International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

Adoption Of Emerging Computer Technologies And Their Impact On Business Operations In India

CA. Dr. Shankar Ghanshamdas Andani
Research Scholar, Department of Commerce, Texas Global University
Mail Id: Omsaisidhi@gmail.com

Abstract
The accelerating diffusion of emerging computer technologies such as artificial intelligence (AI), cloud computing, big data analytics, the Internet of Things (IoT), and blockchain is reshaping how Indian enterprises organise, deliver, and govern their operations. A growing body of empirical studies and several quantitative syntheses have examined why firms adopt these technologies and what performance outcomes follow, yet findings remain dispersed across technologies, sectors, and theoretical lenses. This paper presents a review of past work, with particular attention to prior meta-analytic evidence, on the adoption of emerging computer technologies and their impact on business operations in India. Following a protocol-driven narrative synthesis inspired by systematic review and meta-analytic guidelines, the study organises earlier research around the technology–organisation–environment (TOE) perspective, classical acceptance and diffusion theories, and operational outcomes such as efficiency, quality, agility, and customer responsiveness. The survey indicates that relative advantage, top-management support, digital skills, financial capacity, and supportive public digital infrastructure are consistent enablers, whereas skill shortages, security concerns, legacy systems, and cost pressures on small and medium enterprises are recurring barriers. Evidence of operational benefit is strongest for cloud computing and analytics, promising but uneven for AI and IoT, and still limited for blockchain. The critical analysis highlights methodological weaknesses, including cross-sectional designs, self-reported performance, small samples, and limited comparability of constructs, which constrain the strength and generalisability of pooled conclusions. The paper closes by proposing a research agenda that emphasises longitudinal designs, standardised measurement, and sector-specific meta-analyses in the Indian context, together with practical guidance for managers and policymakers.

Keywords: *Technology adoption; Emerging technologies; Business operations; India; Meta-analysis; TOE framework; Digital transformation.*

1. Introduction

1.1 Background

India's economy has become one of the most dynamic arenas for digital transformation. Over the last decade, a combination of widespread mobile connectivity, public digital infrastructure, a large pool of technical talent, and an active start-up ecosystem has encouraged organisations of every size to experiment with new computing paradigms. Cloud computing, defined by the National Institute of Standards and Technology as an on-demand model for accessing a shared pool of configurable computing resources [1], has lowered the entry barrier for software and infrastructure. Big data analytics promises to convert transactional and behavioural records into managerial insight [2, 3], while artificial intelligence extends automation from routine tasks to prediction, perception, and decision support [4]. The Internet of Things connects physical assets to networks and enables continuous monitoring [5], and blockchain offers a shared, tamper-resistant ledger for multi-party transactions [6]. Together these technologies form the technical backbone of what is often described as Industry 4.0 [7, 8]. For Indian manufacturers, banks, retailers, logistics providers, and service firms, the question is no longer whether to engage with these technologies but how quickly, how deeply, and with what operational consequences.

Received: *27-08-2026*
Revised: *19-09-2026*
Accepted: *29-09-2026*
Published: *15-10-2026*
Citation: *"**Adoption Of Emerging Computer Technologies And Their Impact On Business Operations In India**", ijaicn, vol. 2, no. 4, pp. 24–33, Oct-Dec. 2026.*
Copyright: *© 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).*

International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

The policy environment has reinforced this momentum. Initiatives promoting digital payments, electronic public services, start-up formation, and national strategies for emerging technologies have created demand-side and supply-side conditions that encourage experimentation. At the same time, global competition and shifting customer expectations compel firms to improve speed, accuracy, and personalization, which depend increasingly on data and automation.

1.2 Problem Statement and Motivation

Despite this enthusiasm, adoption in India is uneven. Large technology-intensive enterprises and digitally native firms frequently operate at the frontier, while many small and medium enterprises continue to rely on manual or fragmented processes. Studies conducted in India and in other emerging economies report diverse and sometimes contradictory findings regarding the drivers of adoption, the perceived barriers, and the realized benefits [9, 10]. Part of this inconsistency arises from differences in theoretical framing, sampling, industry context, and the way operational impact is measured. Policymakers and managers therefore face a fragmented evidence base when deciding where to invest. Meta-analytic and systematic-review approaches are designed to address precisely this difficulty by pooling or structurally comparing results across studies [11, 12], yet such syntheses are rarely organised around the Indian business setting or around operational outcomes. This paper is motivated by the need to consolidate past work, to examine what earlier meta-analytic and review evidence can and cannot tell us, and to identify the conditions under which emerging technologies translate into tangible operational improvement in Indian organisations.

A further difficulty is that much of the available guidance is generated by consultancies and vendors whose analyses are valuable but not always transparent about methods, whereas academic studies are often narrow in scope and published in dispersed outlets. As a result, practitioners cannot easily judge which findings are robust, which are context specific, and which are speculative, and researchers cannot easily locate the unresolved questions that deserve priority.

