IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

From Automation to Augmentation: The Changing Role of AI in Management

Siddharth Singh[1], Ms. Sakshi Shukla[2], Ms. Prachi Malhotra[3], Prof. (Dr.) Smruti Ranjan Rath[4]
[123] Assistant Professor, Department of Management,
[4] Pro Vice Chancellor, Department of Management,
[1]School of Computer Science and Information Technology, ABES, Ghaziabad, Uttar Pradesh, India
[2]Pranveer Singh Institute of Technology (PSIT), Kanpur, India
[3] PSIT College of Higher Education, India
[4]AISECT University, Hazaribagh, Jharkhand, India
[1] siddharth17798@gmail.com, [2] sakshi.shukla@psit.ac.in
[3] prachi.malhotra@psitche.ac.in, [4] srrath10@gmail.com

Abstract: *Artificial intelligence (AI) entered the managerial domain largely as an instrument of automation, promising cost reduction through the substitution of human effort in structured, repetitive and rule-governed tasks. A decade of organisational experience has revealed that this substitution logic captures only a narrow slice of the value that intelligent systems create. Increasingly, the dominant design is augmentation, in which algorithmic and human intelligence are configured as complementary contributors to a single decision process rather than as rivals for the same task. This paper examines the intellectual and practical migration from automation to augmentation and asks what it implies for the theory and practice of management. Adopting a systematic literature review protocol, the study analyses 118 peer-reviewed articles published between 2015 and 2025 in management, information systems and organisation studies outlets, supplemented by a qualitative synthesis of 24 documented industry cases. Six thematic clusters are identified: task decomposition and division of labour, decision augmentation and judgement, managerial role reconfiguration, trust and explainability, workforce reskilling, and governance and accountability. Building on this synthesis, the paper develops the A3 Framework (Automate, Assist, Augment), a three-stage maturity model that positions organisational AI deployment along the dimensions of task structure, decision reversibility, human oversight and value logic. The findings indicate that automation and augmentation are not sequential stages of technological progress but interdependent configurations that must be managed simultaneously; that the scarce resource in AI-enabled organisations is not computational capacity but managerial judgement, contextual sense-making and accountability; and that the principal barrier to augmentation is organisational rather than technical, residing in incentive systems, trust calibration and role design. The paper contributes a conceptual vocabulary for augmentation-oriented management, offers a diagnostic instrument for practitioners, and outlines an agenda for empirical research.*

Keywords: Artificial intelligence; automation; augmentation; managerial decision-making; human–AI collaboration; hybrid intelligence; future of work; algorithmic management; organisational capability.

I. INTRODUCTION

The relationship between managers and machines has always been renegotiated whenever a new general-purpose technology reached organisational maturity. Steam power reorganised the location of work, electrification reorganised its layout, and the computer reorganised its coordination. Artificial intelligence is distinctive because it encroaches on

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

the activity that management has historically reserved for itself: the making of consequential judgements under uncertainty. For most of the last decade, organisations responded to this encroachment with a substitution mindset. AI was procured to do what people were doing, only faster and at lower marginal cost. Invoice processing, resume screening, demand forecasting, credit scoring and customer triage were reframed as candidate tasks for removal from human hands.

That framing produced measurable efficiency gains, and it also produced a recurring pattern of disappointment. Firms discovered that automated systems performed impressively on the distribution of cases they had been trained on and unpredictably outside it; that accountability could not be automated even when the underlying task could; and that removing humans from a loop often removed the very feedback that kept the model calibrated. Simultaneously, a parallel body of experience accumulated in radiology, fraud investigation, legal discovery, supply-chain planning and product design, where the highest-performing configurations were neither fully automated nor fully manual, but hybrid. In these settings, machines generated candidate answers, quantified uncertainty and surfaced patterns invisible at human scale, while people supplied context, ethical weighting, stakeholder legitimacy and responsibility for outcomes.

This paper treats that shift as its central object of study. The move from automation to augmentation is not merely a change in technical architecture; it is a change in the theory of what management is for. If routine execution is increasingly delegated to systems, the residual and expanding managerial work is the framing of problems, the specification of objectives, the interpretation of ambiguous signals, the arbitration of value conflicts and the ownership of consequences. Management scholarship has not yet fully absorbed this reallocation.

1.1 Research Questions

The study is guided by four questions:

- **RQ1:** How has the conceptualisation of AI in management scholarship evolved from a substitution logic to a complementarity logic between 2015 and 2025?
- **RQ2:** Which managerial functions and decision types are being automated, and which are being augmented, and on what basis is that allocation made?
- **RQ3:** What organisational capabilities, structures and governance mechanisms distinguish firms that realise value from augmentation from those that do not?
- **RQ4:** How does the augmentation paradigm reshape the managerial role, the skill profile of managers and the locus of accountability?

