



ORGANISATIONAL AI-READINESS PRACTICE AND THE REALISED PRODUCTIVITY GAP FROM AGENTIC AI

Dr. N Subbukrishna Sastry¹, Dr. Manjula Mallya M²

¹Professor, School of Management, CMR University, Bangalore, Karnataka, India. ORCID ID: 0009-0009-0460-7057

²Associate Professor & Head, Dept. of Economics, Government First Grade College for Women Balmatta Mangalore, Karnataka, India. ORCID ID: 0009-0005-8812-6912

ABSTRACT

Agentic artificial intelligence — AI systems that plan, act and complete multi-step tasks with limited human intervention — is diffusing through enterprises far faster than earlier generations of enterprise software, yet the productivity gains organisations report from it remain narrow and uneven. Industry evidence collected between 2022 and 2026 places the share of organisations that convert agentic-AI deployment into measurable, enterprise-level value at somewhere between four and twenty-four per cent, depending on measurement method, while national readiness indices place most organisations only in early or intermediate stages of preparedness. This paper reviews the emerging multidisciplinary literature on organisational AI-readiness practice — examined here across three dimensions: organisational culture, manager support and workflow redesign — and its relationship to the productivity gain organisations actually realise from agentic-AI adoption, as distinct from the gain they anticipate or report as adopted. Building on the technology-organisation-environment framework, dynamic-capabilities theory and the productivity J-curve literature on general-purpose technologies, the paper develops a conceptual framework in which the depth of agentic-AI integration mediates the relationship between readiness practice and realised productivity gain, moderated by sector exposure, firm scale and national labour-market context. Five formal propositions are advanced from a structured review of thirty-eight cited works, of which the paper classifies twenty-seven as substantively engaging at least one of the three readiness dimensions, singly or jointly, and eleven as foundational theoretical grounding rather than dimension-specific evidence. Particular attention is given to India's IT-BPM sector, where labour-cost structure and the readiness gaps identified in national adoption indices interact distinctively with agentic-AI economics. The paper closes with an agenda for primary empirical research — particularly longitudinal and matched-pair designs — needed to move the field from association to causal estimation of the readiness-productivity relationship.

KEYWORDS: Agentic AI; Organisational AI-Readiness; Manager Support; Workflow Redesign; Productivity Paradox; Dynamic Capabilities; India IT-BPM Sector

1. INTRODUCTION

Agentic artificial intelligence refers to AI systems that go beyond single-turn conversational response to plan multi-step tasks, invoke external tools, retain working context across a session, and complete assigned work with reduced human supervision. Microsoft's WorkLab has termed the organisations that combine such systems with redesigned human leadership the "Frontier Firm," reporting that 82% of leaders regarded 2025 as pivotal for rethinking operating models around agents, and that by 2026 agent-adoption growth had accelerated sharply against the prior generation of generative-AI tools (Microsoft WorkLab, 2025, 2026). The pace of this diffusion, layered on top of an already fast generative-AI adoption curve, has made "organisational readiness" — rather than model capability — the binding constraint most frequently cited by practitioners and researchers alike.

Yet the productivity gains organisations actually realise from this diffusion remain narrow relative to the gains anticipated. An MIT-affiliated study of enterprise generative-AI deployment found that despite an estimated \$30–40 billion in enterprise investment, 95% of organisations were obtaining no measurable return, with only about 5% of custom enterprise AI pilots reaching production and extracting measurable value — a pattern the authors termed the "GenAI Divide" (Challapally, Pease, Raskar, & Chari, 2025). Independent surveys converge on a similar order of magnitude: the Boston Consulting Group found only 4% of companies were "substantial value creators" from AI (de Bellefonds et al., 2024), and McKinsey's 2026 global survey classified only 6% of organisations as "high performers" attributing at least 5% of EBIT to AI use, even though 44% reported scaling AI somewhere across the enterprise (McKinsey & Company, 2026). The gap between adoption breadth and value depth is the empirical puzzle this paper addresses. It is also, on reflection, an old warning going unheeded: writing at the start of the current wave of enterprise AI adoption, Davenport and Ronanki (2018) had already argued that unlocking value from AI depends less on selecting the most capable algorithm than on redesigning the process and organisation around it — a claim the evidence reviewed below suggests has only sharpened as agentic systems have taken on more of the work itself.



This pattern is not unprecedented. Robert Solow's 1987 observation that computers were visible "everywhere but in the productivity statistics" opened five decades of research into why general-purpose technologies take years, sometimes decades, to show up in aggregate output — a lag Brynjolfsson, Rock and Syverson (2018/2020) formalised as a "productivity J-curve" driven by unmeasured, complementary intangible investment: retraining, new business processes and organisational redesign. Read through this lens, the low realisation rates reported above are not necessarily evidence that agentic AI lacks productivity potential; they may instead reflect where organisations sit on an intangible-investment curve whose slope is set by organisational, not technical, choices. This paper organises those choices into three readiness dimensions — organisational culture, manager support and workflow redesign — and reviews what the emerging 2024–2026 evidence base says about how each relates to the productivity gain an organisation actually realises from agentic-AI adoption, as distinct from the gain it merely reports having piloted.