1.3 Objectives and Contributions

The paper pursues four objectives. First, it maps the principal theories and models used in earlier studies to explain technology adoption by individuals and firms. Second, it surveys empirical work on five clusters of emerging technologies, namely AI, cloud computing, big data analytics, IoT and Industry 4.0, and blockchain, with particular attention to evidence from India. Third, it evaluates the quality, consistency, and limitations of the past work, including the methodological issues that affect meta-analytic inference. Fourth, it derives a research agenda for scholars and practical implications for managers and policymakers. The contributions are threefold. The paper offers an integrated TOE-based conceptual framework linking adoption determinants to operational outcomes; it provides a technology-by-function synthesis of reported impacts; and it presents a structured taxonomy of barriers and enablers specific to Indian businesses. The remainder of the paper is organised as follows. Section 2 surveys the literature, Section 3 describes the review methodology, Section 4 offers a critical analysis of past work, Section 5 discusses implications, and Section 6 concludes.

The intended audience includes academic researchers who wish to design stronger empirical and meta-analytic studies, managers who must prioritise digital investments, and policymakers who design enabling programmes. By clarifying what is known, what is uncertain, and what remains unknown, the paper aims to support evidence-informed decisions rather than technology-driven enthusiasm.

2. Survey Of Past Work

2.1 Theoretical Foundations of Technology Adoption

Research on technology adoption rests on several complementary theories. The technology acceptance model proposed that perceived usefulness and perceived ease of use determine an individual's intention to use a system [13], and its extension incorporated social influence and cognitive instrumental processes [14]. The unified theory of acceptance and use of technology consolidated eight earlier models and added performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants [15]. At the firm level, diffusion of innovations theory emphasised relative advantage, compatibility, complexity, trialability, and observability [16], while the technology–organisation–environment framework grouped determinants into technological, organisational, and environmental contexts [17]. A review of firm-level models concluded that diffusion theory and the TOE framework are the most frequently applied lenses in organisational studies, and that their explanatory power depends on the technology and setting examined [18]. Integrated models combining individual acceptance constructs with TOE factors have been applied to cloud adoption and show improved explanatory strength [9]. Figure 1 summarises the TOE-based framework used in this paper to organise the literature, in which technological, organisational, and environmental contexts jointly shape adoption decisions and intensity.

International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

These theories differ in their level of analysis. Acceptance models concentrate on the individual user and are therefore useful when explaining employee-level use of enterprise systems, whereas diffusion and TOE perspectives address the organisation and its surrounding conditions, which better matches strategic decisions to adopt AI platforms, cloud services, or industrial IoT.

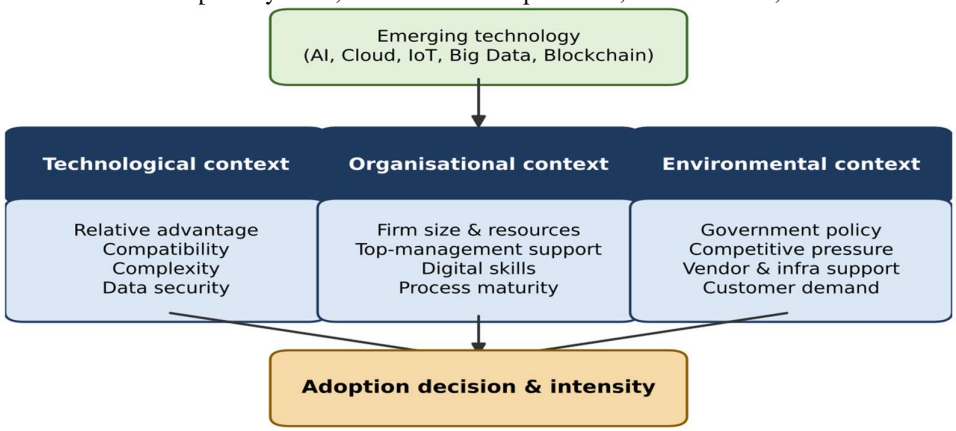


Figure 1: TOE-based conceptual framework for technology adoption

Figure 1 presents the conceptual framework that structures this review. At the top, an emerging technology such as AI, cloud, IoT, big data, or blockchain enters the organisation as a candidate for adoption. Three contexts act on the decision. The technological context covers relative advantage, compatibility, complexity, and data security. The organisational context covers firm size, resources, top-management support, digital skills, and process maturity. The environmental context covers government policy, competitive pressure, vendor and infrastructure support, and customer demand. These contexts converge on the adoption decision and its intensity, which later influences operational outcomes. The framework guides the thematic coding described in Section 3.

2.2 Artificial Intelligence

Artificial intelligence has attracted the largest share of recent attention. Davenport and Ronanki observed that most organisations use AI for process automation, cognitive insight, and cognitive engagement rather than for radical reinvention [4]. A multidisciplinary review of AI scholarship identified benefits in productivity and decision quality alongside concerns about ethics, bias, workforce displacement, and governance [19]. In India, the national strategy published by NITI Aayog positioned AI as a lever for inclusive growth in sectors such as healthcare, agriculture, education, smart mobility, and financial services [20]. Industry applications reported in the literature include credit scoring and fraud detection in banking, demand forecasting and recommendation engines in retail, predictive maintenance in manufacturing, and conversational agents in customer service. Adoption studies repeatedly find that data availability, algorithmic expertise, leadership vision, and organisational readiness drive implementation, whereas data quality problems, ethical uncertainty, and integration with legacy systems delay it [19]. Evidence on measured performance gains remains mixed because many deployments are recent and are evaluated through managerial perceptions rather than audited financial or operational indicators.