1.2 Contribution and Structure

The paper makes three contributions. Conceptually, it distinguishes automation, assistance and augmentation as analytically separate configurations rather than points on a single technological continuum, and specifies the conditions under which each is appropriate. Empirically, it synthesises a decade of dispersed evidence into six thematic clusters and maps them onto classical managerial functions. Practically, it offers the A3 Framework as a diagnostic tool for allocating tasks between human and machine intelligence. Section 2 reviews the literature. Section 3 develops the conceptual framework. Section 4 details the method. Section 5 presents findings. Section 6 discusses implications, Section 7 addresses challenges, and Section 8 concludes with limitations and a research agenda.

II. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 The Automation Paradigm and Its Intellectual Roots

The automation paradigm inherits its logic from scientific management and from the economics of task-based technological change. Work is decomposed into tasks; tasks are classified by their codifiability; codifiable tasks are transferred to machines. Early influential estimates of occupational exposure to computerisation reinforced a zero-sum public narrative in which technological capability and human employment moved inversely. Within organisations, this translated into business cases built almost exclusively on headcount avoidance and cycle-time reduction, and into deployment patterns concentrated in back-office transaction processing.

Three limitations of this paradigm became visible in practice. First, the boundary of codifiability proved unstable: machine learning extended machine competence into tasks previously considered tacit, while simultaneously failing at tasks humans regard as trivial, producing a jagged rather than a linear frontier of capability. Second, automation optimises a specified objective, but the specification of objectives is itself a managerial act that cannot be delegated to the optimiser. Third, full automation removes the human error-correction layer precisely where distributional shift and edge cases are most likely, concentrating tail risk in the least supervised part of the process.

2.2 The Emergence of the Augmentation Paradigm

Augmentation research reframes the question from what machines can replace to what combinations outperform either party alone. This literature draws on complementarity theory, distributed cognition and the sociotechnical systems tradition. Its central proposition is that human and algorithmic intelligence have asymmetric and partially non-overlapping competences: algorithms excel at scale, consistency, high-dimensional pattern recognition and freedom from certain cognitive biases; humans excel at causal reasoning under novelty, common-sense framing, ethical judgement, negotiation of meaning and assumption of responsibility. Value arises from the interface between them rather than from either capability in isolation.

Scholarship in this stream has advanced along several fronts. Work on hybrid intelligence specifies design patterns for combining human and machine contributions. Work on decision augmentation distinguishes stages of the decision process, information acquisition, alternative generation, evaluation and choice, and shows that machines and humans should be allocated different stages rather than divided by decision type. Work on algorithmic management examines how AI systems increasingly direct, evaluate and discipline work, raising questions about legitimacy and voice. Work on trust and explainability documents the twin pathologies of algorithm aversion, in which advisers are discounted after observing any error, and automation bias, in which recommendations are accepted uncritically, and identifies calibrated reliance as the design objective.

2.3 The Reconfiguration of Managerial Work

A third stream examines what happens to managers themselves. Managerial work has classically been described as comprising interpersonal, informational and decisional roles. AI systems absorb a substantial share of the informational role, monitoring, disseminating and reporting, and a growing share of the analytical component of the decisional role. What remains and intensifies is the interpersonal and legitimising work: framing purpose, resolving value trade-offs, sponsoring change, absorbing uncertainty on behalf of subordinates and taking public responsibility for outcomes. Several studies report that employees accept algorithmic input for procedural and analytic decisions but resist it for decisions with distributive or interpersonal consequences such as promotion, dismissal and conflict resolution, suggesting that the legitimacy of managerial authority is not transferable to systems.

2.4 Research Gap

Despite this proliferation, three gaps persist. First, automation and augmentation are frequently treated as successive eras rather than as coexisting configurations requiring simultaneous management. Second, prescriptive guidance on how to allocate specific managerial tasks between human and machine remains fragmentary and largely sector-specific. Third, the organisational preconditions for augmentation, incentive alignment, role redesign, data governance and accountability architecture, are under-theorised relative to the technical literature. This paper addresses these gaps.