The paper makes three contributions. First, it synthesises a fast-moving, cross-disciplinary evidence base — spanning management information systems, labour economics, organisational psychology and large-sample industry surveys — that has not yet been brought together around the specific construct of a "realised productivity gap." Second, it develops a conceptual framework in which the three readiness dimensions act on realised productivity gain through the mediating channel of integration depth, moderated by sector, scale and national context, and expresses this framework as five formal, testable propositions. Third, it examines the distinctive stakes of this relationship for India's IT-BPM sector, whose labour-cost-arbitrage business model interacts with agentic AI's coordination-compression effects in ways the general literature has not yet addressed. Section 2 sets out the theoretical background; Section 3 reviews the literature across the three readiness dimensions and the measurement evidence; Section 4 presents the conceptual model and propositions; Section 5 describes the review method and corpus; Sections 6 and 7 discuss the findings and their implications for India; Section 8 sets a future-research agenda; Section 9 concludes.

2. THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

Organisational readiness for AI has most often been theorised through the technology–organisation–environment (TOE) framework, which separates adoption determinants into technological, organisational and environmental context (Tornatzky & Fleischer, 1990). A recent systematic literature review applying TOE specifically to AI adoption consolidated 124 readiness indicators drawn from the literature into thirty-five factors and twelve core readiness themes, concluding that organisational AI readiness is "a multidimensional and interdependent construct" that cannot be reduced to technical infrastructure alone (Hirtranusi, Ranti, Nugroho, & Jatmiko, 2026). This paper works within the organisational leg of TOE and decomposes it further into culture, manager support and workflow redesign — three dimensions chosen because each recurs, under varying labels, across the industry and academic evidence reviewed in Section 3.

A second anchor is dynamic-capabilities theory, which builds on the resource-based view's contention that heterogeneous, hard-to-imitate resources are a source of sustained competitive advantage (Barney, 1991) by adding the capacity to sense opportunities, seize them through resource reconfiguration, and continuously reconfigure internal routines as itself a further source of advantage (Teece, Pisano, & Shuen, 1997; Teece, 2007). Readiness practice, on this view, is not a one-off investment but an organisational capability that must be exercised repeatedly as agentic-AI tools and use cases evolve — a framing developed at length in the author's own integrated dynamic-capabilities study of HRM practice design under AI, which maps sensing, seizing and reconfiguring mechanisms onto a corpus of HRM-and-AI literature and treats organisational readiness as the reconfiguring mechanism through which firms convert AI capability into economic outcomes (Sastry, 2026).

Third, diffusion-of-innovation theory (Rogers, 2003) and the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003) supply the individual- and group-level mechanisms — relative advantage, compatibility, facilitating conditions, social influence — through which culture and manager support are conventionally understood to shape adoption outcomes, building on Davis's (1989) earlier technology-acceptance model. Fourth, sociotechnical systems theory holds that a technology's effects are jointly determined by the social system built around it, not by the technology in isolation (Trist & Bamforth, 1951; Orlikowski, 1992; Zuboff, 1988) — the theoretical basis on which this paper treats workflow redesign as a necessary complement to, rather than a byproduct of, agentic-AI deployment. Fifth, absorptive-capacity theory (Cohen & Levinthal, 1990) explains why manager support functions as a transmission channel: an organisation's capacity to recognise the value of new external knowledge, assimilate it and apply it commercially depends on prior related knowledge concentrated disproportionately in line management, not in a centralised technology function. Because workflow redesign of the kind Section 3.4 reviews is itself an episode of organisational change, this paper also draws on classical change-management theory, which holds that redesign initiatives fail less often for technical reasons than because organisations skip the sequential work of building a coalition, communicating a case for change and consolidating early wins before declaring victory (Kotter, 1996) — a sequence largely absent from the technology-first deployments the industry evidence in Section 3.1 associates with narrow realised gain.

Figure 1 integrates these strands into the conceptual framework this paper reviews evidence against. The three readiness dimensions are modelled as antecedents whose effect on realised productivity gain is mediated by the depth of agentic-AI integration achieved — from isolated pilot, through workflow-embedded use, to production deployment at scale — and moderated by sector exposure,

firm scale and national context. A feedback loop reflects the productivity-J-curve logic: accumulated intangible capital from earlier readiness investment raises future readiness, a dynamic elaborated in Section 3.5 and illustrated stylistically in Figure 5.

