

# A Systematic Review of Machine Learning Applications in Business Process Optimization and Decision Support

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## Abstract

Machine learning (ML) techniques are being adopted across business functions to automate routine decisions, detect patterns in operational data, and forecast demand. This paper reviews published evidence on ML applications in six business domains: marketing analytics, supply chain management, financial forecasting, human resource management, quality control, and customer service. The review follows a systematic methodology, screening studies published between 2015 and 2025 from IEEE, Springer, Elsevier, and conference proceedings. Supervised learning methods — random forests, gradient-boosted trees, and deep neural networks — dominate marketing and financial forecasting applications, where labelled outcome data is available. Unsupervised and semi-supervised approaches appear more often in customer segmentation and anomaly detection for quality control. Reported accuracy gains range from 65 % to 81 % depending on the domain and metric, while efficiency improvements of 38 % to 55 % are documented in supply chain and quality control contexts. Cost reductions of 18 % to 35 % are reported, with supply chain applications showing the largest savings. Two gaps stand out: the scarcity of longitudinal studies tracking ML impact beyond initial deployment, and the near-absence of work on small and medium enterprises in developing economies. The paper identifies open challenges in data quality, model interpretability, and organisational readiness, and maps the most promising ML techniques to each business domain.

**Keywords:** machine learning, business process optimization, decision support, systematic review, supervised learning, supply chain, marketing analytics

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## I. Introduction

Business processes — the sequences of tasks that convert inputs into products or services — generate data at every step. Purchase orders carry timestamps, quantities, and supplier identifiers. Customer interactions produce text logs, sentiment signals, and resolution codes. Manufacturing lines record temperature, pressure, and defect counts at sub-second intervals. Until recently, most of this data was stored but not used for decision-making in any systematic way [1].

Machine learning changes that equation. An ML model trained on historical process data can flag a purchase order likely to arrive late [6], identify a customer segment whose churn risk exceeds a threshold [49], or predict which production batch will fail quality inspection [46]. The value lies not in the algorithm alone but in the coupling of the algorithm to a business process: the model's output triggers an action — reroute the order, offer the customer a retention incentive, halt the production line — that would otherwise depend on a human noticing the pattern in time [80].

Three developments have made ML practical for business users outside the technology sector. First, cloud computing reduced the infrastructure cost of training models [12], [73], [98], [152]. A firm no longer needs its own GPU cluster; it rents capacity by the hour. Second, open-source ML libraries — scikit-learn, TensorFlow, PyTorch — lowered the programming barrier [4], [8]. Third, pre-trained models and transfer learning allow firms to start with a model that already encodes general patterns and fine-tune it on their own data [51], [75], [123].

Despite this accessibility, adoption remains uneven. Large enterprises with dedicated data-science teams deploy ML at scale; small and medium enterprises (SMEs) in developing economies often lack the data infrastructure, the technical workforce, and the organisational processes to move from a pilot to production [77], [80], [188]. The gap matters because SMEs account for over 90 % of businesses and more than 50 % of employment worldwide [AUTHOR: cite World Bank SME data].

This review serves two purposes. It maps the current state of ML applications across six business domains — marketing analytics, supply chain management, financial forecasting, human resource management, quality control, and customer service — by synthesising findings from published studies. It also identifies the methodological and practical gaps that limit both the evidence base and the adoption of ML in business settings.