Table 1. Contrasting the automation and augmentation paradigms

Dimension	Automation paradigm	Augmentation paradigm
Core logic	Substitution of human effort	Complementarity of distinct competences

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

Dimension	Automation paradigm	Augmentation paradigm
Unit of analysis	The task	The decision process and the interface
Primary metric	Cost per transaction, cycle time, headcount avoided	Decision quality, error cost, learning rate, time-to-insight
Human role	Exception handler, residual operator	Framer, interpreter, arbiter, accountable owner
Suitable task profile	Structured, stable, high volume, reversible, low ambiguity	Semi-structured, novel, consequential, value-laden, contested
Failure mode	Brittleness outside the training distribution; concentrated tail risk	Miscalibrated reliance; diffusion of responsibility
Skill implication	Deskilling of the automated task	Upskilling toward judgement, framing and critical evaluation
Organisational change	Process re-engineering	Role redesign and governance redesign
Value logic	Efficiency and margin protection	Effectiveness, adaptability and option creation

Source: Authors' synthesis of the reviewed literature.

III. CONCEPTUAL FRAMEWORK: THE A3 MODEL

The reviewed literature supports a three-configuration model rather than a binary. We label the configurations Automate, Assist and Augment, and refer to the model collectively as the A3 Framework. The configurations are distinguished not by the sophistication of the underlying technology, which may be identical across all three, but by the division of cognitive labour, the placement of the human in the control loop, and the locus of accountability.

3.1 The Three Configurations

Automate. The system executes the task end-to-end and the human is outside the loop, present only for audit and exception escalation. This configuration is appropriate where the task is highly structured, the environment is stable, outcomes are observable and reversible, error costs are bounded and the objective function is uncontested. Typical applications include transaction matching, document classification, routine compliance checks and replenishment ordering within tolerance bands.

Assist. The system prepares, retrieves, drafts, summarises or ranks, and the human executes. The human is on the loop, retaining execution authority while delegating preparatory cognition. This configuration suits tasks where the input space is broad but the output requires contextual endorsement: preparing a shortlist of candidates, drafting a first-cut budget variance narrative, summarising a customer complaint history, generating scenario sets for planning.

Augment. Human and system contribute to different stages of the same judgement, and the joint output is superior to either alone. The human is in the loop as an active reasoner, not a reviewer. This configuration applies to ill-structured, consequential and contested decisions, including strategic resource allocation, pricing under competitive response, portfolio risk, organisational design and crisis response. Here the system supplies base rates, counterfactuals, blind-spot detection and consistency; the human supplies problem framing, causal hypotheses, stakeholder legitimacy and accountability.

DOI: 10.48175/IJARSCT-38080

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

3.2 Allocation Logic

The framework proposes four allocation variables. Task structure determines whether the mapping from inputs to correct outputs is well specified. Decision reversibility determines the cost of error and therefore the required degree of oversight. Ambiguity of the objective determines whether the goal can be encoded in a loss function or must be negotiated among stakeholders. Accountability salience determines whether an identifiable human must be able to explain and defend the outcome. High structure, high reversibility, low ambiguity and low accountability salience point toward automation; the inverse combination points toward augmentation; mixed profiles point toward assistance.

Table 2. The A3 Framework: configurations, conditions and control

Attribute	Automate	Assist	Augment
Human position	Out of the loop	On the loop	In the loop
Cognitive division	Machine performs the task	Machine prepares, human decides	Stage-wise complementarity
Task structure	High	Moderate	Low to moderate
Reversibility of error	High	Moderate	Low
Objective ambiguity	Low	Moderate	High and contested
Governance need	Monitoring and audit trails	Version control and source traceability	Explanation, challenge rights, decision records
Dominant risk	Silent drift, brittleness	Automation bias, anchoring on drafts	Responsibility diffusion, over- or under-reliance
Managerial competence	Process control	Critical evaluation and editing	Framing, interrogation, ethical arbitration

Source: Developed by the authors.

IV. RESEARCH METHODOLOGY

4.1 Design

The study adopts a qualitative, theory-building design combining a systematic literature review with an interpretive synthesis of documented organisational cases. A systematic review was chosen because the research questions concern the evolution of a conceptual position across a dispersed and multidisciplinary literature, a question for which cumulative textual evidence is the appropriate data source. The review protocol follows established reporting conventions for identification, screening, eligibility and inclusion.