Workforce implications are a recurring theme. Several authors argue that AI will reshape job content more than it eliminates jobs, increasing demand for analytical, supervisory, and creative skills, and they highlight reskilling as a condition for realising benefit.

2.3 Cloud Computing

Cloud computing is arguably the most mature of the emerging technologies and therefore the most extensively studied. Marston et al. described the business perspective of cloud services, highlighting cost flexibility, scalability, and the shift from capital to operating expenditure, while also noting risks related to data security, vendor lock-in, and regulatory compliance [21]. Empirical adoption studies based on the TOE framework identified relative advantage, top-management support, firm size, technological readiness, and competitive pressure as significant determinants [22, 9]. For small and medium enterprises, which form a large segment of the Indian economy, cloud services are attractive because they avoid heavy up-front investment in hardware and specialised staff. Software-as-a-service tools for accounting, inventory, customer relationship management, and e-commerce are commonly cited entry points. At the same time, concerns about data localisation, connectivity reliability outside metropolitan areas, and trust in providers continue to slow deeper migration of core workloads. Overall, the literature supports the view that cloud adoption improves flexibility and cost visibility, although the

magnitude of benefit depends on integration with business processes.

Cloud adoption also acts as an enabler for other technologies, because elastic storage and computing power provide the platform on which analytics, machine learning, and IoT applications are deployed. Hybrid and multi-cloud arrangements are increasingly discussed as a way to balance flexibility with control, particularly for regulated sectors such as banking and healthcare that face strict data-protection obligations.

2.4 Big Data Analytics

Big data and analytics research emphasises the shift from intuition-based to evidence-based management [2]. Chen et al. traced business intelligence and analytics through successive stages and argued that value arises from combining data, methods, and domain knowledge [3]. Gandomi and Haider clarified the defining dimensions of volume, velocity, and variety, and reviewed the methods that make unstructured data usable [23]. A systematic review and longitudinal case study showed that big data can improve decision-making and organisational performance, but only when supported by suitable capabilities and governance [24]. Studies from the Indian manufacturing sector have linked big data analytics to operational and sustainability practices, indicating that analytics capability can support efficiency and environmental objectives [25]. Retail, telecommunications, banking, and insurance firms in India use analytics for customer segmentation, churn prediction, risk assessment, and pricing. Frequently cited obstacles include fragmented data silos, shortage of data scientists, unclear business cases, and privacy concerns, which together explain why many pilot projects fail to scale.

Analytics capability is generally described as more than software ownership. It combines data infrastructure, skilled analysts, managerial data literacy, and a decision culture that acts on insight. Firms that invest in only one of these elements often report disappointing returns, which helps explain why similar tools produce very different results across organisations and sectors.

2.5 Internet of Things and Industry 4.0

The Internet of Things connects sensors, devices, and machines so that physical processes can be monitored and controlled remotely. Atzori et al. surveyed enabling technologies, applications, and open issues in this field [5], and Gubbi et al. proposed a cloud-centric architectural vision linking sensing, analytics, and visualisation [26]. Within manufacturing, IoT forms part of Industry 4.0, which also includes cyber-physical systems, additive manufacturing, robotics, and advanced analytics [7, 8]. Studies of emerging economies reported that Industry 4.0 can strengthen supply chain sustainability, yet adoption is hindered by cost, skill gaps, unclear returns, and weak infrastructure [27]. An inter-country comparison of manufacturing firms found that barrier priorities differ between countries, which cautions against generalising across contexts [10]. A literature review of readiness assessment likewise stressed leadership, strategy, workforce capability, and technology infrastructure as prerequisites [28]. Reported operational benefits include reduced downtime through predictive maintenance, improved asset utilisation, better traceability, and shorter response times, although most evidence derives from pilots in large firms.

Connectivity infrastructure strongly influences feasibility. Reliable power, network coverage, standards for device interoperability, and cyber-security controls are prerequisites for industrial deployments, and several authors note that these conditions vary widely across industrial clusters.

2.6 Blockchain

Blockchain originated with a proposal for a peer-to-peer electronic cash system [29], but its relevance to business extends to any setting where multiple parties need a shared record without a trusted intermediary. Iansiti and Lakhani argued that blockchain is a foundational rather than disruptive technology whose transformative impact will unfold gradually as complementary institutions and applications mature [6]. Kshetri analysed how blockchain may help meet supply chain objectives such as traceability, transparency, speed, and risk reduction [30]. In India, potential use cases discussed in the literature and in industry include trade finance, land and document records, pharmaceutical traceability, and digital identity verification. Empirical evidence on operational impact is thin, because many initiatives remain at proof-of-concept stage and are constrained by scalability, interoperability, regulatory ambiguity, and uncertainty about governance of consortium networks. The literature therefore treats blockchain as a promising but early-stage technology whose benefits are conditional on network participation.

