ADROID Conference Series: Engineering Sciences and Technology
Volume 2, pp 204-219, 2026

The Challenges of AI Implementation in Business

Aditi[1], Pragya Saraswat[2], Palak Sharma[3], Puneet Garg[4]

[1,2,3]SAITM Gurgram, Delhi NCR, India

[4]Associate Professor, KIET (Deemed to be University), Delhi NCR, Ghaziabad, India

aditi02shukla@gmail.com, Saraswatpragya66@gmail.com, palak_253225@saitm.ac.in, puneetgarg.research@gmail.com

Abstract: US dominance in AI was simply assumed for the US to have a place in the 21st-century economy, and thus, it must spearhead this transformative technology. Yet, for all the hype, the road to using AI is a bumpy one. In this article, we cover the science, data stewardship, business, ethical duty, regulatory compliance, change management, and financial obligations surrounding the complex challenge for organisations keen to bring AI-based solutions to market. Based on a systematic review of best-practice literature, emerging industry case studies, and empirical research, the results provide a conceptual framework to overcome barriers and strategically guide the uptake of sustainable, responsible, and value-based AI in business.

Keywords: Artificial Intelligence, AI Adoption, Business Transformation, Machine Learning, Digital Strategy, Data Governance, Ethical AI, Change Management

1. Introduction

Now there are people discussing the impact of AI, but just imagine being present when the head of Google's AI unit states the subject so plainly: Artificial intelligence is not a futuristic idea that rests in R&D labs and is imagined in science fiction stories. It is a reality: businesses across all industries are now applying it to their processes, products, and strategies. From predictive analytics and natural language processing to computer vision and autonomous decision systems, AI solutions are being implemented to reduce costs, improve customer experiences, and generate new revenue streams [1,4,5]. The global AI market was valued at around USD 196.63 billion in 2023 and is expected to grow at the highest CAGR of 37.3% during the forecast period 2023-2030, driven by increasing demand for AI-based transformation [2,6]. Healthcare, finance, manufacturing, retail, logistics, and professional services organizations, in particular, are advancing their AI efforts as they are most likely to be impacted by competitive pressure, digital-first consumer expectations, and the rapid evolution of enablers such as cloud computing, edge infrastructure, and large language models [7,8,9]. However, when it comes to actually implementing AI, there's a big gap between what companies want to do and the results they achieve. Studies continually show that a large number of AI initiatives never progress beyond the proof-of-concept stage. Gartner says 85% of AI projects will fail to deliver on their intent through 2022 [10,11,12]. McKinsey's global survey results also indicate that , although more than half of organisations have deployed AI in at least one business function, only a small proportion have achieved a significant, enterprise-wide impact [13,14].

This paper is an effort to explain such a gap. It plays the whole high-bar gauntlet that any organization wanting to deliver AI at scale had better be ready to come to grips with — from the relatively mundane technical and data issues, all the way through cultural, regulatory and financial considerations [15,16]. These are the questions that anyone bringing (or thinking about bringing) their own institutions to the table will be grappling with, and which will shape the thinking of policy makers, educators and technology vendors as they all engage each other so dynamically today – as they ponder the best ways to shape the wider in and through this ecosystem [17,18,19]. The remainder of this paper is organized as follows: Section 2 introduces the preliminaries, then Section 3 discusses the technical and infrastructure challenges [20,21,22]. Section 4 some questions about data. Section 5: the shortage of talent and skills; 6: institutional and cultural resistance; 7: bias and ethical concerns; 8: regulatory/compliance concerns; 9: financial and ROI concerns; 10: vendor and technology risk; 11: strategic advice; 12: conclusion [23].

2. Conceptual Framework: Understanding AI in Business

Some general conceptual assumptions are helpful before addressing the particular challenges of the deployment of AI technology [24,25]. In the broadest sense, AI is now any system that performs functions that would require human intelligence, such as reasoning, pattern recognition, decision making, natural language processing, or even determining what is in an image. However, in the enterprise space the range of engagement and risk for AI is rapidly moving from science project to production with levels that span [26].

2.1 Types of Business AI

ML is a subset of AI and is probably the one that has been most exposed to the commerce. They are used in prediction, classification and are widely employed in fraud detection, credit scoring, and demand forecasting [27,28]. Unsupervised learning is at the core of customer segmentation, fraud detection and pattern discovery. Reinforcement Learning is progressing in pricing, supply chain, robotics. Natural Language Processing (NLP) Enables chatbots and virtual assistants, sentiment analysis solutions, contract review tools [2] and report generation [29,30]. Quality assurance in manufacturing, identity verification, retail shelf monitoring and even detecting diseases from medical images are some of the applications of computer vision. Generative AI — including large language models (LLMs) and diffusion-based image models — is driving the next wave of content creation, code writing, and knowledge synthesizing as per fig 1 [31,32,33].

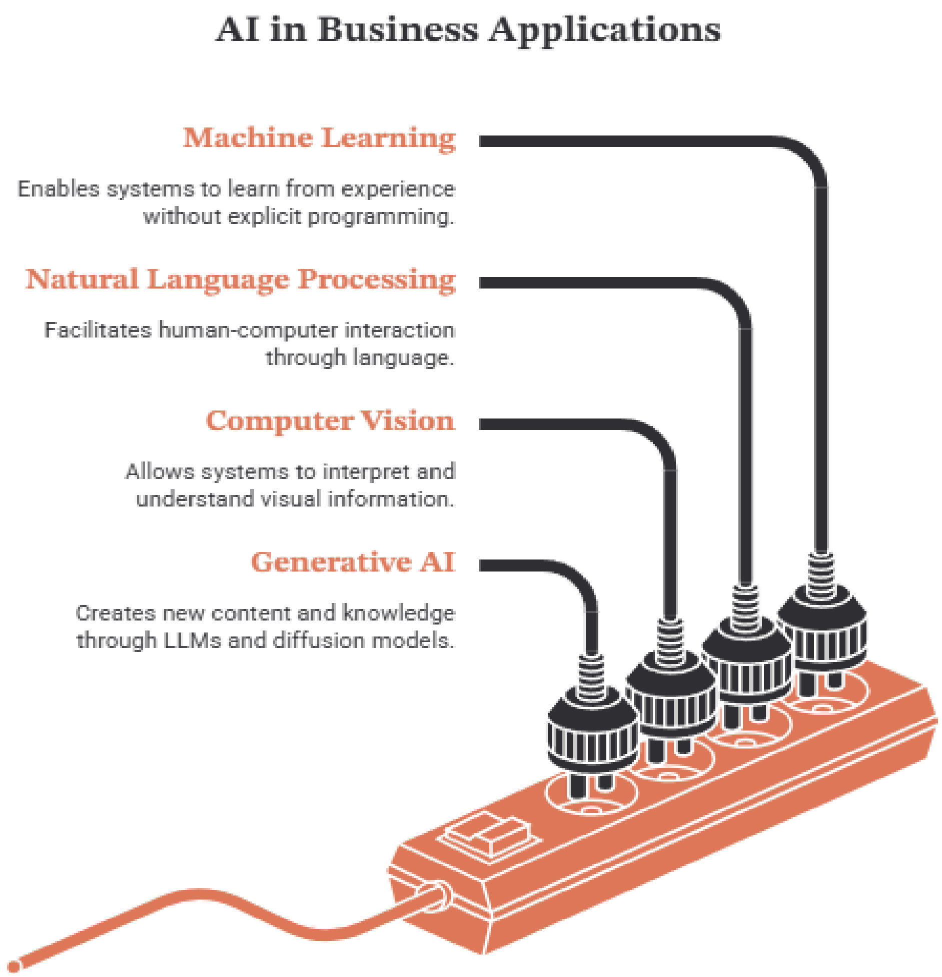

Fig 1; AI in Business Applications

2.2 Lifecycle of AI Application

Enterprises need to consider AI as a process lifecycle that consists of different stages, such as strategic alignment, use case identification, data evaluation, model development, integration and deployment, monitoring, and continuous feedback [34,35]. Various technical, organisational and managerial challenges arise at every stage. Interference at any stage of the life cycle process will lead to cascading failure of interoperability [36,37,38,39], and this seems to be the predominant interpretation of what it means for an organisation to have today and in the future [40,41] as per Table1.