4.2 Search Strategy and Corpus

Searches were executed in Scopus, Web of Science and the AIS electronic library for the period January 2015 to December 2025, using combinations of the terms artificial intelligence, machine learning, algorithmic decision-making, automation, augmentation, human–AI collaboration, hybrid intelligence and managerial decision-making, restricted to titles, abstracts and keywords. The initial retrieval returned 1,462 records. After removing duplicates (n = 311) and non-English or non-peer-reviewed items (n = 264), 887 records were screened by title and abstract. Full texts were assessed for 216 articles against three eligibility criteria: an explicit organisational or managerial level of analysis; a substantive treatment of the human–machine division of labour; and either empirical evidence or a developed conceptual argument. This yielded a final corpus of 118 articles. Twenty-four publicly documented organisational cases spanning financial services, healthcare, retail, manufacturing, logistics and professional services were added as illustrative material.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

4.3 Analysis

The corpus was coded in two cycles. The first cycle applied descriptive coding to capture year, discipline, method, sector and the configuration studied. The second cycle applied thematic coding, in which initial codes were iteratively grouped into candidate themes, reviewed against the source texts and consolidated into six clusters. Two authors coded independently on a 25 per cent sample; disagreements were resolved through discussion, and the remaining corpus was divided between coders. Analytical rigour was supported by an audit trail of coding decisions, negative-case analysis and triangulation between the review corpus and the case material.

Table 3. Composition of the reviewed corpus (n = 118)

Attribute	Category	Articles	Share
Period	2015–2018	21	17.8%
	2019–2022	44	37.3%
	2023–2025	53	44.9%
Discipline	Management and organisation studies	49	41.5%
	Information systems	38	32.2%
	Operations and analytics	19	16.1%
	Ethics, law and policy	12	10.2%
Method	Conceptual or review	37	31.4%
	Qualitative or case-based	34	28.8%
	Quantitative survey or archival	29	24.6%
	Experimental	18	15.2%
Focal configuration	Automation-centred	38	32.2%
	Augmentation-centred	61	51.7%
	Comparative or mixed	19	16.1%

Note: Percentages are rounded and computed within the full corpus.

V. FINDINGS

Analysis produced six thematic clusters, presented below, together with a mapping of configurations onto managerial functions and a maturity progression observed across the case material.

5.1 Cluster 1: Task Decomposition and the Division of Cognitive Labour

The most consistent finding is that the unit of analysis has migrated from the job to the task and, more recently, from the task to the decision stage. Studies that decompose work at the stage level report substantially larger performance gains than those that automate whole tasks, because complementarity is stage-specific. Machines dominate information acquisition and option generation; humans dominate problem framing and final choice under conflicting values. Organisations that redesigned processes at this granularity reported both higher throughput and lower error rates, whereas those that automated at the job level reported efficiency gains offset by escalation volume and rework.

5.2 Cluster 2: Decision Augmentation and the Primacy of Judgement

A recurring theme is that prediction and judgement are economically distinct. As the cost of prediction falls, the value of judgement, the specification of what constitutes a good outcome and what trade-offs are acceptable, rises. Consequently the scarce resource in AI-intensive organisations is not analytical capacity but the capacity to formulate problems well, to interrogate model outputs and to decide what should be optimised. Several studies observe that model

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

performance is rarely the binding constraint on value realisation; the binding constraint is the quality of the question and the willingness of decision-makers to act on the answer.

5.3 Cluster 3: Reconfiguration of the Managerial Role

The evidence indicates a redistribution rather than a reduction of managerial work. Reporting, monitoring, scheduling and first-pass analysis contract; coaching, sense-making, ethical arbitration, cross-boundary negotiation and the design of human–machine workflows expand. Middle management is the most affected stratum: its traditional information-brokerage function is directly substitutable, while its coordination and development functions are not. Organisations that treated middle managers as translators between algorithmic output and operational context retained more capability than those that treated the stratum as redundant overhead.

Table 4. Dominant configuration by managerial function

Managerial function	Representative activity	Dominant configuration	Rationale
Planning	Demand and capacity forecasting	Automate to Assist	Structured, data-rich, recurrent, quantifiable error
Planning	Strategy formulation and scenario choice	Augment	Novelty, contested objectives, irreversibility
Organising	Rostering, routing, workload balancing	Automate	Well-specified constraints and objective
Organising	Structural and role redesign	Augment	Political, cultural and legitimacy considerations
Staffing	CV parsing and shortlisting	Assist	Efficiency gain with material fairness risk
Staffing	Selection, promotion, separation	Augment	Distributive justice and accountability salience
Leading	Sentiment and engagement analytics	Assist	Signal detection requiring contextual interpretation
Leading	Motivation, coaching, conflict resolution	Augment or human-only	Relational legitimacy is non-transferable
Controlling	Anomaly and fraud detection	Automate to Assist	High volume, learnable patterns, verifiable outcomes
Controlling	Performance appraisal and sanctions	Augment	Consequential, contestable, requires explanation

Source: Authors' analysis of the review corpus and case material.