Comparisons with conventional databases and shared platforms are also common in the literature, which cautions that blockchain is not automatically superior and is justified mainly where trust, auditability, and multi-party coordination are central problems. Pilot projects therefore tend to cluster in consortium settings with clear governance and shared incentives, and their success depends on the willingness of competitors to cooperate.

2.7 Operational Impact in the Indian Context

Across technologies, the surveyed work links adoption to four families of operational outcome, namely efficiency and cost, quality and reliability, agility and flexibility, and customer responsiveness.

International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

India offers a distinctive setting because public digital infrastructure, including digital identity, interoperable payments, and the Digital India programme, reduces coordination costs and expands the addressable market for digital services. Figure 3 positions the technologies along an indicative adoption curve, while Figure 4 summarises, in qualitative terms, where past studies report the strongest impact on business functions. These figures are syntheses prepared by the author from the surveyed literature and are not new empirical estimates. Cloud and analytics appear furthest along the curve and report benefits across several functions, AI is accelerating, IoT is concentrated in operations and supply chain, and blockchain remains largely at the experimental edge. Sector differences are also visible: banking and financial services, information technology services, and e-commerce lead adoption, followed by telecommunications, logistics, and large manufacturing, with agriculture and micro-enterprises lagging.

Methodological caution is needed when interpreting such evidence. Reported benefits may reflect self-selection, because firms that already perform well are more likely to invest, and reverse causality cannot be excluded in cross-sectional data. For this reason, the survey treats consistent directional findings across multiple studies as more informative than any single reported coefficient or isolated success story.

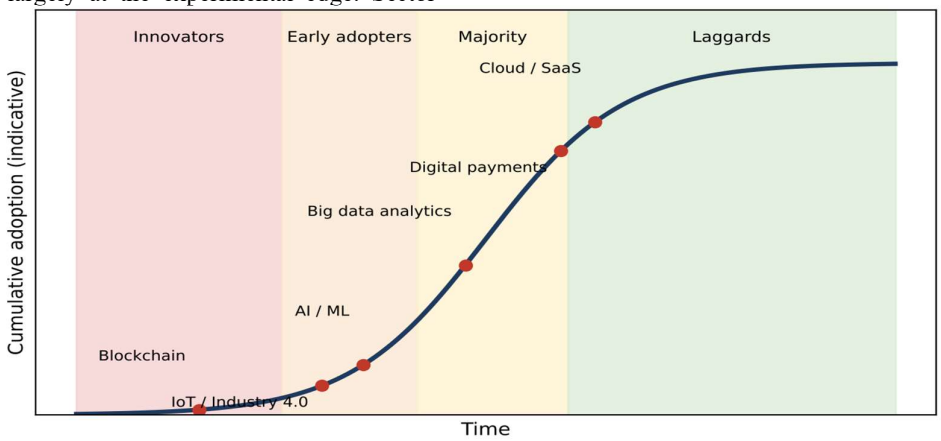


Figure 2: Indicative positions of technologies on the adoption s-curve

Figure 2 shows an indicative adoption S-curve on which the technologies are positioned by the author according to the maturity of evidence in the surveyed studies. The horizontal axis represents time and the vertical axis represents cumulative adoption, divided into innovator, early-adopter, majority, and laggard phases. Cloud services and digital payments appear in the later majority phase, big data analytics occupies the middle region, AI and IoT are moving through the early-adopter stage, and blockchain remains near the innovator stage. The figure is qualitative rather than numerical, and it should be read as a conceptual summary of relative maturity, not as measured adoption rates.

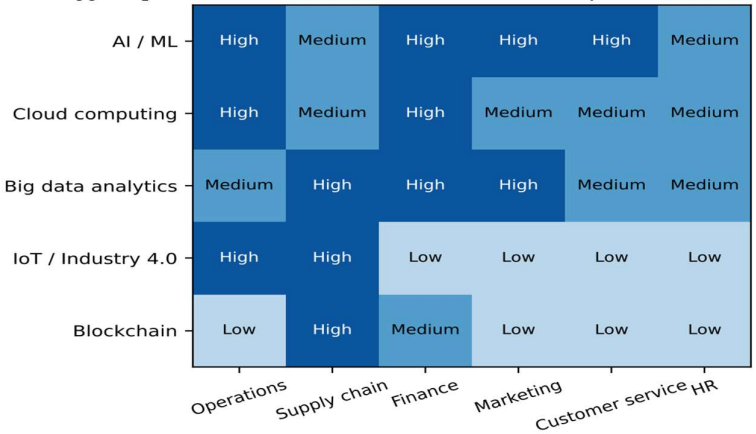


Figure 3: Reported relative impact of technologies on business functions

Figure 3 is a heat map that condenses the qualitative direction of evidence into relative impact levels for each technology and business function. Rows list AI, cloud computing, big data analytics, IoT and

International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

Industry 4.0, and blockchain, while columns list operations, supply chain, finance, marketing, customer service, and human resources. Darker cells indicate that more studies report substantial benefit. Cloud and analytics show broad impact, AI is strong in customer-facing and financial tasks, IoT is concentrated in operations and supply chain, and blockchain is mainly relevant to supply chain. The ratings are ordinal and judgement-based, so they indicate relative emphasis in the literature rather than effect sizes.