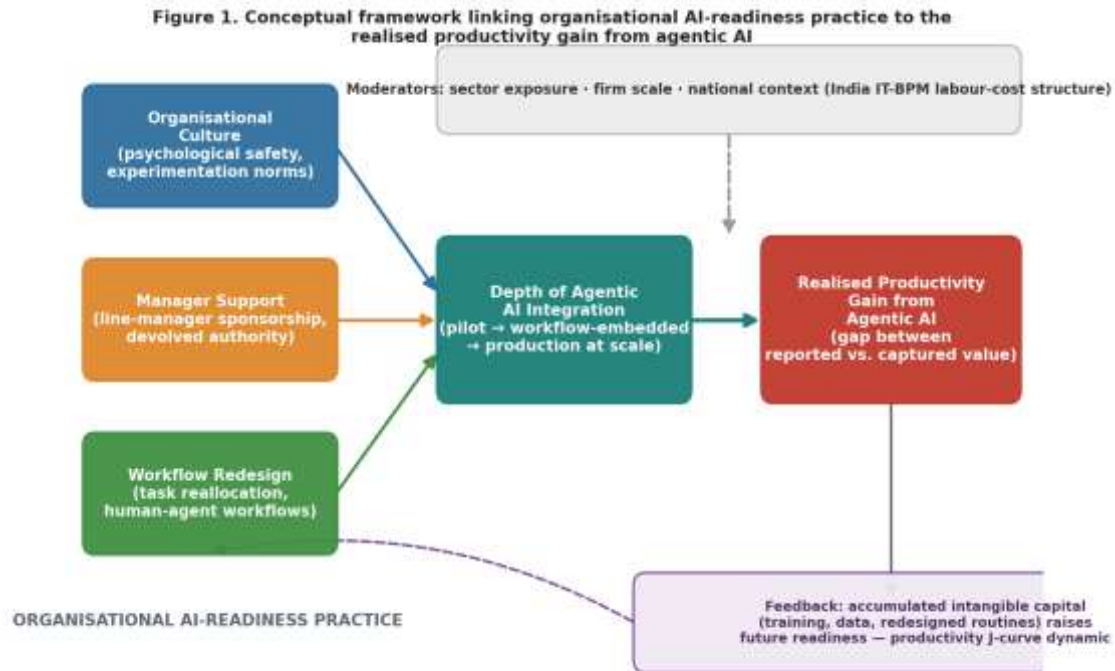


Figure 1. Conceptual framework linking organisational AI-readiness practice to the realised productivity gain from agentic AI.

Readiness Dimension	Working Definition (this paper)	Theoretical Anchor(s)	Representative Evidence
Culture	Shared norms of psychological safety, tolerance for experimentation and failure, and data-driven decision habits that shape whether agentic-AI outputs are trusted, questioned and iterated on.	TOE (organisational context); dynamic capabilities (sensing); sociotechnical systems	Mutale & El-Gayar (2025); Ayoub & Sopuru (2026); Hu et al. (2025)
Manager Support	Line-manager sponsorship and devolved authority to adapt workflows locally, with manager-level accountability for adoption outcomes, as distinct from a centralised AI-function mandate.	Absorptive capacity; UTAUT (facilitating conditions); coordination-cost theory	Farach (2026); Mutale & El-Gayar (2025); McKinsey & Company (2026); Sastry (2025)
Workflow Redesign	Deliberate reallocation of tasks between humans and agentic-AI systems and redesign of process sequencing, rather than insertion of AI into an unchanged process.	Task-based automation theory; sociotechnical systems; dynamic capabilities (reconfiguring)	Acemoglu & Restrepo (2019); Autor et al. (2003); Challapally et al. (2025); Sastry & Manjula Mallya (2025); Sastry & Ravish (2025)

3.1 Agentic AI and the Re-emergence of the Productivity Paradox

The most detailed account of the realisation gap comes from Challapally et al. (2025), whose survey and interview-based study of enterprise generative- and agentic-AI deployment found that while 80% of organisations had explored general-purpose large language models, only about 5% of custom enterprise tools reached production. Deployments built through vendor partnerships reached production roughly twice as often as internally built tools, and back-office automation — customer-service and business-process outsourcing functions — generated markedly higher return than front-office sales and marketing use cases, despite the latter absorbing about half of AI budgets. The authors attribute the divide to a "learning gap": most deployed systems do not retain



feedback or adapt to organisational context over time, so employees revert to flexible general-purpose tools for exploratory work and abandon AI systems for mission-critical tasks.

Boston Consulting Group's contemporaneous review of AI value creation reached a structurally similar conclusion from a different sample: only 4% of companies were extracting substantial value, and the practices separating them from the rest were organisational rather than technical — targeting core processes, setting ambitious value targets, concentrating effort rather than scattering pilots, and, in the authors' words, prioritising "people and processes over technology and algorithms" (de Bellefonds et al., 2024). McKinsey's 2026 global survey extends the picture into the agentic-AI period specifically: although 44% of organisations reported scaling AI somewhere across the enterprise (up from 38% in 2025) and 80% of individual respondents reported improved personal productivity, only 37% attributed EBIT gains to AI, unchanged from the prior year despite materially broader deployment. The 6% of organisations McKinsey classified as high performers were distinguished by workflow redesign, strong senior-leadership commitment, formal impact-measurement processes and IT budget shares above 15% devoted to AI (McKinsey & Company, 2026).