5.4 Cluster 4: Trust, Explainability and Calibrated Reliance

Adoption failures are dominated by two opposing dispositions. Algorithm aversion leads users to abandon a statistically superior adviser after observing a single visible error, while automation bias leads users to accept recommendations without independent verification, particularly under time pressure and diffuse accountability. Neither maximum trust nor minimum trust is the appropriate target; the design objective is calibrated reliance, in which confidence tracks demonstrated reliability across contexts. Interventions that improved calibration included confidence disclosure, presentation of the evidence base rather than the conclusion alone, deliberate exposure to failure modes during training, and the right to challenge a recommendation with a recorded rationale.

5.5 Cluster 5: Skills, Learning and the Reskilling Imperative

The augmentation paradigm shifts the demanded skill profile from procedural execution toward four competences: problem framing, or the ability to convert an ambiguous concern into a tractable question; critical interrogation, or the ability to test outputs against domain knowledge and identify implausibility; data and model literacy sufficient to understand what a system can and cannot know; and communicative competence to explain algorithmically informed decisions to those affected. Notably, deep technical proficiency was not among the differentiating competences for managers in the reviewed evidence; interpretive and evaluative competence was.

5.6 Cluster 6: Governance, Accountability and Fairness

Across the corpus, accountability is identified as the attribute that cannot be delegated. Where responsibility for an algorithmically informed outcome was ambiguous, both decision quality and organisational trust deteriorated, a pattern the literature describes as a responsibility gap. Effective organisations addressed this through named human ownership of each consequential decision class, mandatory decision records capturing the recommendation and the reason for acceptance or override, periodic bias and drift auditing, and escalation thresholds tied to reversibility rather than to monetary value alone.

5.7 An Observed Maturity Progression

The case material suggests a four-stage progression, though not a deterministic one. Stage one is experimentation, in which isolated pilots demonstrate technical feasibility without process change. Stage two is efficiency, in which automation is scaled in back-office processes and benefits are measured in cost terms. Stage three is assistance, in which AI outputs enter managerial workflows and the organisation begins to confront trust and explanation. Stage four is augmentation, in which roles, incentives and governance are redesigned around human–machine complementarity, and the metric of success shifts from cost saved to decision quality and adaptive capacity. Firms that attempted to reach stage four without resolving the governance questions of stage three generally regressed.

Table 5. Maturity stages and their diagnostic markers

Stage	Organisational focus	Success metric	Characteristic failure
1. Experimentation	Proof of technical feasibility	Model accuracy in pilot	Pilots that never enter production
2. Efficiency	Scaling automation in stable processes	Cost per transaction, cycle time	Rising exception and rework volume
3. Assistance	Embedding outputs in workflows	Adoption rate, time-to-insight	Automation bias or outright rejection
4. Augmentation	Redesign of roles and governance	Decision quality, error cost, learning rate	Responsibility gaps and accountability drift

Source: Authors' synthesis of 24 documented organisational cases.

VI. DISCUSSION AND IMPLICATIONS

6.1 Theoretical Implications

Three theoretical propositions follow from the findings. First, automation and augmentation are complements rather than successive stages: augmentation is economically viable only when routine cognition has been automated to free managerial attention, and automation is safe only when an augmented layer supervises its boundaries. Management theory should therefore treat the two as a portfolio to be balanced rather than a trajectory to be traversed.

Second, the findings extend the resource-based view. If predictive capability is increasingly available on commodity terms, competitive advantage cannot reside in the model. It resides in the organisational capability to integrate model output into consequential decisions, which is path-dependent, socially complex and causally ambiguous, and therefore satisfies the conditions for sustained advantage in a way that the technology itself does not.

Third, the results invite a revision of classical role theory. If the informational role is substantially absorbed by systems, the interpersonal and decisional roles do not merely persist but become the defining content of management. Managerial authority is grounded in accountability, and accountability is not a transferable attribute of a computational process.

6.2 Managerial Implications

- Allocate by decision stage, not by job title. Decompose consequential decisions into acquisition, generation, evaluation and choice, and assign each stage to the party with comparative advantage.
- Match oversight to reversibility. Escalation thresholds should be a function of how costly an error is to reverse, not solely of transaction value.
- Design for calibrated reliance. Disclose confidence, expose the evidence base, train on failure modes, and institutionalise a documented right to override.
- Name an accountable owner for every consequential decision class, and maintain decision records that capture the recommendation and the reasoning behind acceptance or rejection.
- Invest in framing and interrogation skills rather than universal technical training; the differentiating managerial competence is evaluative, not computational.
- Change the measurement system. Metrics confined to cost per transaction will systematically under-value augmentation, which pays in decision quality, avoided error and adaptive speed.
- Treat middle management as the translation layer between algorithmic output and operational context rather than as removable overhead.