Table 1: AI Implementation Lifecycle and Challenge Areas

Phase of Implementation	Key Challenge Area
Strategic Alignment	Business Case Development, Stakeholder Support
Data Assessment	Quality, Availability, Governance, Privacy
Model Development	Talent, Tooling, Validation, Bias
Integration & Deployment	Legacy Systems, APIs, Scalability
Monitoring & Iteration Drift,	Performance Decay, Explainability

3. Technical and Infrastructure Challenges

The first source of complication is technical in nature, and has a direct impact on how an enterprise can go about deploying AI [42,43]. Even when there is strategic will and investment, there may not be a suitable technical foundation, causing the AI projects to be either unworkable or poorly planned [44,45].

3.1 Legacy Systems and Integration Complexity

The overwhelming majority of incumbents are running on legacy IT infrastructure that was never meant to accommodate the AI and machine learning age [46,47]. These platforms are usually decades old and were not built to handle real-time data, API-driven integrations, or the computing requirements many of the most sophisticated AI applications today require [48,49]. Powered by proven products with modern AI tool chain integration – challenges of integrating vs. reliance on middleware, data transformation pipelines, and in some cases massive reengineering of existing systems. For example a manufacturer looking to deploy predictive maintenance ai might discover its legacy SCADA system not only isn't pushing out sensor data but that data isn't in a format that current ML inference engines can consume [50,51].

3.2 Computational Infrastructure Requirements

Training and inference in large models, such as in deep learning based models, is time-consuming [52]. A lot of the heavy-duty AI work needs special hardware — that's graphics processing units (GPUs) or tensor processing units (TPUs) — and that hardware can be extremely expensive. Some of these costs are mitigated by cloud AI infrastructure but this brings in data sovereignty, latency, and ongoing operational costs [53,54].
Edge AI and models do inferences on the edge devices at the edge Inkjet Printing on Flexible Substrates is Ramping Up in Production The rallying spin-off of flexible electronics packaging will foster the establishment of a roll-to-roll production-centric ecosystem [55,56]. Edge provisioning is also constrained by hardware and model optimization (quantization, pruning) bottlenecks and by edge device management challenges that virtually no company can manage today, both in terms of are reduction of latency and bandwidth needs as per Fig 2 [57,58,59].

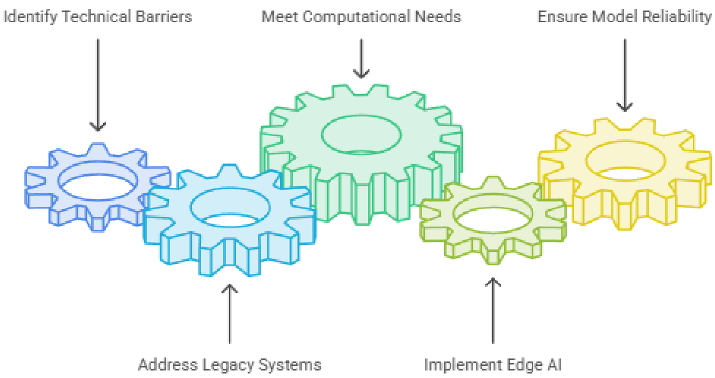

Fig 2: AI Implementation Challenges Sequence

3.3 Model Performance and Reliability

AI models are probability distributions, not deterministic precision quantities. Processes within the large companies that had been long implemented via rule-based logic will be now asked to be reconsidered, to adapt and change in light of AI outputs – uncertain outputs by the definition – becoming inputs of those processes [60,61]. Building models that we can believe in to hold up over the entire range of real-world conditions — especially in safety-critical domains (such as health care diagnosis, financial lending, or self-driving cars) — is a difficult challenge, and will require strong validation methods, continuously monitoring performance, and clearly defined fall-back plans [62,63].

4. Data Governance and Quality Challenges

Data is the oil that keeps the AI engine running. The most advanced AI algorithms are unable to produce meaningful results without access to high-fidelity, well-managed, and suitably formatted data. Challenges related to data are, in many surveys, the most commonly reported hurdle for successful AI adoption in any sector [64,65].

4.1 Data Quality and Completeness

Authentic data from the enterprises are rarely clean, complete and structured. Missing values, duplicate entries, inconsistent formatting, outdated information and incorrect labelling are common to a number of operational data storage systems. The challenge is even more so for organisations that have grown by acquisition, as multiple data architectures need to be consolidated before AI training can commence[66,67]. Supervised learning models, in particular, are highly dependent on the quality of training data. Biased or incomplete training data leads to models that perform badly in production and magnify the imperfections of the inputs [68,69]. Delivering data quality requires as much (or more) attention to detail applied to profiling, cleaning, standardising, and enriching data that many organisations chronically underestimate [70,71].

4.2 Data Silos and Fragmentation

Most companies hold their data captive in departmental silos — isolated systems for sales, operations, finance, and HR that don't talk to one another. Being able to bring together and integrate fragmented data sets in multiple dimensions is what enables the AI models to find patterns across behavioural and operational measures [72,73]. Eradicating data silos is often more about organization than technology, and may include creating cross-functional data governance to foster trust and the sharing of data, as well as invest in enterprise data platforms as per fig 3[74,75].

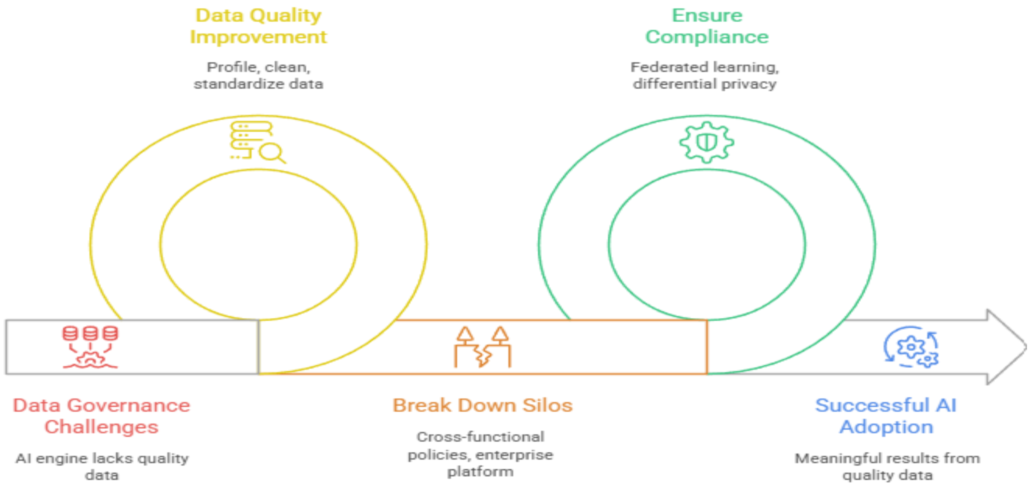

Fig 3: Overcoming Data Challenges for AI Success

4.3 Privacy, Security, and Regulatory Compliance in Data Use

AI tools trained on PII or sensitive corporate data end up being privacy and compliance nightmares. The General Data Protection Regulation (GDPR) in Europe, the California Consumer Privacy Act (CCPA) in the US, and a number of national data protection regulations are setting stringent requirements on how personal data can be collected, stored, processed, and used for automated decision-making as per Table 2 [76,77].