A field experiment offers a mechanism for why aggregate adoption statistics can coexist with such narrow realised gain. Dell'Acqua et al. (2025) randomly assigned Boston Consulting Group consultants to complete tasks with and without access to a large language model and found sharp, heterogeneous effects: performance rose substantially on tasks within the AI's capability frontier, particularly for below-average performers, but fell for tasks just outside that frontier, where consultants who trusted AI output uncritically performed worse than those without AI access at all. The authors describe this uneven, unpredictable capability boundary as a "jagged technological frontier." Read together, these four independent evidence sources — spanning a research-lab survey, a strategy-consulting review, a global management-consulting survey and a randomised field experiment — converge on the same structural finding: the technology is broadly capable, but the organisational conditions surrounding its use, not the model itself, gate how much of that capability converts into realised productivity gain. That convergence motivates decomposing organisational readiness into the three dimensions examined next.

3.2 Organisational Culture as a Readiness Dimension

Qualitative evidence from nine technology leaders at United States-based firms identified organisational culture, senior-leadership support, technical capability and data-governance maturity as intertwined determinants of AI-implementation success, with culture repeatedly described as the factor that determined whether the other three translated into outcomes rather than remaining formally present but practically inert (Mutale & El-Gayar, 2025). A large-sample quantitative study of 254 senior United States executives specified the mechanism more precisely: AI-enabled dynamic capability raises firm performance substantially through a data-driven culture that operationalises AI-generated insight into evidence-based decision routines, with organisational learning acting as a secondary mediating channel (Ayoub & Sopuru, 2026). The same study, however, identified an important boundary condition — a "dark side" in which excessively rigid adherence to data-driven norms paradoxically weakens performance by constraining the managerial discretion that turbulent markets require. Culture's contribution to readiness, in other words, is not monotonic: more formalisation is not always better, a nuance returned to in Section 6.

At the individual level, Hu, Gao, Agafari, Zhang and Cong (2025) found that AI adoption promotes employee knowledge-sharing primarily by creating learning opportunities, and that this indirect pathway is strengthened both by employees' personal disposition toward new technology ("technophilia") and by paradoxical leadership — leaders who balance self-centred and other-centred behaviour and balance imposed constraints with granted discretion. Framed against the culture dimension in Table 1, this evidence suggests culture operates less as a static trait an organisation either has or lacks, and more as an emergent property of how leaders and employees jointly interpret AI systems as developmental opportunities rather than as threats — an interpretation that in turn depends heavily on the manager-support dimension examined next.

3.3 Manager Support and the Coordination Channel

A distinctive contribution to the manager-support literature reframes agentic AI's organisational effect around coordination cost rather than task automation. Farach (2026) models AI that reduces the cost of coordinating work across an organisation — "coordination-compressing capital" — as a force that expands the number of people a single manager can effectively oversee, flattens hierarchies, and reduces the total demand for middle-management layers, regardless of which of two distributional regimes an organisation falls into. Crucially, the model implies that where access to coordination-compressing tools is broad, productivity gains are shared; where access is concentrated among senior managers, the same technology instead widens the manager-worker gap. For the manager-support dimension of readiness practice, the implication is that support cannot be reduced to "having sponsors": how broadly agentic-AI fluency and authority are distributed through the management layer is itself a distinct readiness choice with distributional consequences.

This connects directly to what the large-sample surveys report. MIT NANDA's interviews found that organisations crossing the GenAI Divide typically "empower line managers rather than centralised AI functions" (Challapally et al., 2025), and McKinsey's 2026 survey found that high-performing organisations were distinguished partly by strong senior-leadership commitment even as



47% of mid-level managers and individual contributors reported AI-related strain from the pace of change (McKinsey & Company, 2026) — evidence that the middle-management layer is simultaneously where support must be built and where the disruptive pressure of coordination-compressing tools is felt most acutely. The author's own analysis of how the middle-management role is evolving under these pressures argues that the layer's persistence depends on its members shifting from routine coordination and status reporting toward judgment-intensive tasks — dispute resolution, contextual interpretation of ambiguous agent output, and localised workflow adaptation — precisely the tasks that remain outside the "jagged frontier" documented by Dell'Acqua et al. (2025) (Sastry, 2025). Manager support, on this reading, is not simply encouragement from above; it is the specific organisational mechanism by which absorptive capacity (Cohen & Levinthal, 1990) is exercised at the point where agentic-AI systems meet day-to-day work.

3.4 Workflow Redesign and Task Reallocation

The labour-economics literature on automation has long distinguished between technologies that simply displace tasks and those that create new task categories requiring human judgment — the "reinstatement" effect (Acemoglu & Restrepo, 2019), building on the earlier finding that computerisation substitutes for routine tasks while complementing non-routine analytical and interpersonal tasks (Autor, Levy, & Murnane, 2003). Agentic AI complicates this framework because, unlike earlier automation, it can itself perform some non-routine coordination tasks previously reserved for humans — the same capability that generates the heterogeneous, jagged performance effects Dell'Acqua et al. (2025) documented. The practical implication, consistent with Farach's (2026) coordination-compression model, is that realising productivity gain requires deliberately reallocating task bundles across the human-agent boundary rather than assuming the boundary is fixed by job title.