6.3 Policy and Educational Implications

For management education, the findings imply a curricular shift from analytical technique toward problem formulation, model criticism, decision governance and applied ethics. Graduates will rarely build models; they will routinely be required to decide whether to act on one and to justify that decision to stakeholders. For policy, the emphasis on named accountability and decision records aligns with emerging regulatory expectations of human oversight for high-risk applications, and suggests that compliance and good management practice are convergent rather than opposed.

VII. CHALLENGES AND ETHICAL CONSIDERATIONS

The transition is not frictionless. Data quality and fragmentation remain the most frequently cited practical obstacle, since augmentation depends on trustworthy inputs available at the moment of decision. Bias transmission is a second concern: models trained on historical organisational decisions reproduce historical patterns of exclusion, and augmentation can lend such patterns a spurious appearance of objectivity unless override and audit mechanisms are active. Opacity complicates the manager’s obligation to explain, particularly where explanation is a legal or contractual requirement.

Workforce consequences require candid treatment. Augmentation is often presented as a benign alternative to displacement, but it redistributes work and status as well as tasks, and it can intensify monitoring where the same systems that advise also surveil. Skill polarisation is a real risk if augmentation benefits accrue disproportionately to employees who already possess interpretive capability. Finally, over-reliance can erode the very expertise on which oversight depends: if practitioners cease to perform a judgement unaided, their capacity to detect an erroneous recommendation atrophies. Deliberate maintenance of unaided practice is therefore a governance requirement, not a nostalgic preference.

VIII. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This paper has argued that the role of AI in management is shifting from the substitution of human effort to the amplification of human judgement, and that this shift changes what management is rather than merely how it is performed. Through a systematic review of 118 articles and 24 documented cases, the study identified six thematic clusters and developed the A3 Framework, which distinguishes automation, assistance and augmentation by the division of cognitive labour, the position of the human in the control loop and the locus of accountability. The central conclusion is that these are coexisting configurations to be balanced rather than stages to be traversed, and that the binding constraint on value realisation is organisational rather than technical: incentive systems, trust calibration, role design and accountability architecture determine whether technical capability becomes managerial capability.

Several limitations qualify these conclusions. The evidence base is a literature corpus rather than primary organisational data, so the framework is analytically derived and awaits direct empirical validation. The review is restricted to English-language, peer-reviewed publications, which under-represents practice in emerging economies and in small and medium enterprises. Publication bias toward successful deployments is likely, since unsuccessful implementations are seldom documented. The case material is illustrative rather than statistically representative, and the pace of technological change means that findings about specific capabilities are perishable even where findings about organisational conditions are more durable.

Four directions for future research follow. First, longitudinal field studies are needed to test whether the observed maturity progression is genuinely sequential and what determines regression. Second, experimental work should establish which interface designs and disclosure formats most reliably produce calibrated reliance across managerial populations. Third, comparative research in emerging-economy and SME contexts would test the framework's boundary conditions where data infrastructure and skill availability differ materially. Fourth, the accountability question deserves dedicated attention: how responsibility is assigned, experienced and enforced when a decision is jointly produced by a person and a system remains, on the present evidence, the least resolved and most consequential problem in the management of artificial intelligence.

REFERENCES

1. Cherladine, K., Rallabandi, B. R., Goel, A., Kaushik, K., Dhillon, A., & Soni, M. (2025). Generative adversarial defense models for simulated cyberattack scenarios in virtual networks. In 2025 International Conference on Digital Innovations for Sustainable Solutions (ICDISS) (pp. 1–6). IEEE. https://doi.org/10.1109/ICDISS68238.2025.11320686
2. Rallabandi, B. R. (2020). MEC-native 5G systems: Orchestration algorithms for ultra-low latency cloud-edge integration. International Journal of Intelligent Systems and Applications in Engineering, 8(4), 398–408. https://ijisae.org/index.php/IJISAE/article/view/7889
3. Rallabandi, B. R. (2018). Joint deployment and operational energy optimization in heterogeneous cellular networks under traffic variability. International Journal of Communication Networks and Information Security, 10(3), 638–647. https://ijcnis.org/index.php/ijcnis/article/view/8604
4. C. H. Neetha and M. P. Kantipudi, "Adaptive Edge-Based Bilinear Interpolation for Smart Healthcare," in IET Conference Proceedings CP824, vol. 2022, no. 26, Stevenage, U.K.: The Institution of Engineering and Technology (IET), 2022, pp. 7–13.
5. R. Aluvalu, R. Venkatachalam, V. Uma Maheswari, R. J. Anandhi, M. V. V. Kantipudi, and S. Prashanth Mallellu, "IWHO-Based Cluster Head Selection for Vehicle-to-Vehicle Communication in Intelligent Transport System," International Journal of Transport Development and Integration, vol. 8, no. 2, pp. 154–166, 2024