Table 2*:* Data Challenges and Their Business Impacts

Data Challenge	Business Impact
Poor data quality	Inaccurate models, flawed decisions
Data silos	Incomplete features, limited model scope
Privacy regulations	Restricted data use, compliance risk
Labeling gaps	Unable to train supervised models
Data volume insufficiency	Underfitting, poor generalization

5. The AI Talent and Skills Gap

Talent gap: The need for AI expertise is the largest, and most enduring, barrier to effective AI adoption within industry and region. The need for data scientists, ML engineers, AI researchers, and data engineers is greater than the supply, leading to competition and considerable cost implications [78,79].

5.1 Supply-Demand Imbalance

AI and machine learning job titles have been growing by nearly 74% year over year for the past four years, according to LinkedIn's 2023 Emerging Jobs Report, but there aren't enough graduates from universities or training pipelines being developed quickly enough to fulfil this need [80]. Companies continually outbid each other for the scarce resource of AI talent – and many mid-tier firms, and public sector organizations, find the salary of an experienced data scientist or ML engineer prohibitive [81,82].

The shortage of talent is just as severe, if not more so, in areas such as computer vision, natural language processing, reinforcement learning, and AI system engineering [83,84]. There are more generalised skills in data science; the level of specialisation that the complexity that enterprise AI implementations require is actually quite rare [85,86].

5.2 The Interdisciplinary Competence Requirement

The success of AI is not just a story about technology. Good AI projects are multi-disciplinary collaborations between technologists, business professionals, ethicists and project managers [87]. A fraud detection model is different from doing machine learning; it is having an understanding of financial crime patterns, regulatory requirements and so on from those sets of fraud investigators [88].

It is bad enough to find technically capable people who understand the domain. This problem is usually dealt with by forming a cross-functional team and yes it's a team effort, but it does take some coordination and common vocabulary which is not always inherent between the business and the data scientists [89,90].

5.3 AI Literacy Across the Organization

Have AI but it's not specialised The issue is that, together with the core team of AI developers, the organisation needs a significantly larger number of people who can critically review AI outputs to find blind spots and weaknesses in models and who can engage with the question "What are your human biases going into this?" and prudently employ AI-augmented tools [91,92]. If they can't, there's a risk we'll get too much of that comically misplaced trust in AI (with outputs accepted without question) or too little of that (with scientists digging in their heels and distrusting this newfangled way of doing things) [139,140]. oh, and train the current workforce on what AI is and how to think about data and use it responsibly, all of which are bets that will help companies save money down the line but that will require scaffolding, easy-to-understand instructional materials, and culture support from leadership [93,94]. "It's part of building organisational capability which is regularly missed in AI strategies that concentrate far too heavily on technology adoption." technology strategies that focus too narrowly on technology deployment." And ethical AI use needs to be an on-going investment in training, in the content that is available to help educate, and in cultural [95,96].

6. Organizational Culture and Change Management

Perhaps the strongest underappreciated cultural barrier to AI adoption is that it is fundamentally cultural. The technical and data issues are indeed challenging, but the technical difficulties can generally be surmounted through sufficient expertise and funding [97,98]. Cultural resistance, inertia in the bureaucracy, and ill-advised attempts at changing management often constitute even more insuperable barriers that snuff out the saltiest plans for AI endeavors [99,100].

6.1 Resistance to Change

Increasingly enhanced by workflows, decisions and responsibilities performed by AI Integration is being increasingly reinforced by workflows, decisions and responsibilities performed by the AI [137,138]. For example, those who are anti-AI, who have a stronger professional identity or are more unsure about their employment are the ones most likely to be resistors to the adoption and even to be passively non-compiled with or actively sabotaging of the implementation [101,102].

Studies of organisational behaviour have consistently found that resistance to change is best ameliorated by open lines of communication, participatory design activities, apparent leadership commitment, and believable messages regarding implications for the workforce [103]. When organisations focus on AI as a technical project – and ignore the human aspects of execution – they invariably see lower adoption rates and weaker business results [104,105].

6.2 Siloed Governance and Lack of Executive Sponsorship

AI programmes without strong executive sponsorship and cross-organisational governance often come to a halt amid turf wars, competition for resources, and no ability to make decisions at the point of implementation [135,136]. When AI work is isolated in the IT department or a centralised data science team with little or no business unit ownership, the solutions that emerge are often dysfunctional as operational tools and lack the organisational support needed for long-term deployment [106,107].

Setting up a Chief AI Officer (CAIO) position and/or a similar cross-functional AI governance committee is being increasingly understood as a structural enabler for enterprise-wide AI adoption [108].

6.3 Risk Aversion and Innovation Culture

The AI adoption rate is clearly a function of how much risk an enterprise wants to take. Overregulated industries (financial services, insurance, healthcare, energy) have historically been risk averse, and probabilistic AI models appear to conflict with compliance and accountability frameworks that date back centuries [109,110].

7. Ethical Considerations and Algorithmic Bias

The AI ethical questions aren't just the domain of academics today, but very much those of executives. These systems are now being used to affect decisions of high consequence—Is someone creditworthy? Should they be hired? Medically diagnosed? Predicted to commit a crime? —and the fairness, accountability, and transparency of these automated systems has far-reaching societal implications [111,112].

7.1 Algorithmic Bias and Discrimination

Nearly every one of the ML models in production is trained on historical data, and that data reflects – and may contain – biases of society and the institutions in the worlds from which the data is derived [133,134]. A facial recognition algorithm, trained mostly on light- skinned faces will have its worst performance on dark-skinned ones. A credit-scoring algorithm trained on past lending data may repeat discriminatory lending practices of the past. A automated resume-screening system 'that learns' from prior hiring decisions might be biased against minority applicants [113,114]. Identification and correction of algorithmic bias must be intentionally built into the lifecycle of model development: i) understanding the composition of training data, ii) appropriate fairness metrics, iii) adversarial testing of demographic groups, and iv) continuous monitoring of real-world outcomes. There is no one technical solution that completely solves bias, because many definitions of fairness are mathematically incompatible – a reality that requires organisations to make explicit ethical trade-offs [115,116].

7.2 Explainability and the Black Box Problem

Most state-of-the-art AI models — notably deep neural networks and ensemble methods like gradient-boosted trees — are hard or impractical to interpret in human terms [117]. The inability to explain why a model generated a certain output causes issues in areas where decisions need to be justifiable, auditable, or contestable. Explainability of credit decisions is a requirement of financial services regulators, for example. Medical personnel have to know the basis of an AI diagnostic recommendation to make appropriate clinical decisions [118]. Post-hoc interpretability tools (for instance SHAP (Shapley Additive explanations), LIME (Local Interpretable Model-Agnostic Explanations), attention visualisation and more) provide approximations of model explanans and not actual transparency of the execution process beneath [119,120].