Industry evidence bears this out directly. Challapally et al. (2025) found that the AI deployments most likely to reach production and generate measurable return were those embedded in redesigned back-office processes through external vendor partnerships, rather than layered onto unchanged front-office workflows managed internally — a pattern McKinsey's 2026 survey corroborates in finding that its "high performer" organisations "fundamentally redesign workflows rather than inserting AI into existing processes," a practice distinguishing them from the much larger group reporting AI use without EBIT impact (McKinsey & Company, 2026). The author's study of AI-analytics-enabled recruitment illustrates this distinction at function level: efficiency gains materialised not from adding an AI screening step to an otherwise unchanged, sequential hiring process, but from redesigning the workflow so that sourcing, screening and structured-interview scheduling ran as parallel, analytics-informed stages — a workflow-level rather than tool-level change (Sastry & Manjula Mallya, 2025). A related study of delegation and resource provision in Indian workplaces found that increasing employees' decision latitude and access to resources was a precondition for the kind of local process adaptation sociotechnical systems theory predicts is necessary once a new technology is introduced (Sastry & Ravish, 2025) — the redesign literature's individual-level counterpart to the organisational-level task-reallocation argument above.

3.5 Measuring the Realised Productivity Gap: Evidence from Industry Surveys

Table 2 and Figure 2 summarise the headline value-realisation statistics across the six major sources reviewed above, ranging from 4% (BCG's "substantial value creators") to 61% (NASSCOM-EY's overall readiness-maturity score expressed as a share of the maximum). These figures are not directly comparable: they measure different constructs (value creation, EBIT attribution, production deployment, enterprise-wide rollout, readiness maturity) using different samples, self-report instruments and, in several cases, methodologies disclosed by vendors with a commercial interest in AI adoption narratives. MIT NANDA's academic affiliation offers a partial, though not complete, mitigant against this concern; the BCG, McKinsey and Microsoft figures should be read as directionally informative rather than precisely comparable estimates of a single underlying rate.

With that caveat, the pattern across sources is consistent enough to be informative: realised, enterprise-level value from agentic AI is concentrated in a minority of organisations, and every source that examined the differentiator identified an organisational rather than a technical one. Read against the productivity-J-curve logic (Brynjolfsson, Rock, & Syverson, 2018/2020; Solow, 1987), these low current realisation rates are also consistent with an early-stage general-purpose-technology trajectory in which measured productivity lags while organisations accumulate the intangible capital — retraining, redesigned routines, governance structures — that later shows up as output. Figure 5 illustrates this logic stylistically, without presenting it as estimated data: readiness practice does not eliminate the initial productivity dip that accompanies deployment of a general-purpose technology, but it is hypothesised to shorten it and raise the eventual plateau, a claim formalised as Proposition 4 in Section 4. Dell'Acqua et al.'s (2025) finding of wide within-sample heterogeneity in AI's effect on individual task performance further suggests that the aggregate percentages in Table 2 likely mask substantial variance tied to exactly the readiness dimensions reviewed in Sections 3.2 to 3.4.

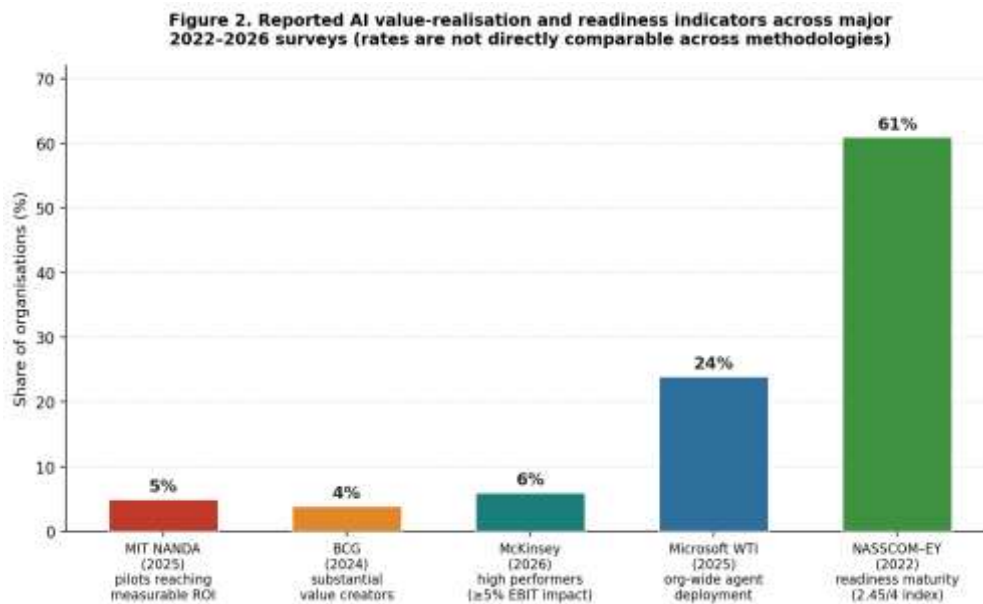


Figure 2. Reported AI value-realisation and readiness indicators across major 2022–2026 surveys (rates are not directly comparable across methodologies).