3. Methodology

This paper adopts a protocol-driven narrative review with a meta-analytic orientation. Because the underlying empirical studies use heterogeneous constructs, samples, and statistical reporting, a purely quantitative pooling of effect sizes was judged inappropriate. Instead, the review follows the logic of systematic review guidance [11] and the reporting principles of the PRISMA statement [12] to structure scoping, selection, appraisal, and synthesis. The review questions concern which factors explain adoption of emerging computer technologies by Indian organisations, what operational impacts have been reported, and how reliable the accumulated evidence is. The scope covers five technology clusters, namely AI, cloud computing, big data analytics, IoT with Industry 4.0, and blockchain, and focuses on organisational rather than purely consumer adoption. Figure 2 outlines the six stages of the workflow. The review also distinguishes between primary empirical studies and secondary syntheses. Primary studies supply evidence on determinants and outcomes, whereas earlier reviews and meta-analyses indicate where results converge and where they conflict.

The protocol specifies that literature be identified through indexed bibliographic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, supplemented by government and policy documents. Search strings combine technology terms with adoption, diffusion, impact, performance, and India-related terms, together with the words meta-analysis, systematic review, and literature review to capture prior syntheses. Inclusion criteria require that a source be peer reviewed or issued by a recognised institution, address organisational adoption or operational impact, and report a clear theoretical or empirical basis. Sources with an exclusively consumer, purely technical, or non-analytical focus are excluded. Appraisal considers sample adequacy, construct validity, analytic rigour, and transparency of reporting, so that stronger evidence receives greater interpretive weight. Time coverage focuses on the period in which these technologies became commercially significant, while seminal theoretical works are included regardless of date because they supply the conceptual foundations. Where a study draws on samples from several countries, it is retained only if the contribution of Indian or comparable emerging-economy evidence can be identified.

Data extraction records the technology studied, theoretical lens, country and sector, sample size, research design, adoption determinants, reported operational outcomes, and stated limitations. Findings are coded under the technological, organisational, and environmental contexts of the TOE framework and under four outcome families: efficiency and cost, quality and reliability, agility and flexibility, and customer responsiveness. A narrative and thematic synthesis then compares consistency across studies, and a qualitative vote-counting logic is used to judge whether a determinant is supported, mixed, or unsupported. Figs. 3 and 4 are products of this qualitative synthesis and do not represent pooled statistical estimates. The principal limitations of the approach are subjectivity in coding, possible publication bias towards significant findings, and the absence of formal effect-size aggregation, which are revisited in Section 4. To limit bias, coding follows a predefined scheme and ambiguous cases are resolved by reference to the original study rather than to secondary descriptions. Conflicting findings are not discarded but are reported as mixed evidence, and conclusions are weighted by the quality of supporting studies.

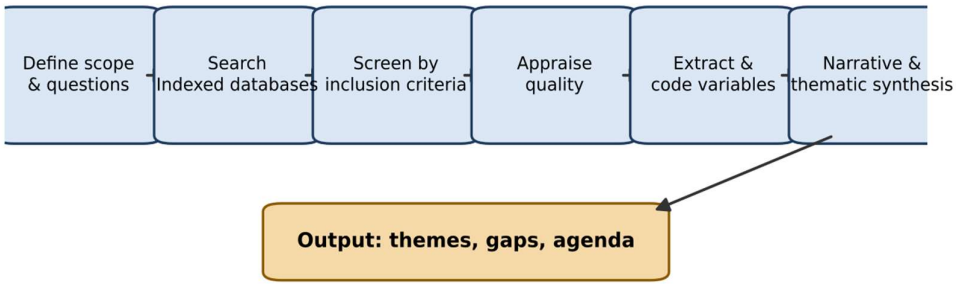


Figure 4: Review protocol workflow

Figure 4 depicts the review protocol as a six-stage workflow. The process begins by defining scope and review questions, followed by searching indexed databases with structured keyword strings. Retrieved records are screened against inclusion criteria, and the remaining sources are appraised for quality using indicators such as sample adequacy and construct validity. Information is then extracted and coded by technology, context, and outcome. The final stage combines narrative and thematic synthesis into themes, gaps, and a research agenda. The figure emphasises that the review is sequential and transparent, which allows other researchers to replicate or update the work.

4. Critical Analysis Of Past Work

Past work displays strong theoretical convergence but limited theoretical innovation. TOE, diffusion theory, and variants of the technology acceptance model dominate the literature [18]. These frameworks are valuable for organising determinants, yet they are largely static and explain adoption decisions better than post-adoption use, value realisation, or discontinuance. Many studies include the same set of predictors, which produces replication but also redundancy. Moreover, constructs such as relative advantage or compatibility are operationalised differently across studies, limiting comparability. Few studies integrate dynamic-capability, resource-based, or institutional perspectives that could explain why firms with similar determinants achieve different operational results.