7.3 Accountability Frameworks

It is tempting to ask, when an AI system is harmful a loan application is unfairly denied, a medical alert is ignored, or a hiring algorithm discriminates who should be held responsible [121]. Established legal and regulatory regimes were built to handle these types of things, where harm arises out of the interactions of black-box algorithmic systems, massive training datasets, and human institutions [122].

8. Regulatory and Compliance Challenges

Multinational businesses are facing a bewildering array of ai rules, standards and guidance — some formed years before they can find a final shape of regulatory certainty [123].

8.1 The EU AI Act and Risk-Based Regulation

Effective 2024, the EU Artificial Intelligence Act (AIA) is by some distance the most far-reaching (and most ambitious) regulation of AI worldwide. It adopts a risk-based approach with four categories of risk: 1) unacceptable risk (ban) 2) high-risk (strict requirements) 3) limited risk (transparency obligations) and 4) minimal risk (basically unregulated). High-risk systems such as AI for recruitment, credit scoring, standardized testing and critical infrastructure undergo conformity assessments, and are subject to data governance and human oversight requirements, and must be disclosed in a public E.U. database [124,125]. The EU AI Act will require organisations to make large investments in paperwork, risk management procedures and human oversight of AI. This complicates the compliance picture for multinationals, which must grapple with other local regulations [126].

8.2 Sector-Specific Regulatory Requirements

In addition to general AI laws, in certain sectors, use of AI is further restricted by sector-specific laws. Financial services firms are subject to model risk management guidance from regulators, including the Federal Reserve and the OCC in the US and the EBA in Europe [141,142]. Healthcare AI in the US or CE marking in Europe for software as a medical device (SaMD) for FDA regulatory good clinical practices for use classification. These industry-specific requirements require specialized compliance know-how, which many organisations are still acquiring as per Table 3[127,128].

Table 3: Sector-Specific AI Regulatory Landscape

Sector	Key Regulation	Requirement at a Glance	Compliance Implication
Financial Services	SR 11-7 (USA)	Model Risk Management	Explainability and validation
Healthcare	FDA SaMD Guidance	Evidence of safety and effectiveness	Cost of clinical validation
EU Market (all)	EU AI Act	Risk Classes	Documentation requirements
Data Processing	GDPR / CCPA	Privacy by design	Managing consent
Aviation	EASA AI Roadmap	Certification Basis	Determinism Requirements

9. Cost, ROI, and Financial Justification

Obtaining funding for AI projects and proving value for that investment are enduring hurdles for AI leaders and business executives. Unlike traditional software projects, where cost and benefit curves are fairly well known, AI projects involve a great deal of uncertainty about both how long they will take to develop and how much value they will deliver [129].

9.1 Total Cost of AI Implementation

The entire price tag of an enterprise AI project is far greater than just training models. Enterprises need to factor in costs for acquiring and preparing data (usually the biggest cost driver); infrastructure; talent; third-party tools and platform licences; integration engineering; compliance and audit requirements; ongoing model monitoring and maintenance; and the organisational change management required for successful adoption [130,143]. According to McKinsey, the full operational cost of using AI can be 2-3 times the initial development cost once these downstream demands are taken into account [144,145].

9.2 Measuring and Communicating AI ROI

“Effects on Workers and Work Studies of how AI may affect employees and working conditions are difficult to conduct because the impacts are indirect, delayed, and may be diffused across various procedures within the same company.” “Efficiency enhancements due to automation based on AI may be balanced out by a transitory productivity loss as adopters embrace the technology.” For example, personalisation algorithms may contribute to a rise in revenue that cannot be so easily separated from the influence of other simultaneous marketing strategies [146,147]. Yet, the reduction in risk from AI-enabled fraud detection or quality inspection, while real and substantial, is counterfactual, and therefore difficult to communicate to non-quant audiences [112,131].

There are mature sensible ways to measure value out of AI – both financial and operational KPIs, and getting these well-defined with baselines and clean models of attribution – but that’s not something most orgs have really gotten to.. Without tangible results, AI investments are at risk of being cut if the long-term payoffs don’t materialize [102,132].

9.3 The Opportunity Cost of Delayed Adoption

The price of not adapting and adopting earlier is a cost that is ignored in the economics of AI [148,149]. In a “healthy” market — think the best companies using AI to give customers better experiences, at lower price with more rapid innovation — dis-employing the technology will find them behind, caught in a negative feedback loop of competition [150]. The strategic need to develop AI capabilities — but without obvious short-term ROI — is more a question of competitive survival than of discretionary spending [116,120].

10. Conclusion

The In-Demand Auditing Profession is Open to all Industries with AI Influence. It can uncover intelligence that has never been seen before; it can personalize at scale in a manner which was never thought possible; it can unlock new levels of efficiency; and it can help accelerate innovation in product design and delivery. This is not some hypothetical capability — it exists, today, for the enterprises that have cleared the obstacles to AI adoption.

However, the report demonstrates that there is a long and complex road ahead for both governments and businesses to turn AI ambition into enterprise business benefit. Infrastructure and other technology-driven data quality and governance constraints, talent scarcity, cultural resistance, ethical hazards, tacit complexity regulatory, financial uncertainty, supplier dependency all meld together into a formidable implementation challenge that is likely to demand a long-term and enterprise-wide coordinated effort if the best opportunity for success is to be had.

The single most useful takeaway from this paper is that an AI system failing is very rarely a single technical failure. It's technology, data, people, process, culture, governance and strategy all wrapped up in one-system failure. Those organizations that are too far off the mark, and treat AI as a technology project rather than the business transformation project it truly is, will always be lacking.

In the age of AI, the companies likely to generate long-term good returns are not necessarily those that spend the most on AI, or the most expensive technical talent. The ones that do will be those that are able to better align AI and business strategy than anyone else, that can develop real organisational AI literacy, that treat foundational data capabilities as a long-term play, that meet demanding ethical standards, and that build real change management muscle to lead their people through transformation.

As AI technology itself continues to develop — with large language models, multimodal systems, and autonomous AI agents pushing the boundaries of what is achievable — the difficulties in applying it are sure to change, if not disappear. If anything, they will increase. And the best candidates to take advantage of the next stage in AI development will be organizations that already have established the governance, talent, data, and cultural underpinnings necessary to deploy AI in a responsible and scalable way.

Reference

[1] P. Garg, “Survey of Load Balancing Strategies in Fog-Cloud Architectures for IoT Integration,” *Int. J. Res. Publ. Eng. Technol. Manag.*, vol. 9, no. 2, pp. 595–604, 2026.

[2] P. Saraswat and P. Garg, “Breaking Data Boundaries Federated Learning in Digital Healthcare,” 2026.

[3] P. Garg and S. K. Oruganti, “AI Assisted Routing Optimization in Opportunistic IoT Networks using Machine Learning: A Comprehensive review on Protocols & Simulators,” in *Sustainable Global Societies Initiative*, Vibrasphere Technologies, 2026.

[4] P. Garg, K. Arora, R. Bawane, C. Gupta, and K. Ahmed, “Detection and Prevention of Cyber Attack and Threat using AI,” 2025.

[5] D. Upadhyay, P. Garg, and N. Babbar, “Blockchain and IoT based smart contract framework for efficient and secure product life management,” *Discov. Internet Things*, 2026.