Source	Year	Scope / Method	Headline Statistic	Readiness Factor Highlighted
MIT Nanda	2025	Enterprise survey + interviews, generative/agent AI deployment	95% of organisations report zero measurable ROI; ~5% of custom tools reach production	Vendor-partnership deployment; back-office focus; devolved line-manager sponsorship
Boston Consulting Group	2024	Global executive survey	Only 4% of companies are "substantial value creators"	Focus on people and process over technology; concentrated (not scattered) initiatives
McKinsey & Company	2026	Global executive/employee survey	44% scaling AI; only 6% "high performers" (≥5% EBIT impact)	Fundamental workflow redesign; senior-leadership commitment; formal impact measurement
Microsoft WorkLab	2025	Global leader/employee survey (Work Trend Index)	24% report organisation-wide agent deployment; 12% still in pilot	"Frontier Firm" model combining agents with redesigned human leadership
Dell'Acqua et al.	2025	Randomised field experiment, management consultants	Sharp, heterogeneous task-level performance effects ("jagged frontier")	Task-level calibration of trust in AI output; training on frontier boundaries
NASSCOM–EY	2022	India enterprise index, four focus sectors	Overall readiness maturity 2.45 of 4 ("Enthusiast" stage)	Strategy embedding, budget allocation and benefit-quantification capability

3.6 The Indian IT-BPM Context

India's own enterprise AI-readiness evidence, though pre-dating the agentic-AI period, remains the most detailed national baseline available. The NASSCOM–EY India Enterprise AI Adoption Index placed overall organisational readiness at 2.45 on a 4-point scale — an "Enthusiast" stage — with fewer than 15% of surveyed enterprises embedding AI strategy into corporate-level planning, 67% allocating less than 10% of IT budget to AI on a largely ad-hoc basis, and more than half lacking standardised data at business-unit level. The leading barrier organisations cited was an inability to quantify AI benefit objectively (59%), ahead of an immature external AI ecosystem (56%) and budget constraints (55%), with cultural and behavioural resistance — the disposition-level construct Oreg (2003) operationalised as a measurable individual-differences trait rather than a vague organisational mood — flagged as a rising concern (NASSCOM & EY, 2022). These figures describe generative-AI-era readiness rather than agentic-AI-



specific readiness, and more recent sector reporting suggests India's large enterprises have since moved toward at-scale adoption in several functions; the structural gaps in strategy embedding and benefit quantification the index identified are nonetheless the same gaps the global agentic-AI evidence in Sections 3.1–3.5 associates with narrow productivity realisation.

The macroeconomic stakes of closing that gap are large. NITI Aayog has projected that increased AI adoption could add US\$500–600 billion to India's GDP by 2035, and the Reserve Bank of India's Deputy Governor has separately estimated generative AI's contribution at US\$359–438 billion by FY30 (as reported in Indian financial media). Both projections are aggregate extrapolations rather than firm-level productivity estimates, and both are conditional, implicitly, on organisations closing the readiness gaps the NASSCOM–EY index documents; the enterprise-level "GenAI Divide" evidence in Section 3.1 suggests that absent such readiness investment, national-level projections risk describing a technically feasible ceiling rather than a realised outcome. The skilling dimension of this challenge is not unique to India: the World Economic Forum's 2025 Future of Jobs Report projects 78 million net new jobs globally by 2030 alongside an urgent reskilling requirement affecting a large share of the existing workforce (World Economic Forum, 2025), a global pattern that gives India's IT-BPM sector both an opportunity — its scale and existing training infrastructure — and a readiness burden proportionate to that scale.

India's IT-BPM sector carries a further, structurally distinctive exposure that the general readiness literature has not yet addressed directly: its dominant commercial model prices services substantially by billable effort or headcount. Farach's (2026) coordination-compressing-capital framework implies that agentic AI's principal organisational effect is to let existing staff coordinate and complete more work per unit of managerial and coordination overhead — a mechanism that, left unaddressed at the commercial-contract level, compresses billable volume for a given client engagement. Realised productivity gain for the client and realised revenue for the vendor are not the same quantity under an unmodified billable-effort contract; workflow redesign that raises internal efficiency without corresponding redesign of the commercial model risks transferring the productivity gain to buyers rather than retaining it within the adopting organisation. This is not a finding drawn from the sources reviewed — it is a gap in the literature this paper flags as a priority for India-specific research, formalised as Proposition 5 below.

4. CONCEPTUAL MODEL AND FORMAL PROPOSITIONS

The literature reviewed in Section 3 supports five formal propositions linking the three readiness dimensions to realised productivity gain through the mediating and moderating structure set out in Figure 1. The propositions are offered as a research agenda to be tested against primary data, not as findings already established by the descriptive and largely cross-sectional evidence reviewed here — a distinction elaborated in Sections 5 and 8.