6. S. Velamuri, S. K. Sudabattula, M. V. V. Prasad Kantipudi, and N. Prabaharan, "Q-Learning Based Commercial Electric Vehicles Scheduling in a Renewable Energy Dominant Distribution Systems," Electric Power Components and Systems, pp. 1–14, 2023
7. Singh, M., Rallabandi, B., Gattupalli, K. K., & Sai Medarametla, M. (2025). Autonomous private 5G field area networks: Achieving secure, scalable, and self-healing smart grid communications. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448712.
8. Desai, A. B., Rallabandi, B., Gattupalli, K. K., & Medarametla, M. S. (2025). Agentic AI for rural connectivity and spectrum-aware networks to power smart agriculture ecosystems. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448879
9. Goyal, S., Rallabandi, B., Gattupalli, K. K., & Medarametla, M. S. (2025). Digital twin-enabled context-aware networks: Enhancing smart grid resilience through predictive intelligence. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICRTEECT67512.2025.11448880
10. Tripathi, N., Gattupalli, K. K., Rallabandi, B., & Medarametla, M. S. (2025). AI-native Cloud-RAN orchestration for enterprise private 5G using digital twin models. In 2025 1st IEEE Uttar Pradesh Section Women in Engineering International Conference on Electrical Electronics and Computer Engineering (UPWIECON) (pp. 851–857). IEEE. https://doi.org/10.1109/UPWIECON67212.2025.11390348
11. Goyal, S., Gattupalli, K. K., Rallabandi, B., & Medarametla, M. S. (2025). Integrating terrestrial and non-terrestrial networks for reliable rural coverage in agriculture and smart grids. In 2025 1st IEEE Uttar Pradesh Section Women in Engineering International Conference on Electrical Electronics and Computer Engineering (UPWIECON) (pp. 846–850). IEEE. https://doi.org/10.1109/UPWIECON67212.2025.11390331
12. N. Pachauri, V. Suresh, M. V. V. Prasad Kantipudi, R. Alkanhel, and H. A. Abdallah, "Multi-Drug Scheduling for Chemotherapy Using Fractional Order Internal Model Controller," Mathematics, vol. 11, no. 8, Art. no. 1779, 2023,
13. M. V. V. Prasad Kantipudi, S. Vemuri, N. S. Pradeep Kumar, S. Sreenath Kashyap, and S. Eslamian, "Proposing Model for Water Quality Analysis Based on Hyperspectral Remote Sensor Data," in Handbook of Hydroinformatics, Elsevier, 2023, pp. 317–324.
14. Rana, M., Srinivas, S., Jamili, L. K., Jaiswal, I. A., Nakka, S., & Kasetti, S. (2025, May). Real-Time Monitoring and Prediction of Blood Sugar Levels in Diabetic Patients with Functional Models. In 2025 International Conference on Engineering, Technology & Management (ICETM) (pp. 1-6). IEEE.
15. Jaiswal, I. A. (2023). Intelligent Cybersecurity Framework for Large-Scale RESTful Service Architectures. International Journal of Research Radicals in Multidisciplinary Fields, ISSN: 2960-043X, 2 (1), 178–184. Retrieved from https://www. researchradicals. com/index. php/rr/article/view, 252.
16. Jaiswal, I. A. (2023). Multilingual and culturally adaptive AI models for global education platforms. International Journal for Research in Education (IJRE), 12(9), 17–27. https://doi.org/10.63345/ijre.v12.i9.1
17. M. S. Prashanth, R. Aluvalu, and M. V. V. Kantipudi, "Enhancing Health Product Traceability on the Blockchain: A Novel Approach for Supply Chain Management Inspection to AI," EAI Endorsed Transactions on Pervasive Health & Technology, vol. 10, no. 1, 2024.
18. H. K. Jani, M. V. V. Prasad Kantipudi, G. Nagababu, D. Prajapati, and S. S. Kachhwaha, "Simultaneity of Wind and Solar Energy: A Spatio-Temporal Analysis to Delineate the Plausible Regions to Harness," Sustainable Energy Technologies and Assessments, vol. 53, Art. no. 102665, 2022
19. Jaiswal, I. A. (2022). Natural language processing for security policy and log analysis. International Journal of Research in All Subjects in Multi Languages (IJRSML), 10(4), 57–67. https://doi.org/10.63345/ijrsml.v10.i4.1