[6] P. Garg, “Comparative Analysis of Various Neural Networks for Galaxies Classification,” in *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)*, IEEE, 2025, pp. 697–701.

[7] P. Garg, M. Bhatt, R. Parmar, and M. Arsalan, “Generative AI: Evolution, Applications, Challenges And Future Prospects,” *Appl. Challenges Futur. Prospect. (May 17, 2025)*, 2025.

[8] S. Gupta, P. Garg, J. Agarwal, H. K. Thakur, and S. P. Yadav, “Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2),” 2025.

[9] P. Garg, S. Pranav, and A. Prerna, “Green internet of things (G-IoT): A solution for sustainable technological development,” in *Green Internet of Things for Smart Cities*, CRC Press, 2021, pp. 23–46.

[10] P. Saraswat and P. Garg, “Water Quality Prediction Using IOT Sensors and Deep Networks,” 2026.

[11] P. Saraswat and P. Garg, “Soft Computing In AI Agents,” 2026.

[12] P. Saraswat, P. Garg, and Z. Siddiqui, “AI & the Indian Stock Market: A Review of Applications in Investment Decision,” in *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, 2025.

[13] P. Saraswat and P. Garg, “Human AI Collaboration the future of clinical decision making,” 2026.

[14] P. Garg, A. Aditi, and B. Roy, “A System of Computer Network: Based On Artificial Intelligence,” 2025.

[15] M. Bucholtz and K. Hall, “Identity and interaction: A sociocultural linguistic approach,” *Discourse Stud.*, vol. 7, no. 4–5, pp. 585–614, 2005.

[16] P. Garg, A. Dixit, P. Sethi, and P. R. Pinheiro, “Impact of node density on the qos parameters of routing protocols in opportunistic networks for smart spaces,” *Mob. Inf. Syst.*, vol. 2020, no. 1, p. 8868842, 2020.

[17] Aditi, P. Saraswat, V. Sharma, and P. Garg, “Advances in Aerial Platforms and Edge Computing,” *Edge Comput. Aer. Platforms*, pp. 123–143, 2026.

[18] N. Sharma and P. Garg, “Ant colony based optimization model for QoS-Based task scheduling in cloud computing environment,” *Meas. Sensors*, vol. 24, p. 100531, 2022.

[19] A., P. Garg, and B. Roy, “A System of Computer Networks: Based On Artificial Intelligence,” pp. 169–175, 2025, doi: 10.63169/gcared2025.p24.

[20] P. Saini, B. Nagpal, P. Garg, and S. Kumar, “Evaluation of remote sensing and meteorological parameters for yield prediction of sugarcane (Saccharum officinarum L.) crop,” *Brazilian Arch. Biol. Technol.*, vol. 66, p. e23220781, 2023.

[21] P. Saini, B. Nagpal, P. Garg, and S. Kumar, “CNN-BI-LSTM-CYP: A deep learning approach for sugarcane yield prediction,” *Sustain. Energy Technol. Assessments*, vol. 57, p. 103263, 2023.

[22] Garg, P., Dixit, A., & Sethi, P. (2022). Ml-fresh: novel routing protocol in opportunistic networks using machine learning. *Computer Systems Science & Engineering, Forthcoming*. Tech Science Press.

[23] Yadav, P. S., Khan, S., Singh, Y. V., Garg, P., & Singh, R. S. (2022). A Lightweight Deep Learning-Based Approach for Jazz Music Generation in MIDI Format. *Computational Intelligence and Neuroscience*, *2022*.

[24] Soni, E., Nagpal, A., Garg, P., & Pinheiro, P. R. (2022). Assessment of Compressed and Decompressed ECG Databases for Telecardiology Applying a Convolution Neural Network. *Electronics*, *11*(17), 2708.

[25] Pustokhina, I. V., Pustokhin, D. A., Lydia, E. L., Garg, P., Kadian, A., & Shankar, K. (2021). Hyperparameter search based convolution neural network with Bi-LSTM model for intrusion detection system in multimedia big data environment. *Multimedia Tools and Applications*, 1-18.

[26] Khanna, A., Rani, P., Garg, P., Singh, P. K., & Khamparia, A. (2021). An Enhanced Crow Search Inspired Feature Selection Technique for Intrusion Detection Based Wireless Network System. *Wireless Personal Communications*, 1-18.

[27] Garg, P., Dixit, A., Sethi, P., & Pinheiro, P. R. (2020). Impact of node density on the qos parameters of routing protocols in opportunistic networks for smart spaces. *Mobile Information Systems*, *2020*.

[28] Upadhyay, D., Garg, P., Aldossary, S. M., Shafi, J., & Kumar, S. (2023). A Linear Quadratic Regression-Based Synchronised Health Monitoring System (SHMS) for IoT Applications. Electronics, 12(2), 309.

[29] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). CNN-BI-LSTM-CYP: A deep learning approach for sugarcane yield prediction. *Sustainable Energy Technologies and Assessments*, *57*, 103263.

[30] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). Evaluation of Remote Sensing and Meteorological parameters for Yield Prediction of Sugarcane (Saccharumofficinarum L.) Crop. Brazilian Archives of Biology and Technology, 66, e23220781.

[31] Beniwal, S., Saini, U., Garg, P., & Joon, R. K. (2021). Improving performance during camera surveillance by integration of edge detection in IoT system. *International Journal of E-Health and Medical Communications (IJEHMC)*, *12*(5), 84-96.

[32] Garg, P., Dixit, A., & Sethi, P. (2019). Wireless sensor networks: an insight review. *International Journal of Advanced Science and Technology*, *28*(15), 612-627.

[33] Sharma, N., & Garg, P. (2022). Ant colony based optimization model for QoS-Based task scheduling in cloud computing environment. *Measurement: Sensors*, 100531.

[34] Kumar, P., Kumar, R., & Garg, P. (2020). Hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks. *International Journal of Advanced Science and Technology*, *29*, 766-775.

[35] Raj, G., Verma, A., Dalal, P., Shukla, A. K., & Garg, P. (2023). Performance Comparison of Several LPWAN Technologies for Energy Constrained IOT Network. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(1s), 150-158.

[36] Garg, P., Sharma, N., & Shukla, B. (2023). Predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(2s), 165-173.

[37] Patil, S. C., Mane, D. A., Singh, M., Garg, P., Desai, A. B., & Rawat, D. (2024). Parkinson's Disease Progression Prediction Using Longitudinal Imaging Data and Grey Wolf Optimizer-Based Feature Selection. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 441-451.

[38] Gudur, A., Pati, P., Garg, P., & Sharma, N. (2024). Radiomics Feature Selection for Lung Cancer Subtyping and Prognosis Prediction: A Comparative Study of Ant Colony Optimization and Simulated Annealing. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 553-565.

[39] Khan, A. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *J. Electrical Systems*, *20*(6s), 1051-1058.

[40] Sharma, K. K., Verma, P. K., & Garg, P. (2024). IoT-Enabled Energy Management Systems For Sustainable Energy Storage: Design, Optimization, And Future Directions. *Frontiers in Health Informatics*, *13*(8).

[41] Gupta, S., Yadav, N., Singh, K., & Garg, P. (2025). APPLICATIONS OF SIMULATIONS AND QUEUING THEORY IN SUPERMARKET. *Reliability: Theory & Applications*, *20*(1 (82)), 135-140.

[42] Beniwal, S., Garg, P., Rajpal, R., Sharma, N., & Mittal, H. K. (2025). Fusion of Opportunistic Networks with Machine Learning: Present and Future. *Metallurgical and Materials Engineering*, *31*(1), 311-324.