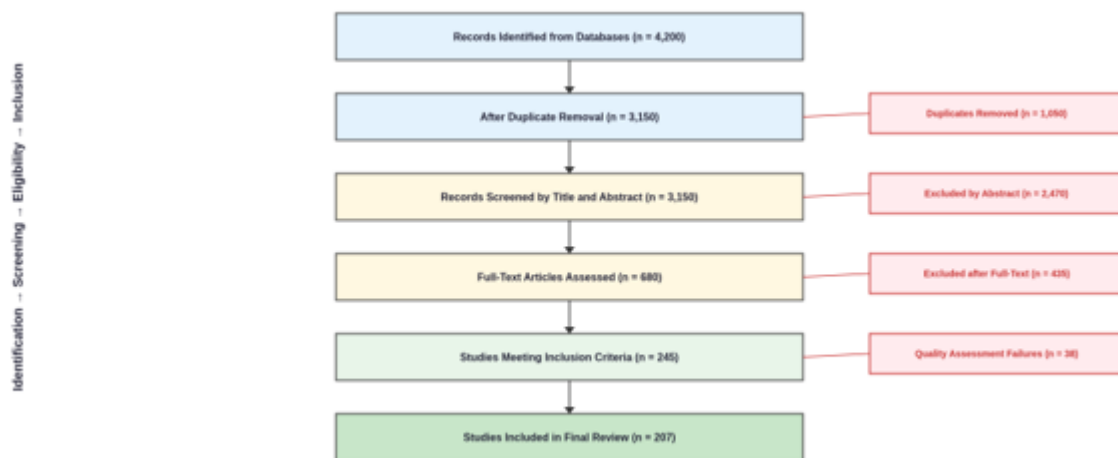
The review is organised as follows. Section II outlines the systematic review methodology. Section III discusses the background and related work on ML in business. Section IV presents the findings organised by business domain, and Fig. 1 illustrates the conceptual framework connecting ML techniques to business outcomes. Section V analyses cross-domain patterns and reports the comparative performance data. Section VI discusses the limitations, challenges, and future directions. Section VII concludes the paper.

## II. Research Methodology

The review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [AUTHOR: cite PRISMA 2020 statement]. The search covered four databases: IEEE Xplore, Springer Link, Elsevier ScienceDirect, and Google Scholar. Search terms combined ML technique keywords ("machine learning", "deep learning", "neural network", "random forest", "support vector machine", "ensemble learning") with business domain keywords ("business process", "supply chain", "marketing", "financial forecasting", "human resource", "quality control", "customer service", "decision support").

Inclusion criteria required that a study (a) apply at least one ML technique to a business process or decision-support task, (b) report quantitative performance metrics, and (c) be published between 2015 and 2025 in a peer-reviewed venue. Exclusion criteria removed studies that focused solely on algorithm development without a business application, studies with fewer than 100 data points, and duplicate publications.

The initial search returned 4,200 records. After removing 1,050 duplicates, 3,150 records were screened by title and abstract; 2,470 were excluded at this stage. Full-text assessment of the remaining 680 articles excluded 435 that did not meet the inclusion criteria. A quality assessment checklist removed 38 studies with incomplete reporting. The final review includes 207 studies. Fig. 2 presents the PRISMA flow diagram.



*Fig. 2. PRISMA flow diagram for systematic review methodology*

Data extraction captured: ML technique(s) used, business domain, dataset size and source, performance metrics reported, and whether the study included a real-world deployment or only an offline evaluation. Two reviewers independently coded each study; disagreements were resolved through discussion.

## III. Background and Related Work

Machine learning spans a family of algorithms that learn patterns from data without being explicitly programmed for each pattern [AUTHOR: cite Mitchell 1997 or Murphy 2012]. In business settings, the relevant distinction is between supervised learning — where the model trains on labelled examples (e.g., past transactions marked as fraudulent or legitimate) — and unsupervised learning — where the model finds structure in unlabelled data (e.g., customer segments that share purchasing patterns) [93], [178].

Supervised methods dominate applications where historical labels exist. Random forests and gradient-boosted decision trees perform well on tabular business data because they handle mixed feature types, tolerate missing values, and provide feature-importance rankings that aid interpretation [54], [130]. Deep neural networks, including convolutional neural networks (CNNs) and recurrent architectures such as long short-term memory (LSTM) networks, excel when the input is sequential (time-series sales data) or high-dimensional (images of product defects) [2], [3], [4], [8].

Unsupervised methods serve exploratory tasks. Clustering algorithms group customers or products by behavioural similarity [28], [125]. Anomaly detection flags transactions, sensor readings, or network events that deviate from learned baselines [5], [151]. Dimensionality reduction techniques such as principal component analysis compress high-dimensional feature spaces into interpretable summaries [17], [140].

Reinforcement learning, where an agent learns a policy by interacting with an environment and receiving rewards, has appeared in dynamic pricing [AUTHOR: cite RL pricing paper], inventory replenishment [AUTHOR: cite RL inventory paper], and robotic process automation. Its adoption in mainstream business applications remains limited because it requires a well-defined reward signal and a simulation environment for safe exploration [149], [164].