Methodologically, the majority of empirical studies rely on cross-sectional surveys of managers analysed with structural equation modelling or regression. Such designs cannot establish causality and are prone to common-method bias when both predictors and outcomes are self-reported. Samples are often small, purposive, or concentrated in particular regions and industries, which weakens generalisation to the diversity of Indian business. Operational impact is frequently captured through perceived rather than objective measures such as cost per unit, cycle time, defect rates, or inventory turns. These features matter for meta-analysis because pooled estimates inherit the biases of their components, and heterogeneity in measures makes effect-size aggregation difficult. Additionally, much of the Indian evidence is derived from convenience samples drawn from a few metropolitan regions, which limits claims about national patterns.

Coverage of evidence is uneven. Cloud computing and big data analytics have attracted the most empirical attention, whereas research on AI, IoT, and blockchain is dominated by conceptual discussion, case descriptions, and technical proposals [19, 30]. India-specific evidence is smaller than evidence from developed economies, and cross-country comparisons [10] show that barrier rankings vary by context, which means that findings imported from other markets cannot be assumed to hold in India. Large firms are over-represented relative to small enterprises, and sectoral studies in agriculture, healthcare delivery, and the informal economy are scarce. Publication bias is also a concern because studies reporting significant or favourable results are more likely to appear in print, which may overstate the benefits of adoption.

Measurement of operational impact deserves particular scrutiny. Efficiency, quality, agility, and responsiveness are conceptually distinct but are often collapsed into a single perceptual scale, which hides trade-offs such as higher speed at the expense of flexibility. Time lags between adoption and benefit are seldom modelled, although learning curves, integration effort, and process redesign mean that gains may appear only after substantial delay. Studies that capture performance immediately after implementation may therefore understate long-run value or, conversely, capture short-lived novelty effects. Few studies include control groups of non-adopters, so counterfactual reasoning remains weak.

Another limitation concerns the unit of analysis and the treatment of heterogeneity. Firms differ in size, ownership, sector, and digital maturity, yet many studies pool them into one sample and report average effects. Small enterprises, family-owned businesses, and public-sector organisations in India face different incentives and constraints, and averaging across them can obscure meaningful variation. Moderator analysis, which is central to meta-analysis, is rarely feasible because the underlying studies do not report sufficient descriptive detail about their samples. Greater transparency in reporting, including correlation matrices and sample characteristics, would make future quantitative synthesis considerably easier.

Ethical and societal considerations also receive modest attention. Algorithmic bias, privacy, employment effects, energy consumption, and the digital divide are discussed mainly in conceptual papers, while adoption studies seldom measure them. Because these factors can shape public acceptance, regulation, and long-run legitimacy, their omission limits the practical value of the evidence for responsible decision-making. Integrating such outcomes with conventional operational measures is an important direction for subsequent work. Replication across sectors and time periods would also help to separate durable patterns from transient effects.

Despite these weaknesses, the literature has clear strengths. It has identified a stable core of enablers

and barriers, documented sector-specific use cases, and produced reasonably validated measurement scales for several adoption constructs. A further positive feature is the growing attention to sustainability and supply chain outcomes [25, 27]. The main gaps are the scarcity of longitudinal and quasi-experimental designs, the shortage of studies that connect adoption to audited financial or operational indicators, limited treatment of workforce and ethical consequences, and the lack of India-specific meta-analyses that pool effect sizes by technology and sector. Addressing these gaps would raise the credibility of future syntheses and give managers more actionable guidance.

A final concern is the pace of technological change. Studies completed even a few years ago may describe technologies, vendor offerings, and regulatory conditions that have since changed, for example with the rise of generative AI and expanding data-protection regulation. Consequently, findings on adoption barriers must be interpreted with attention to the date of data collection, and periodic updating of syntheses is essential. Several authors have also begun to apply machine-learning and text-mining tools to review large literatures, which may reduce coding subjectivity.

5. Discussion

Synthesising the surveyed work, a coherent picture emerges. Adoption of emerging technologies by Indian businesses is shaped by the interaction of technological attributes, organisational capabilities, and environmental conditions, as summarised in Figure 1 and Figure 5. Relative advantage, leadership commitment, financial capacity, and digital skills are the most consistently supported enablers, while public digital infrastructure and competitive pressure form a distinctive environmental push in India. Barriers cluster around skills, cost, security and privacy, legacy infrastructure, and regulatory uncertainty. These patterns echo findings from other emerging economies [10, 27], but their relative weight differs across firm size and sector.

The relationship between adoption and operational outcomes is best understood as conditional rather than automatic. Technology creates potential, but realised value depends on complementary investments in skills, data quality, process redesign, and governance. This explains why firms with similar technologies report different results and why measures of adoption intensity often correlate only weakly with performance. Evidence from analytics and Industry 4.0 research supports this view, since benefits are reported mainly where capabilities and strategy are aligned [24, 28]. The implication is that managers should evaluate adoption as an organisational change programme and not merely as a purchase decision.