[43] Garg, P. (2025). Explainable AI & Model Interpretability in Healthcare: Challenges & Future Directions. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 104-133.

[44] Rani, P. (2025). From Data to Diagnosis: Unleashing AI and 6G in Modern Medicine. *EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR*, *46*(1), 69-103.

[45] Dixit, A., Garg, P., Sethi, P., & Singh, Y. (2020, April). TVCCCS: Television Viewer's Channel Cost Calculation System On Per Second Usage. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012046). IOP Publishing.

[46] Sethi, P., Garg, P., Dixit, A., & Singh, Y. (2020, April). Smart number cruncher–a voice based calculator. In *IOP Conference Series: Materials Science and Engineering* (Vol. 804, No. 1, p. 012041). IOP Publishing.

[47] S. Rai, V. Choubey, Suryansh and P. Garg, "A Systematic Review of Encryption and Keylogging for Computer System Security," *2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT)*, 2022, pp. 157-163, doi: 10.1109/CCiCT56684.2022.00039.

[48] L. Saraswat, L. Mohanty, P. Garg and S. Lamba, "Plant Disease Identification Using Plant Images," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 79-82, doi: 10.1109/CCiCT56684.2022.00026.

[49] L. Mohanty, L. Saraswat, P. Garg and S. Lamba, "Recommender Systems in E-Commerce," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 114-119, doi: 10.1109/CCiCT56684.2022.00032.

[50] C. Maggo and P. Garg, "From linguistic features to their extractions: Understanding the semantics of a concept," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 427-431, doi: 10.1109/CCiCT56684.2022.00082.

[51] N. Puri, P. Saggar, A. Kaur and P. Garg, "Application of ensemble Machine Learning models for phishing detection on web networks," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 296-303, doi: 10.1109/CCiCT56684.2022.00062.

[52] R. Sharma, S. Gupta and P. Garg, "Model for Predicting Cardiac Health using Deep Learning Classifier," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 25-30, doi: 10.1109/CCiCT56684.2022.00017.

[53] Varshney, S. Lamba and P. Garg, "A Comprehensive Survey on Event Analysis Using Deep Learning," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 146-150, doi: 10.1109/CCiCT56684.2022.00037.

[54] Dixit, A., Sethi, P., Garg, P., & Pruthi, J. (2022, December). Speech Difficulties and Clarification: A Systematic Review. In *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)* (pp. 52-56). IEEE.

[55] Garg, P., Dixit, A., Sethi, P., & Pruthi, J. (2023, December). Strengthening Smart City with Opportunistic Networks: An Insight. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 700-707). IEEE.

[56] Rana, S., Chaudhary, R., Gupta, M., & Garg, P. (2023, December). Exploring Different Techniques for Emotion Detection Through Face Recognition. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 779-786). IEEE.

[57] Mittal, K., Srivastava, K., Gupta, M., & Garg, P. (2023, December). Exploration of Different Techniques on Heart Disease Prediction. In *2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech)* (pp. 758-764). IEEE.

[58] Gautam, V. K., Gupta, S., & Garg, P. (2024, March). Automatic Irrigation System using IoT. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 100-103). IEEE.

[59] Ramasamy, L. K., Khan, F., Joghee, S., Dempere, J., & Garg, P. (2024, March). Forecast of Students' Mental Health Combining an Artificial Intelligence Technique and Fuzzy Inference System. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 85-90). IEEE.

[60] Rajput, R., Sukumar, V., Patnaik, P., Garg, P., & Ranjan, M. (2024, March). The Cognitive Analysis for an Approach to Neuroscience. In *2024 International Conference on Automation and Computation (AUTOCOM)* (pp. 524-528). IEEE.

[61] Dixit, A., Sethi, P., Garg, P., Pruthi, J., & Chauhan, R. (2024, July). CNN based lip-reading system for visual input: A review. In *AIP Conference Proceedings* (Vol. 3121, No. 1). AIP Publishing.

[62] Bose, D., Arora, B., Srivastava, A. K., & Garg, P. (2024, May). A Computer Vision Based Framework for Posture Analysis and Performance Prediction in Athletes. In *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)* (pp. 942-947). IEEE.

[63] Singh, M., Garg, P., Srivastava, S., & Saggu, A. K. (2024, April). Revolutionizing Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 516-522). IEEE.

[64] Kumar, R., Das, R., Garg, P., & Pandita, N. (2024, April). Duplicate Node Detection Method for Wireless Sensors. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 512-515). IEEE.

[65] Bhardwaj, H., Das, R., Garg, P., & Kumar, R. (2024, April). Handwritten Text Recognition Using Deep Learning. In *2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT)* (pp. 506-511). IEEE.

[66] Gill, A., Jain, D., Sharma, J., Kumar, A., & Garg, P. (2024, May). Deep learning approach for facial identification for online transactions. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 715-722). IEEE.

[67] Mittal, H. K., Dalal, P., Garg, P., & Joon, R. (2024, May). Forecasting Pollution Trends: Comparing Linear, Logistic Regression, and Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 411-419). IEEE.

[68] Malik, T., Nandal, V., & Garg, P. (2024, May). Deep Learning-Based Classification of Diabetic Retinopathy: Leveraging the Power of VGG-19. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 645-651). IEEE.

[69] Srivastava, A. K., Verma, I., & Garg, P. (2024, May). Improvements in Recommendation Systems Using Graph Neural Networks. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 668-672). IEEE.

[70] Aggarwal, A., Jain, D., Gupta, A., & Garg, P. (2024, May). Analysis and Prediction of Churn and Retention Rate of Customers in Telecom Industry Using Logistic Regression. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 723-727). IEEE.

[71] Mittal, H. K., Arsalan, M., & Garg, P. (2024, May). A Novel Deep Learning Model for Effective Story Point Estimation in Agile Software Development. In *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)* (pp. 404-410). IEEE.

[72] Shukla, S. M., Magoo, C., & Garg, P. (2024, November). Comparing Fine Tuned-LMs for Detecting LLM-Generated Text. In *2024 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON)* (pp. 1-8). IEEE.

[73] Kumar, B., IQBAL, M., Parmer, R., Garg, P., Rani, S., & Agrawal, A. (2025, March). The Role of AI in Optimizing Healthcare Appointment Scheduling. In *2025 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 881-887). IEEE.

[74] Kumar, B., Garg, V., Ahmed, K., Garg, P., Choudhary, S., & Baniya, P. (2025, March). Enhancing Healthcare with Blockchain: Innovations in Data Privacy, Security, and Interoperability. In *2025 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 932-938). IEEE.

[75] Raj, V., Prakash, B. K., Kumar, A., & Garg, P. (2024, December). Optimize the Time a Mercedes-Benz Spends on the Test Bench Using Stacking Ensemble Learning. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 445-450). IEEE.

[76] Kaushik, N., Kumar, H., Raj, V., & Garg, P. (2024, December). Proactive Fault Prediction in Microservices Applications Using Trace Logs and Monitoring Metrics. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 410-415). IEEE.

[77] Kumar, A. A., Sri, C. V., Bohara, K. S. K., Setia, S., & Garg, P. (2024, December). Capnivesh: Financing Platform for Startups. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 261-265). IEEE.

[78] Bhandari, P., Setia, S., Kumar, K., & Garg, P. (2024, December). Optimizing Cross-Platform Development with CI/CD and Containerization: A Review. In *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)* (pp. 175-180). IEEE.