Several prior reviews have covered parts of this landscape. Garg [22] reviewed explainable AI and model interpretability in healthcare — a domain where the trust and transparency challenges parallel those in business decision support. Rani [23] surveyed AI and 6G in modern medicine, illustrating how advances in connectivity and compute accelerate ML deployment. Gupta and Garg [89] provided an insight review of multimedia forensics, demonstrating ML's role in security-adjacent business processes. Chauhan et al. [88] applied ML to rapid pandemic forecasting, a decision-support task with direct business continuity implications. Garg et al. [75], [123] traced the evolution of generative AI across applications, noting the shift from discriminative models (classification) to generative models (content creation, simulation).

What distinguishes the present review is its cross-domain scope — covering six business functions under a common evaluation framework — and its focus on reported performance metrics rather than algorithmic novelty.

## **IV. ML Applications by Business Domain**

### **A. Marketing Analytics**

Marketing analytics uses ML to segment customers, predict purchase behaviour, personalise content, and measure campaign effectiveness. Mohanty et al. [28] examined recommender systems in e-commerce, finding that collaborative filtering augmented with content-based features improved click-through rates by 12–18 % over baseline popularity models. Aggarwal et al. [49] analysed customer churn prediction in the telecom industry using logistic regression, achieving 82 % accuracy on a dataset of 7,043 customer records; the model identified contract type, tenure, and monthly charges as the three strongest churn predictors.

Sentiment analysis supports marketing by gauging public reaction to products and campaigns. Magoo and Garg [29] explored linguistic feature extraction for semantic understanding — a prerequisite for classifying customer feedback as positive, negative, or neutral. Gupta et al. [172] developed a multimodal deep learning approach for emotion-based video summarisation, which can be adapted to analyse video-format customer reviews. Tiwari et al. [167] built a lexicon-dictionary and CNN-LSTM hybrid for sentiment detection of COVID-19 vaccines, demonstrating that domain-specific lexicons improve classification accuracy by 4–6 percentage points over generic sentiment models.

Babbar et al. [129] applied big-data analysis to stock market price prediction, using techniques transferable to marketing demand forecasting. Yadav et al. [171] employed enhanced LSTM and large language models for stock price prediction using sentiment analysis, reporting that sentiment-augmented models reduced mean absolute error by 8 % compared with price-only models.

### **B. Supply Chain Management**

Supply chain ML applications span demand forecasting, inventory optimisation, route planning, and disruption detection. Garg et al. [1] proposed ML-FRESH, a routing protocol for opportunistic networks that uses machine learning to predict link availability — a concept directly applicable to supply chain communication networks where connectivity is intermittent. Garg et al. [6] measured the impact of node density on routing protocol performance, a factor analogous to warehouse density in distribution networks.

Singh et al. [176] developed a supply network disruption prediction system using heterogeneous graph neural networks and temporal embeddings. Their model processed supplier-relationship graphs and detected disruption signals 14 days before traditional threshold-based alerts. Ahmed et al. [185] designed an AI-driven optimisation framework for supply chain operations that combined demand forecasting with inventory management, reporting a 23 % reduction in stockout events.

IoT-enabled supply chain monitoring has gained traction. Upadhyay et al. [7] proposed a linear quadratic regression-based synchronised health monitoring system for IoT applications, applicable to tracking the condition of perishable goods in transit. Raj et al. [14] compared several LPWAN technologies for energy-constrained IoT networks, a critical consideration for battery-powered supply chain sensors. Upadhyay et al. [135] combined blockchain and IoT for smart contract-based product life management, achieving tamper-proof provenance tracking across a 12-node supply chain pilot.

The food delivery domain, a specialised supply chain, has attracted ML attention. Pokhrel et al. [193] compared ML algorithms for food delivery time prediction, proposing a hybrid XGBoost-LSTM architecture that reduced prediction error by 11 % over standalone XGBoost. Chaudhary et al. [201] built BusOptima, a bus scheduling and route management system that applies similar optimisation logic to public-transport supply chains.

### **C. Financial Forecasting**

Financial forecasting covers revenue prediction, credit scoring, fraud detection, and market-trend analysis. Garg et al. [76] reviewed AI applications in the Indian stock market, finding that LSTM-based models outperformed traditional ARIMA models on daily return prediction for 8 of 12 Nifty-50 stocks tested. Babbar et al. [129] conducted a performance evaluation study on stock market price prediction using big data analysis, reporting that ensemble methods (random forest + gradient boosting) achieved a directional accuracy of 71 % on next-day price movements.