Proposition 1 (Culture). Organisational culture characterised by high psychological safety and tolerance for experimentation is positively associated with the depth of agentic-AI integration an organisation achieves, though this relationship is bounded rather than monotonic: culture that is excessively formalised around rigid data-driven norms is associated with reduced managerial discretion and, at the margin, weaker realised gain.

Proposition 2 (Manager Support). Manager support — operationalised as devolved authority and line-manager sponsorship rather than centralised AI-function control — is positively associated with the depth of agentic-AI integration achieved, and this relationship is strengthened where coordination-compression effects expand managers' effective span of control.

Proposition 3 (Workflow Redesign). Workflow redesign that reallocates tasks between humans and agentic-AI systems, rather than inserting agentic AI into an otherwise unchanged workflow, is a necessary condition for realised productivity gain; technology deployment without workflow redesign yields at most transient or non-significant gain.

Proposition 4 (Trajectory). The magnitude of the realised productivity gap — the difference between anticipated or reported value and captured value — narrows over time as intangible readiness capital accumulates, consistent with a productivity-J-curve trajectory, and this narrowing occurs faster where Propositions 1 through 3 hold jointly than where any single readiness dimension is weak.

Proposition 5 (Commercial-Model Moderation). In labour-cost-arbitrage-dependent service sectors such as India's IT-BPM industry, the realised productivity gain retained by the adopting organisation is moderated by commercial-model redesign — for example, a shift from billable-effort to outcome-based pricing; absent such redesign, internal productivity gains accrue disproportionately to buyers rather than to the adopting firm.



No.	Readiness Dimension	Proposition (summary)	Theoretical Grounding
P1	Culture	High psychological safety and experimentation tolerance raise integration depth; effect is bounded — excessive data-driven rigidity reduces discretion and weakens gain.	TOE; dynamic capabilities; Ayoub & Sopuru (2026) "dark side" finding
P2	Manager Support	Devolved, line-manager sponsorship raises integration depth more than centralised AI-function control; strengthened by coordination-compression's span-of-control effect.	Absorptive capacity; UTAUT; Farach (2026)
P3	Workflow Redesign	Task reallocation between humans and agents is a necessary, not merely sufficient, condition for realised gain.	Sociotechnical systems; task-based automation theory
P4	Trajectory (joint)	The realised productivity gap narrows over time with accumulated readiness capital, faster where all three dimensions are strong.	Productivity J-curve (Brynjolfsson, Rock, & Syverson, 2018/2020)
P5	Commercial-model moderation (India IT-BPM)	Retained (vs. transferred-to-buyer) productivity gain depends on commercial-model redesign under billable-effort contracts.	Coordination-compressing capital (Farach, 2026); author's extension

5. METHOD: REVIEW PROTOCOL AND CORPUS

This paper follows a structured integrative review protocol rather than a formal PRISMA-style systematic review. That choice reflects the state of the phenomenon rather than a preference: agentic AI, as a distinct category from earlier generative AI, is an emergent construct for which almost all cited industry evidence post-dates 2024 and almost all cited peer-reviewed evidence post-dates 2025. A formal systematic-review search-and-screening protocol, with its associated identification, screening and inclusion counts, requires a stable enough literature to search exhaustively against defined databases and terms; for a construct this young, reporting such counts would imply a precision the underlying search process cannot actually deliver. The thirty-eight works in the reference list were instead identified purposively across four channels: (i) large-sample industry and consulting surveys with disclosed methodology (MIT NANDA, Boston Consulting Group, McKinsey, Microsoft WorkLab, NASSCOM–EY); (ii) peer-reviewed empirical and conceptual studies in management, information systems and organisational-psychology outlets published 2024–2026; (iii) foundational theoretical works establishing the technology–organisation–environment, dynamic-capabilities, diffusion-of-innovation, sociotechnical-systems and productivity-paradox literatures; and (iv) the author's own prior published and in-preparation work on HRM practice design under AI, cited selectively — four of the thirty-eight reference-list works, approximately ten per cent — at the specific points in the review where that work engages directly with the argument under discussion, consistent with disciplinary norms for a submission to an indexed journal.

Figure 3 places the evidence base on a timeline to make its recency visible: all but a handful of the empirical sources cited fall within a thirty-month window between late 2023 and mid-2026, underscoring both the topicality and the immaturity of the evidence available. Each of the thirty-eight reference-list works was then read in full and classified by the author into a single primary category — culture, manager support, workflow redesign, cross-cutting (addressing more than one dimension without a clearly dominant one), or foundational theory (establishing a construct used across the paper without itself reporting an AI-specific empirical finding). Table 3 and Figure 4 report this classification. It is offered as a descriptive map of the evidence base assembled for this review, not as a validated content-analysis instrument; a single-coder classification of this kind is a limitation discussed further in Section 8.