A second theme is the role of context. India combines advanced technology clusters with large segments of low digital maturity, and public digital platforms coexist with infrastructural and regulatory constraints. Findings from Western or East Asian settings therefore transfer imperfectly. At the same time, India's scale and experience with interoperable digital public infrastructure offer potential lessons for other emerging economies, and comparative research could clarify which elements of the Indian model are transferable. The limitations of this review, notably its qualitative synthesis and its reliance on published sources, should also be kept in mind when interpreting its conclusions. Cross-sector learning, for example from the experience of banking with digital payments to manufacturing's use of data platforms, could further accelerate beneficial diffusion.

For managers, the evidence suggests that adoption should be sequenced rather than simultaneous. Cloud and analytics offer comparatively proven returns and can build the data foundations and skills on which AI and IoT initiatives depend. Investment in people and process redesign appears at least as important as investment in technology, because operational gains materialise only when workflows, incentives, and governance are adapted. Small and medium enterprises may benefit from subscription-based services, shared platforms, and industry clusters that spread cost and expertise. Security and data-protection practices should be embedded from the outset to sustain customer and partner trust.

For policymakers, the findings support continued investment in digital infrastructure, skilling programmes, and clear data-governance rules, together with targeted incentives for small firms. For researchers, the review underlines the need for longitudinal studies, objective performance data, and meta-analyses that pool effect sizes by technology, sector, and firm size. Standardised constructs and open data sharing would improve comparability, while qualitative case research could illuminate how Indian firms combine global technologies with local institutional conditions. Future syntheses should also consider ethical, environmental, and workforce dimensions of adoption.

International Journal of Artificial Intelligence and Communication Networks
Volume: 02, Issue: 04, October-December 2026, pp: 24-33
ISSN: 3071-3358

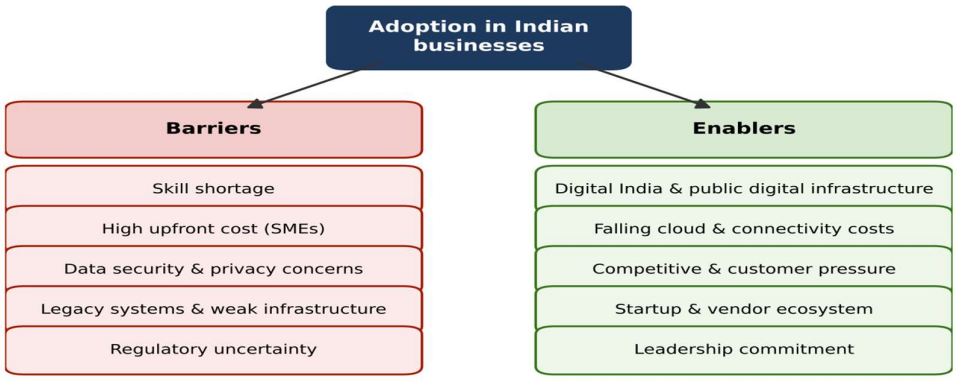


Figure 5: Taxonomy of barriers and enablers identified in the literature

Figure 5 organises the barriers and enablers identified in the literature into a two-sided taxonomy. The left branch lists barriers: shortage of skills, high up-front cost for small and medium enterprises, concerns about data security and privacy, legacy systems and weak infrastructure, and regulatory uncertainty. The right branch lists enablers: public digital infrastructure associated with Digital India, falling cloud and connectivity costs, competitive and customer pressure, a vibrant start-up and vendor ecosystem, and leadership commitment. Both branches feed the adoption outcome of Indian businesses. The taxonomy is a synthesis of recurring themes and does not rank factors by strength.

6. Conclusion

This review examined past work, including meta-analytic and systematic review evidence, on the adoption of emerging computer technologies and their impact on business operations in India. Using a TOE-based organising framework and a protocol-driven narrative synthesis, the paper surveyed research on artificial intelligence, cloud computing, big data analytics, the Internet of Things with Industry 4.0, and blockchain. The evidence shows a stable set of enablers, namely relative advantage, leadership support, digital skills, financial capacity, and public digital infrastructure, and a stable set of barriers, namely skill shortages, security and privacy concerns, legacy systems, cost constraints, and regulatory uncertainty. Operational benefits are best documented for cloud and analytics, are emerging for AI and IoT, and remain largely prospective for blockchain.

The critical analysis revealed that the strength of existing conclusions is limited by cross-sectional designs, perceptual performance measures, small and uneven samples, inconsistent constructs, and possible publication bias. Consequently, quantitative claims about the size of operational gains should be treated cautiously. Future research should prioritise longitudinal and quasi-experimental studies, objective operational indicators, standardised measurement, and India-specific meta-analyses by technology and sector. Managers are advised to sequence investments, to pair technology with skills and process redesign, and to embed security from the start. Policymakers can accelerate beneficial adoption through infrastructure, skilling, and clear governance. Taken together, these insights provide a foundation for a more rigorous and context-sensitive understanding of digital transformation in Indian business. Overall, the review suggests that disciplined, capability-led adoption is more likely to deliver lasting operational gains than rapid but unfocused technology acquisition.