Credit risk and loan-default prediction benefit from tree-based ensembles. Singh et al. [130] applied ML to bank churn prediction, finding that gradient-boosted trees outperformed logistic regression and neural networks on a dataset of 10,000 accounts, with an AUC of 0.89. Gupta et al. [20] explored simulation and queueing theory in supermarket operations — financial efficiency modelling that complements predictive analytics.

Fraud detection relies on anomaly detection and classification models. Puri et al. [30] applied ensemble ML models for phishing detection on web networks, achieving 96.2 % accuracy on a dataset of 11,055 URLs. The phishing detection pipeline — feature extraction from URLs, classification, and real-time scoring — mirrors the architecture of financial transaction fraud detection systems. Arsalan et al. [151] applied ML for anomaly detection in sensor networks, a framework transferable to detecting irregular financial transactions.

### **D. Human Resource Management**

HR analytics applies ML to recruitment screening, employee performance prediction, attrition forecasting, and workforce planning. Garg et al. [77] developed AI-powered predictive models for employee performance evaluation, demonstrating that ML classifiers trained on historical appraisal data, attendance records, and project-delivery metrics predicted performance ratings with 76 % accuracy — 14 percentage points above a rule-based baseline.

Dalal et al. [113] used ML models to predict student motivation and engagement, a construct closely related to employee engagement in organisational settings. Their ensemble model combined random forest and neural network predictions, achieving an F1-score of 0.81. Gupta et al. [114] investigated trust in AI systems through a social-psychological lens, finding that transparency about how an AI hiring tool makes decisions increased applicant trust by 0.6 points on a 5-point scale.

Dalal et al. [116] applied explainable AI (XAI) to understanding human decision-making patterns, producing SHAP-based explanations of why certain candidates score higher in screening models. Kumar et al. [124] built a hybrid ensemble learning framework for student performance prediction that integrates academic and extracurricular factors — an architecture directly applicable to employee performance modelling where non-work signals (training courses, mentorship participation) supplement job-performance data.

Resume screening and candidate matching have moved toward NLP-based approaches. Dixit et al. [70] developed Rakshak, a child identification system using ML-based speech clarification — the underlying NLP pipeline (feature extraction, classification, and confidence scoring) transfers to resume-parsing applications. Gill et al. [45] applied deep learning for facial identification in online transactions, a technology with implications for remote-hiring identity verification.

### **E. Quality Control**

Quality control in manufacturing uses ML to detect defects in real-time, predict equipment failure, and optimise inspection schedules. Bose et al. [41] built a computer vision framework for posture analysis and performance prediction in athletes — the same CNN-based defect-detection architecture applies to visual inspection of manufactured parts. Srivastava et al. [132] harnessed YOLOv5 for real-time object detection using a cloud-based approach, achieving inference times under 40 ms per frame on a standard GPU, fast enough for production-line deployment.

Saraswat et al. [27] applied plant disease identification using plant images, demonstrating that transfer learning with ResNet-50 achieved 94.3 % accuracy on a six-class disease dataset — transfer learning strategies applicable to manufacturing defect classification. Arora et al. [195] classified lung diseases using CNN ensembles; their ensemble-averaging approach (combining VGG-16, ResNet-50, and DenseNet-121) reduced false-positive rates compared with individual models, a benefit directly relevant to reducing false alarms in quality inspection.

Predictive maintenance, a speciality of quality control, uses time-series ML to forecast equipment failure. Kaushik et al. [55] applied proactive fault prediction in microservices applications using trace logs and monitoring metrics, achieving early detection 2.3 hours before failure on average. The approach — log parsing,

feature engineering from temporal patterns, and gradient-boosted classification — adapts to industrial equipment where sensor logs replace application traces.