[79] Chaudhary, A., & Garg, P. (2014). Detecting and diagnosing a disease by patient monitoring system. *International Journal of Mechanical Engineering And Information Technology*, *2*(6), 493-499.

[80] Malik, K., Raheja, N., & Garg, P. (2011). Enhanced FP-growth algorithm. *International Journal of Computational Engineering and Management*, *12*, 54-56.

[81] Garg, P., Dixit, A., & Sethi, P. (2021, May). Link Prediction Techniques for Opportunistic Networks using Machine Learning. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.

[82] Garg, P., Dixit, A., & Sethi, P. (2021, April). Opportunistic networks: Protocols, applications & simulation trends. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*.

[83] Garg, P., Dixit, A., & Sethi, P. (2021). Performance comparison of fresh and spray & wait protocol through one simulator. *IT in Industry*, *9*(2).

[84] Malik, M., Singh, Y., Garg, P., & Gupta, S. (2020). Deep Learning in Healthcare system. *International Journal of Grid and Distributed Computing*, *13*(2), 469-468.

[85] Gupta, M., Garg, P., Gupta, S., & Joon, R. (2020). A Novel Approach for Malicious Node Detection in Cluster-Head Gateway Switching Routing in Mobile Ad Hoc Networks. *International Journal of Future Generation Communication and Networking*, *13*(4), 99-111.

[86] Gupta, A., Garg, P., & Sonal, Y. S. (2020). Edge Detection Based 3D Biometric System for Security of Web-Based Payment and Task Management Application. *International Journal of Grid and Distributed Computing*, *13*(1), 2064-2076.

[87] Garg, P., & Raman, P. K. (2011). Broadcasting Protocol & Routing Characteristics With Wireless ad-hoc networ s. *Int. J. Comput. Emg. Manag*, *12*(1), 36-40.

[88] Garg, P., Arora, N., & Malik, T. (2011). Capacity Improvement of WI-MAX In presence of Different Codes WI-MAX: Speed & Scope of fu-ture. *IJCEM*, *12*.

[89] Garg, P., Saroha, K., & Lochab, R. (2011). Review of wireless sensor networks-architecture and applications. IJCSMS International Journal of Computer Science & Management Studies, 11(01), 2231-5268.

[90] Yadav, S., &Garg, P. Development of a New Secure Algorithm for Encryption and Decryption of Images.

[91] Dixit, A., Sethi, P., & Garg, P. (2022). Rakshak: A Child Identification Software for Recognizing Missing Children Using Machine Learning-Based Speech Clarification. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-15.

[92] Shukla, N., Garg, P., & Singh, M. (2022). MANET Proactive and Reactive Routing Protocols: A Comparison Study. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-14.

[93] Arya, A., Garg, P., Vellanki, S., Latha, M., Khan, M. A., & Chhbra, G. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. *Journal of Electrical Systems*, *20*(6s), 1051-1058.

[94] Garg, P. (2025). Cloud security posture management: Tools and techniques. Technix International Journal for Engineering Research, 12(3).

[95] Tyagi, P., Sharma, S., Srivastava, A., Rajput, N. K., Garg, P., & Kumari, M. (2025). AI in Healthcare:Transforming Medicine with Intelligence. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p4

[96] Garg, P., Bhatt, M., Parmar, R., & Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges And Future Prospects. *Applications, Challenges And Future Prospects (May 17, 2025)*.

[97] Garg, P., Saraswat, P., & Siddiqui, Z. (2025). AI & the Indian Stock Market: A Review of Applications in Investment Decision. https://doi.org/10.63169/GCARED2025.p10

[98] Garg, P., Sharma, S., Mittal, S., Tevatia, R., Tyagi, V. K., & Kapoor, S. (2025). Unlocking Workforce Potential: AI-Powered Predictive Models for Employee Performance Evaluation. https://doi.org/10.63169/GCARED2025.p21

[99] Shrivas, N., Kalia, A., Roy, R., Sharma, S., Garg, P., & Agarwal, G. (2025). OSINT: A Double-edged Sword. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p22

[100]Garg, P., Aditi, A., & Roy, B. (2025). A System of Computer Network: Based On Artificial Intelligence. https://doi.org/10.63169/GCARED2025.p24

[101]Parmar, R., Kapoor, S., Saifi, S., & Garg, P. (2025). Case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p28

[102]Singh, R., Sharma, R., Kumar, R., Nafis, A., Siddiqui, M. A. M., & Garg, P. (2025). Detection of Unauthorize Construction using Machine Learning: A Review. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p30

[103]Garg, P., Kapoor, S., Singh, V., Sharma, S., & Ankita, A. (2025). A Bridge between Blockchain and Decentralized Applications Web3 and Non-Web3 Crypto Wallets. https://doi.org/10.63169/GCARED2025.p35

[104]Verma, M., Sharma, S., Garg, P., & Singh, A. (2025). The Hidden Dangers of Prototype Pollution: A Comprehensive Detection Framework. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p36

[105]Sharma, A., Sharma, S., Garg, P., & Bhardwaj, P. (2025). LockTalk: A Basic Secure Chat Application. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India.

[106]Arora, K., Bawane, R., Gupta, C., Ahmed, K., & Garg, P. (2025). Detection and Prevention of Cyber Attack and Threat using AI. In *First Global Conference on AI Research and Emerging Developments (G-CARED 2025)*, New Delhi, India. https://doi.org/10.63169/GCARED2025.p38

[107]Garg, P., Dhruv, D., Rahman, A. A., Rai, A., Siddiqui, M., & Yadav, D. (2025). Easeviewer: An Esports Production Tool. https://doi.org/10.63169/GCARED2025.p46

[108]Garg, P., Lakshita, L., Mehwish, M., Nazia, N., & Ahmed, K. (2025). Emerging Trend in Computational Technology: Innovations, Applications, and Challenges. *Applications, and Challenges (May 17, 2025)*. https://doi.org/10.63169/GCARED2025.p51

[109]Chauhan, S., Singh, M., & Garg, P. (2021). Rapid Forecasting of Pandemic Outbreak Using Machine Learning. *Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies*, 59-73.

[110]Gupta, S., & Garg, P. (2021). An insight review on multimedia forensics technology. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 27.

[111]Shrivastava, P., Agarwal, P., Sharma, K., & Garg, P. (2021). Data leakage detection in Wi-Fi networks. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 215.

[112]Meenakshi, P. G., & Shrivastava, P. (2021). Machine learning for mobile malware analysis. *Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms*, *11*, 151.

[113]Nanwal, J., Garg, P., Sethi, P., & Dixit, A. (2021). Green IoT and Big Data: Succeeding towards Building Smart Cities. In *Green Internet of Things for Smart Cities* (pp. 83-98). CRC Press.

[114]Gupta, M., Garg, P., & Agarwal, P. (2021). Ant Colony Optimization Technique in Soft Computational Data Research for NP-Hard Problems. In *Artificial Intelligence for a Sustainable Industry 4.0* (pp. 197-211). Springer, Cham.

[115]Magoo, C., & Garg, P. (2021). Machine Learning Adversarial Attacks: A Survey Beyond. *Machine Learning Techniques and Analytics for Cloud Security*, 271-291.