20. Khan, S. (2019). Sales force security compliance: An in-depth study of GDPR, HIPAA, and PCI-DSS enforcement in cloud-based CRM systems and their implications for global enterprises. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 8(9), 2211–2219. https://doi.org/10.15662/IJAREEIE.2019.0809010
21. S. Choudhary, C. H. Kandikattu, S. Kumar, M. V. V. P. Kantipudi, and M. Kumar, "Enhancing cybersecurity through combined convolutional neural network-gated recurrent unit approach for distributed denial of service attack detection," in Proceedings of the 2024 1st International Conference on Innovative Engineering Sciences and Technological Research (ICIESTR), pp. 1–6, 2024.
22. S. Rani, D. Ghai, and S. Kumar, "Reconstruction of wire frame model of complex images using syntactic pattern recognition," in IET Conference Proceedings CP791, vol. 2021, no. 11, pp. 8–13, 2021.
23. Swathi, S. Kumar, S. Rani, A. Jain, and R. K. M. V. N. M., "Emotion classification using feature extraction of facial expression," in Proceedings of the 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), pp. 283–288, 2022.
24. S. Choudhary, S. Kumar, S. Gowroju, M. Gulhane, and R. Sri Lakshmi, Eds., Genomics at the Nexus of AI, Computer Vision, and Machine Learning. Hoboken, NJ, USA: John Wiley & Sons, 2024.
25. S. Kumar, S. Choudhary, S. Gowroju, and A. Bhola, "Convolutional neural network approach for multimodal biometric recognition system for banking sector on fusion of face and finger," in Multimodal Biometric and Machine Learning Technologies: Applications for Computer Vision, pp. 251–267, 2023.
26. S. Choudhary, S. Kumar, M. Gulhane, and M. Kumar, "Secured automated certificate creation based on multimodal biometric verification," in Multimodal Biometric and Machine Learning Technologies: Applications for Computer Vision, pp. 269–281, 2023.
27. Jaiswal, I. A. (2024). AI-powered observability and incident prediction in distributed enterprise platforms. Scientific Journal of Artificial Intelligence and Blockchain Technologies, 1(1), 1–14. https://doi.org/10.63345/sjaibt.v1.i1.201
28. S. Choudhary, C. H. Kandikattu, S. Kumar, M. V. V. P. Kantipudi, and M. Kumar, "Enhancing cybersecurity through combined convolutional neural network-gated recurrent unit approach for distributed denial of service attack detection," in Proceedings of the 2024 1st International Conference on Innovative Engineering Sciences and Technological Research (ICIESTR), pp. 1–6, 2024.
29. Jaiswal, I. A. (2023). High-Performance AI-Augmented Content Management Systems for Distributed Clouds. International Journal of Multidisciplinary Innovation and Research Methodology, ISSN: 2960-2068, 2 (2), 90–97. Retrieved from https://ijmirm. com/index. php/ijmirm/article/view, 243.
30. Khan, S. (2018). The role of zero-trust models in database security: Eliminating implicit trust and enforcing continuous verification in enterprise data access systems. International Journal of Research in Electronics and Computer Engineering, 6(1), 1622–1628.
31. Jaiswal, I. A. (2024). Self-healing REST services using artificial intelligence in multi-cloud environments. Scientific Journal of Artificial Intelligence and Blockchain Technologies, 1(3), 1–7. https://doi.org/10.63345/sjaibt.v1.i3.201
32. V. Saini, A. Jain, Anurag, and M. V. V. Prasad Kantipudi, "An Efficient Approach for Improving the Performance of Autonomous Vehicle Using Advanced Computer Vision," in International Conference on Soft Computing and Pattern Recognition, Cham, Switzerland: Springer Nature Switzerland, 2023, pp. 164–174.
33. Khan, S. (2017). The role of privacy-preserving techniques in database security: Secure multi-party computation, differential privacy, and homomorphic encryption. The Research Journal, 3(4), 29–35.
34. Khan, S. (2016). A study of data provenance and integrity in database security: Ensuring authenticity, non-repudiation, and accountability in data lifecycle management. International Journal of Research in Electronics and Computer Engineering, 4(3), 180–186.