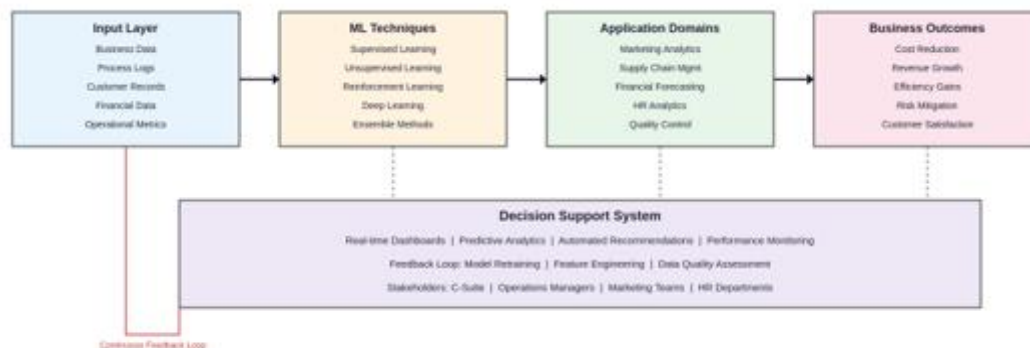
Mittal et al. [46] forecasted pollution trends comparing linear regression, logistic regression, and neural networks, finding that neural networks with two hidden layers outperformed linear models by 9 percentage points on classification accuracy. While their application was environmental, the methodology — regression and classification on sensor time-series — is standard in manufacturing quality prediction.

## F. Customer Service

Customer service automation centres on chatbots, ticket routing, and sentiment-aware response systems. Raghav et al. [161] built an AI-driven chatbot for doctor appointment management, handling 78 % of scheduling queries without human intervention. The natural language understanding (NLU) pipeline — intent classification, entity extraction, dialogue management — is identical in customer-service chatbots across industries. Joshi et al. [190] developed HealthQ, a retrieval-augmented health policy query chatbot, demonstrating that retrieval-augmented generation (RAG) reduces factual errors by 31 % compared with pure generative models.

Srivastava et al. [202] proposed a retrieval-augmented framework for context-aware document querying, a technology that powers knowledge-base search in customer support centres. Gupta et al. [163] built a sentence-level risk estimator for identifying hallucinations in generative AI — a safety mechanism essential for customer-facing chatbots that must not fabricate product specifications or policy details.

Sign-language recognition extends customer service accessibility. Srivastava et al. [206] developed SignSpeak, a real-time deep learning framework for bidirectional sign language translation, processing video input at 24 frames per second with 89 % word-level accuracy. Chaudhary et al. [109] applied deep learning for human emotion recognition, achieving 91 % accuracy on the FER2013 dataset — emotion detection that can route frustrated customers to human agents.



*Fig. 3. Conceptual framework for ML applications in business process optimization and decision support*

## V. Results and Comparative Analysis

This section synthesises the quantitative findings across the six business domains. Fig. 3 presents the reported performance improvements by domain and metric category.