References

[1] P. Mell and T. Grance, "The NIST definition of cloud computing," Nat. Inst. Standards Technol., Gaithersburg, MD, USA, Spec. Publ. 800-145, Sep. 2011.

[2] A. McAfee and E. Brynjolfsson, "Big data: The management revolution," Harvard Bus. Rev., vol. 90, no. 10, pp. 60–68, Oct. 2012.

[3] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," MIS Quart., vol. 36, no. 4, pp. 1165–1188, Dec. 2012.

[4] T. H. Davenport and R. Ronanki, "Artificial intelligence for the real world," Harvard Bus. Rev., vol. 96, no. 1, pp. 108–116, Jan.–Feb. 2018.

[5] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Comput. Netw., vol. 54, no. 15, pp. 2787–2805, Oct. 2010.

[6] M. Iansiti and K. R. Lakhani, "The truth about blockchain," Harvard Bus. Rev., vol. 95, no. 1, pp. 118–127, Jan.–Feb. 2017.

[7] L. D. Xu, E. L. Xu, and L. Li, "Industry 4.0: State of the art and future trends," Int. J. Prod. Res., vol. 56, no. 8, pp. 2941–2962, 2018.

[8] Y. Lu, "Industry 4.0: A survey on technologies, applications and open research issues," J. Ind. Inf. Integr., vol. 6, pp. 1–10, Jun. 2017.

[9] S. Gangwar, H. Date, and R. Ramaswamy, "Understanding determinants of cloud computing adoption using an integrated TAM-TOE model," J. Enterp. Inf. Manage., vol. 28, no. 1, pp. 107–130, 2015.

[10] A. Raj, G. Dwivedi, A. Sharma, A. B. Lopes de Sousa Jabbour, and S. Rajak, "Barriers to the adoption of Industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective," Int. J. Prod. Econ., vol. 224, Art. no. 107546, Jun. 2020.

[11] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," Brit. J. Manage., vol. 14, no. 3, pp. 207–222, Sep. 2003.

[12] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and The PRISMA Group, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," PLoS Med., vol. 6, no. 7, Art. no. e1000097, Jul. 2009.

[13] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quart., vol. 13, no. 3, pp. 319–340, Sep. 1989.

[14] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," Manage. Sci., vol. 46, no. 2, pp. 186–204, Feb. 2000.

[15] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," MIS Quart., vol. 27, no. 3, pp. 425–478, Sep. 2003.

[16] E. M. Rogers, Diffusion of Innovations, 5th ed. New York, NY, USA: Free Press, 2003.

[17] L. G. Tornatzky and M. Fleischer, The Processes of Technological Innovation. Lexington, MA, USA: Lexington Books, 1990.

[18] T. Oliveira and M. F. Martins, "Literature review of information technology adoption models at firm level," Electron. J. Inf. Syst. Eval., vol. 14, no. 1, pp. 110–121, 2011.

[19] Y. K. Dwivedi et al., "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," Int. J. Inf. Manage., vol. 57, Art. no. 101994, Apr. 2021.

[20] NITI Aayog, "National strategy for artificial intelligence: #AIforAll," Government of India, New Delhi, India, Discussion Paper, Jun. 2018.

[21] S. Marston, Z. Li, S. Bandyopadhyay, J. Zhang, and A. Ghalsasi, "Cloud computing—The business perspective," Decis. Support Syst., vol. 51, no. 1, pp. 176–189, Apr. 2011.

[22] C. Low, Y. Chen, and M. Wu, "Understanding the determinants of cloud computing adoption," Ind. Manage. Data Syst., vol. 111, no. 7, pp. 1006–1023, 2011.

[23] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," Int. J. Inf. Manage., vol. 35, no. 2, pp. 137–144, Apr. 2015.

[24] S. F. Wamba, S. Akter, A. Edwards, G. Chopin, and D. Gnanzou, "How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study," Int. J. Prod. Econ., vol. 165, pp. 234–246, Jul. 2015.

[25] R. D. Raut et al., "Linking big data analytics and operational sustainability practices for sustainable business management," J. Clean. Prod., vol. 224, pp. 10–24, Jul. 2019.

[26] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Gener. Comput. Syst., vol. 29, no. 7, pp. 1645–1660, Sep. 2013.

[27] S. Luthra and S. K. Mangla, "Evaluating challenges to Industry 4.0 initiatives for supporting supply chain sustainability in emerging economies," Process Saf. Environ. Prot., vol. 117, pp. 168–179, Jul. 2018.

[28] M. Sony and S. Naik, "Key ingredients for evaluating Industry 4.0 readiness for organizations: A literature review," Benchmarking Int. J., vol. 27, no. 7, pp. 2213–2232, 2020.

[29] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008. [Online]. Available: https://bitcoin.org/bitcoin.pdf

[30] N. Kshetri, "Blockchain's roles in meeting key supply chain management objectives," Int. J. Inf. Manage., vol. 39, pp. 80–89, Apr. 2018.