[116]Garg, P., Srivastava, A. K., Anas, A., Gupta, B., & Mishra, C. (2023). Pneumonia Detection Through X-Ray Images Using Convolution Neural Network. In *Advancements in Bio-Medical Image Processing and Authentication in Telemedicine* (pp. 201-218). IGI Global.

[117]Gupta, S., & Garg, P. (2023). 14 Code-based post-quantum cryptographic technique: digital signature. *Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity*, 193.

[118]Prakash, A., Avasthi, S., Kumari, P., & Rawat, M. (2023). PuneetGarg 18 Modern healthcare system: unveiling the possibility of quantum computing in medical and biomedical zones. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 249.

[119]Gupta, S., & Garg, P. (2024). Mobile Edge Computing for Decentralized Systems. *Decentralized Systems and Distributed Computing*, 75-88.

[120]Gupta, M., Garg, P., & Malik, C. (2024). Ensemble learning-based analysis of perinatal disorders in women. In Artificial Intelligence and Machine Learning for Women's Health Issues (pp. 91-105). Academic Press.

[121]Malik, M., Garg, P., & Malik, C. (2024). Artificial intelligence-based prediction of health risks among women during menopause. *Artificial Intelligence and Machine Learning for Women's Health Issues*, 137-150.

[122]Garg, P. (2024). Prediction of female pregnancy complication using artificial intelligence. In *Artificial Intelligence and Machine Learning for Women's Health Issues* (pp. 17-35). Academic Press.

[123]Pokhrel, L., Arsalan, M., Rani, P., Garg, P., & Pinheiro, P. R. (2026). AI-Powered Healthcare Solutions: Bridging the Medical Gap in Underserved Communities Worldwide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 57-86). IGI Global Scientific Publishing.

[124]Kapoor, S., Parmar, R., Sharma, N., Garg, P., & Singh, N. J. (2026). AI and Computational Intelligence in Healthcare: An Introductory Guide. In *Applied AI and Computational Intelligence in Diagnostics and Decision-Making* (pp. 1-26). IGI Global Scientific Publishing.

[125]Pokhrel, L., Kumar, A., Garg, P., Anand, N., & Singh, N. (2026). AI and IoT in Global Health: Ethical Lessons From Pandemic Response. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 367-394). IGI Global Scientific Publishing.

[126]Parmar, R., Singh, A., Garg, P., Sharma, T., & Pinheiro, P. R. (2026). Blockchain for Ethical Supply Chains: Transparency in Medical IoT Manufacturing. In *Development and Management of Eco-Conscious IoT Medical Devices* (pp. 337-366). IGI Global Scientific Publishing.

[127]Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2024). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 1). https://doi.org/10.2174/97898153130311240301

[128]Gupta, S., Chaudhary, G., & Garg, P. (2013). Modified AODV Routing Protocol through Cache Memory for Finding New Routing Paths in MANETs. *International Journal of Computer Science & Management Studies*, *13*(3).
[129]Gupta, A., & Garg, P. (2021). Emerging Techniques for Handling Pandemic Challenges. *Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies*, 189-209.
[130]Chaudhary, A. P., Mishra, A., Kumar, D., & Garg, P. (2023, April). Human Emotion Recognition using Deep Learning. In *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)* (pp. 191-197). IEEE.
[131]Nagpal, S., Garg, P., Gaba, S., & Aggarwal, A. (2023). 13 An improved genetic quantum cryptography model for network communication. *Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity*, 177.
[132]Yadav, M., Swami, V., Kumar, N., & Garg, P. (2025). Comparative study of Repairable Juice Plants using RPGT. *Reliability: Theory & Applications*, *20*(2 (84)), 776-783.
[133]Sharma, K. K., Verma, P. K., Garg, P., & Shrotriya, V. K. (2025, October). Predicting costs and benefits of IoT-based energy management for optimizing sustainable energy storage in rural areas. In *AIP Conference Proceedings* (Vol. 3343, No. 1, p. 040017). AIP Publishing LLC.
[134]Ahmed, K., Baranwal, A., Sharma, N., Garg, P., & Singh, N. (2026). The Role of Federated Learning in AI-Powered Integrated Healthcare Solutions. In *Enabling Collaborative Health Intelligence With Federated Learning* (pp. 421-448). IGI Global Scientific Publishing.
[135]Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2025). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2). Bentham Science Publishers. https://doi.org/10.2174/97898153222241250301
[136]Garg, P., Pranav, S., & Prerna, A. (2021). Green internet of things (G-IoT): A solution for sustainable technological development. In *Green Internet of Things for Smart Cities* (pp. 23-46). CRC Press.
[137]Malik, A., Nandal, D., Gupta, V., Garg, P., & Nandal, V. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.
[138]Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (Eds.). (2025). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2).
[139]Garg, P., Bhatt, M., Parmar, R., & Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges And Future Prospects. *Applications, Challenges And Future Prospects (May 17, 2025)*.
[140]Kumar, N., Kumar, Y., Khurana, D., Kumar, S., & Garg, P. (2025, November). A Hybrid Ensemble Learning Framework for Interpretable Student Performance Prediction Using Academic and Extracurricular Factors. In *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)* (pp. 666-672). IEEE.
[141]Khurana, D., Kumar, Y., Kumar, N., Kumar, S., & Garg, P. (2025, November). Transformer-Based Movie Recommendation System with Autoencoder-Enhanced Feature Compression. In *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)* (pp. 685-690). IEEE.
[142]Garg, P. (2025, November). Comparative Analysis of Various Neural Networks for Galaxies Classification. In *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)* (pp. 697-701). IEEE.
[143]Saggu, A. K., Babbar, N., & Garg, P. (2025, November). Health-Guard AI: Integrated Health Report Management and Analysis. In *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)* (pp. 614-623). IEEE.
[144]Kumar, S., Kumar, Y., Kumar, N., Khurana, D., & Garg, P. (2025, November). Hybrid FCM-DNN Model for Uncertainty-Aware Air Quality Classification Using Multi-Pollutant Data. In *2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS)* (pp. 679-684). IEEE.
[145]Babbar, N., Singh, H. V., Bendale, S., & Garg, P. (2025, November). Stock Market Price Prediction Using Big Data Analysis: A Performance Evaluation Study. In *2025 3rd International Conference on Computational Intelligence and Network Systems (CINS)* (pp. 1-6). IEEE.
[146]Singh, A. K., Kori, G., Garg, P., & Srivastava, G. (2025, November). Bank Churn Prediction Using Machine Learning. In *2025 IEEE 7th International Conference on Computing, Communication and Automation (ICCCA)* (pp. 1-6). IEEE.
[147]Bhardwaj, A., Das, A., Garg, P., & Yadav, S. (2026). Material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analog Applications. *Journal of Electronic Materials*, *55*(1), 1099-1110.

[148]Srivastava, A. K., Shankdhar, D., Ror, R., & Garg, P. (2026). Harnessing YOLOv5 for real-time object detection: A cloud-based approach. In *Recent Advances in Computational Methods in Science and Technology* (pp. 441-450). CRC Press.

[149]Srivastava, A. K., Shukla, A., Gupta, H., Saxena, K., & Garg, P. (2026). Towards intelligent attendance management system with face recognition using LBPH algorithm. In *Recent Advances in Computational Methods in Science and Technology* (pp. 8-15). CRC Press.

[150]Srivastava, A. K., Garg, P., & Pandey, H. (2026). Vedcure: Towards intelligent ayurvedic drug recommendation and disease prediction. In *Recent Advances in Computational Methods in Science and Technology* (pp. 16-23). CRC Press.