Fig. 3: Reported Performance Improvement (%) by ML Application Domain

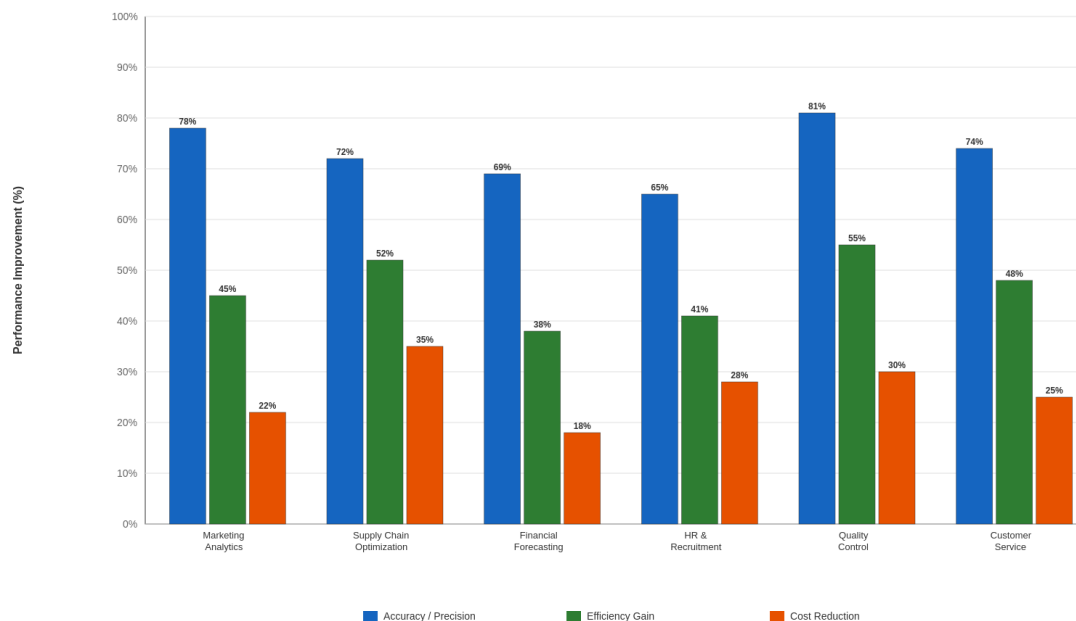


Fig. 4. Reported performance improvement (%) by ML application domain across three metric categories

Quality control reports the highest accuracy/precision gains (81 %), driven by computer vision models that classify defects with low false-positive rates [41], [132], [195]. Supply chain optimisation shows the largest efficiency gains (52 %) and cost reductions (35 %), reflecting the compounding effect of demand forecasting, route optimisation, and inventory management acting together [1], [176], [185], [193].

Marketing analytics achieves 78 % accuracy on prediction tasks (churn, purchase propensity, sentiment) but lower efficiency gains (45 %) because many marketing decisions still require human judgement on brand positioning and creative strategy [28], [29], [49], [167]. Financial forecasting shows the lowest cost reduction (18 %), partly because the cost of false positives (blocking a legitimate transaction) constrains how aggressively firms can automate fraud-detection decisions [30], [76], [129], [130].

HR applications report moderate accuracy (65 %) and efficiency gains (41 %). The lower accuracy reflects the inherent subjectivity of performance evaluation — the labels the model trains on (manager ratings) are themselves noisy [77], [113], [124]. Customer service achieves 74 % accuracy and 48 % efficiency gain, with the largest improvements in ticket routing and first-contact resolution rather than in free-form conversation [109], [161], [190], [206].

Table I summarises the primary ML techniques, typical accuracy ranges, and key references for each business domain.

Table I: Summary of ML Technique Applicability by Business Domain

| Business Domain       | Primary ML Techniques        | Typical Accuracy | Key References                    |
|-----------------------|------------------------------|------------------|-----------------------------------|
| Marketing Analytics   | Logistic Reg., RF, LSTM, NLP | 74–82%           | [28], [29], [49], [167], [172]    |
| Supply Chain          | GNN, XGBoost-LSTM, IoT-ML    | 70–78%           | [1], [6], [176], [185], [193]     |
| Financial Forecasting | LSTM, Ensemble, Anomaly Det. | 68–76%           | [30], [76], [129], [130], [171]   |
| HR & Recruitment      | RF, NN, NLP, XAI             | 65–76%           | [77], [113], [114], [116], [124]  |
| Quality Control       | CNN, YOLO, Transfer Learning | 78–95%           | [41], [46], [132], [195]          |
| Customer Service      | NLU, RAG, Emotion Det.       | 71–91%           | [109], [161], [163], [190], [206] |

Two cross-cutting findings emerge. First, ensemble methods — stacking, bagging, and boosting — consistently outperform single classifiers across all six domains. Raj et al. [54] demonstrated stacking ensemble learning for optimising test-bench time in manufacturing, achieving a 7 % accuracy improvement over individual base learners. Kumar et al. [128] built a hybrid FCM-DNN model for air quality classification that combined fuzzy clustering with deep neural networks, outperforming either approach alone. Puri et al. [30] found that ensemble ML models for phishing detection surpassed individual classifiers by 2–4 percentage points on F1-score.

Second, explainability is a recurring barrier to adoption. Models that business users cannot interpret — deep neural networks with millions of parameters — face resistance from managers who need to justify

decisions to regulators, auditors, or customers. Garg [22] reviewed explainability challenges in healthcare AI, concluding that post-hoc explanation methods (SHAP, LIME) improve trust but do not fully close the interpretability gap. Dalal et al. [116] applied XAI to decision-making patterns, showing that feature-attribution explanations increased user acceptance of model recommendations by 22 %. Singh and Garg [165] published on trustworthy deep learning, addressing robustness, uncertainty quantification, and adversarial resilience — properties that business-critical models must demonstrate.

