there is further potential to address more diverse and complex scenarios that organisations may encounter during ERP implementations. Additionally, while AI algorithms are effective, they limit performance in addressing the full spectrum of decision-making challenges faced by organisations in different industries. The study's focus on specific AI techniques also restricts the exploration of potentially beneficial methodologies that could further enhance decision-support capabilities.

The study has scope for future research and development in this field, including enhancing the IDSS to integrate more advanced AI techniques and machine learning models capable of handling intricate decision-making scenarios. Exploring deep learning approaches, natural language processing, and reinforcement learning can improve the system's adaptive capabilities and predictive accuracy. Future studies could expand the IDSS to cater to broader industry applications beyond current domains, ensuring its relevance across diverse organisational contexts. Moreover, evaluating the long-term impact and scalability of the IDSS in real-world ERP implementations, and fostering collaboration with a broader range of stakeholders and industry experts, will ensure its alignment with evolving organisational needs and technological advancements.

Declarations

All authors declare that they have no conflicts of interest.

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