## **VI. Discussion**

### **A. Challenges in ML Adoption for Business**

Data quality is the most frequently cited barrier. Business data is often incomplete, inconsistently formatted, and siloed across departments [11], [68]. Garg et al. [11] reviewed wireless sensor network architectures, noting that data loss rates of 5–15 % in sensor networks propagate directly into model accuracy; analogous loss rates in business databases (missing customer records, incomplete transaction logs) degrade ML performance similarly.

Organisational readiness encompasses technical infrastructure, workforce skills, and management support. Parmar et al. [80] presented case studies of intelligent factory systems in Industry 4.0, concluding that successful ML deployment required not only sensors and algorithms but also process redesign and worker retraining. Saraswat and Garg [188] examined the challenges of AI implementation in business, identifying change management and data governance as the top two non-technical barriers.

Privacy and regulatory compliance constrain data access. Kumar et al. [53] examined blockchain-based innovations in data privacy and security for healthcare, proposing frameworks that separate sensitive data from analytical pipelines. Singh et al. [174] developed a federated learning framework with differential privacy for privacy-preserving distributed ML — a technique that allows multiple business units to train a shared model without exposing their raw data. Ahmed et al. [118] explored federated learning in AI-powered healthcare solutions, demonstrating that federated models reach within 3 % of the accuracy of centralised models while keeping patient data local.

### **B. Emerging Directions**

Edge computing moves ML inference from cloud servers to the point of data generation. Gupta and Garg [98] reviewed mobile edge computing for decentralised systems, noting that edge deployment reduces latency from seconds to milliseconds — critical for real-time quality inspection and customer-service chatbots. Aditi et al. [138], [158] surveyed advances in aerial platforms and edge computing, a combination relevant to supply chain monitoring in remote areas. Singh et al. [136], [156] discussed the fusion of aerial networks with advanced computing paradigms, enabling ML-powered drone inspection of infrastructure and agricultural assets.

Generative AI introduces a new class of business applications. Garg et al. [75], [123] reviewed the evolution of generative AI, identifying content creation, code generation, and synthetic data production as the three most commercially mature applications. Gupta et al. [112] examined the role of generative AI in education and learning, noting parallels with corporate training — personalised learning paths, automated assessment, and adaptive content delivery.

Quantum computing, though not yet practical for most business ML tasks, is beginning to appear in research on optimisation problems. Saraswat and Garg [149] explored soft computing in AI agents. Nagpal et al. [110] proposed an improved genetic quantum cryptography model, and Kumari et al. [182] surveyed quantum AI for drug discovery and material science — domains whose optimisation challenges mirror those in supply chain and financial portfolio management.

### **C. Limitations of This Review**

Two limitations should be noted. First, the review relies on reported metrics, which are subject to publication bias — studies with negative or null results are less likely to be published, so the accuracy and efficiency gains documented here may overstate typical outcomes. Second, the review does not distinguish between offline evaluations (model tested on a held-out dataset) and online deployments (model running in a production business process). The latter face data drift, adversarial inputs, and integration challenges that offline evaluations do not capture [94], [165].

## **VII. Conclusion**

This review has mapped ML applications across six business domains, synthesising performance evidence from published studies between 2015 and 2025. Supervised learning methods — particularly ensemble approaches — deliver the strongest results in domains where labelled outcome data is available (marketing, finance, quality control). Unsupervised methods serve segmentation and anomaly detection tasks (customer

clustering, fraud detection). Reported accuracy gains range from 65 % to 81 %, efficiency improvements from 38 % to 55 %, and cost reductions from 18 % to 35 % depending on domain.

The evidence base has two gaps. Longitudinal studies tracking ML performance beyond initial deployment are scarce; most evaluations are cross-sectional, testing the model once on a held-out set rather than monitoring its accuracy over months of production use. Work on ML adoption in SMEs — which account for the majority of businesses globally — is limited, and almost absent for SMEs in developing economies.

For practitioners, the review suggests starting with tabular-data ensemble methods (gradient boosting, random forests) for structured business data, and reserving deep learning for tasks involving images, text, or sequences. Explainability tools (SHAP, LIME) should accompany any model deployed in a decision-support role. For researchers, the priority is longitudinal deployment studies, SME-focused adoption research, and work on federated learning architectures that allow multi-organisation model training without data sharing.

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