Figure 3. Timeline of the evidence base cited in this review, 2018–2026 (ordered chronologically; horizontal spacing is by sequence, not to scale)

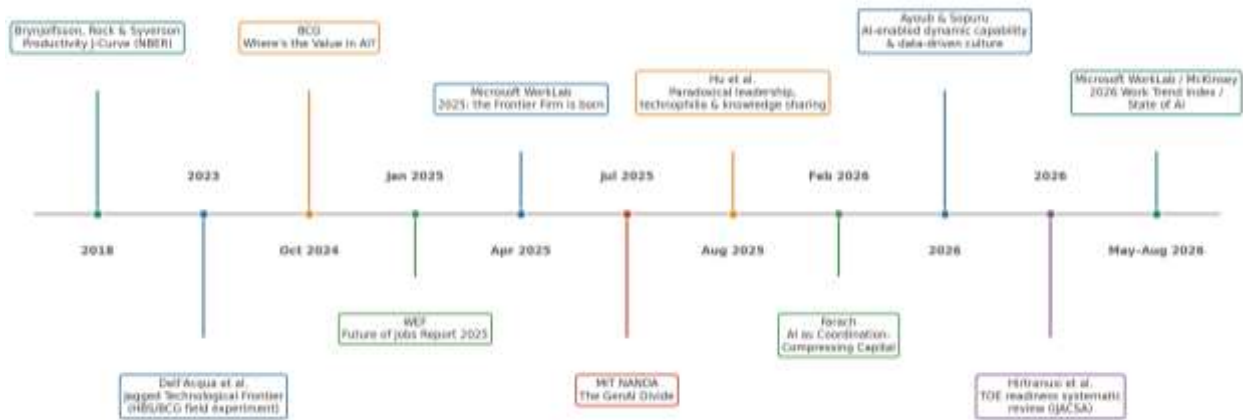


Figure 3. Timeline of the evidence base cited in this review, 2018–2026 (ordered chronologically; horizontal spacing is by sequence, not to scale).

Figure 4. Reviewed evidence base classified by primary AI-readiness dimension addressed (author's classification of the 38 works cited in this review)

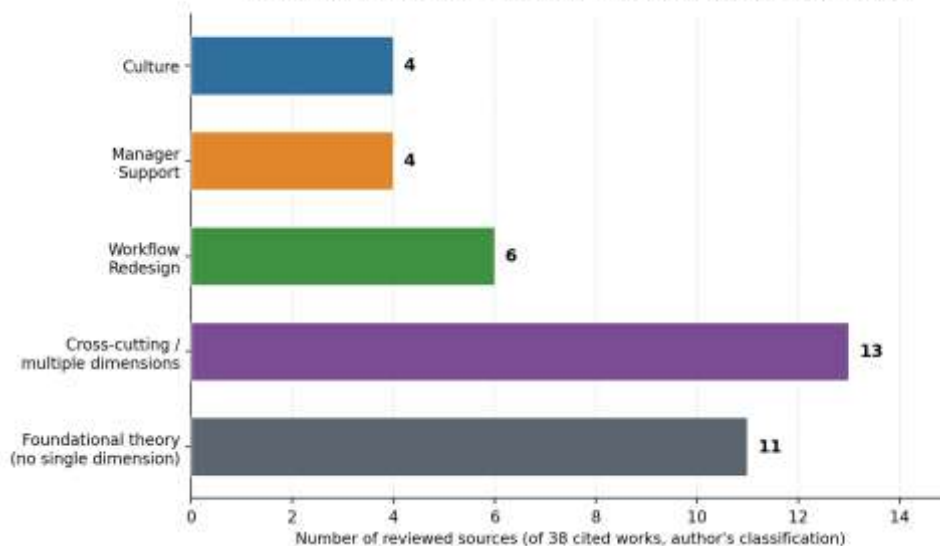


Figure 4. Reviewed evidence base classified by primary AI-readiness dimension addressed (author's classification of the works cited in this review).

Dimension	n (of 38)	Representative Works
Culture	4	Mutale & El-Gayar (2025); Ayoub & Sopuru (2026); Hu et al. (2025); Oreg (2003).
Manager Support	4	Farach (2026); Sastry (2025); Cohen & Levinthal (1990); Venkatesh et al. (2003).
Workflow Redesign	6	Acemoglu & Restrepo (2019); Autor et al. (2003); Sastry & Manjula Mallya (2025); Sastry & Ravish (2025); Kotter (1996); Davenport & Ronanki (2018).
Cross-cutting / multiple dimensions	13	Challapally et al. (2025); de Bellefonds et al. (2024); McKinsey & Company (2026); Microsoft WorkLab (2025, 2026); Dell'Acqua et al. (2025); NASSCOM & EY (2022); Hirtranusi et al. (2026); Priyanga (2025); Sastry (2026); World Economic Forum (2025); NITI Aayog (2026); Patra (2024).
Foundational theory (no single empirical dimension)	11	Tornatzky & Fleischer (1990); Teece (2007); Teece, Pisano, & Shuen (1997); Barney (1991); Rogers (2003); Davis (1989); Trist & Bamforth (1951); Orlikowski (1992); Zuboff (1988); Brynjolfsson, Rock, & Syverson (2018/2020); Solow (1987) — grounding constructs used throughout rather than reporting an AI-specific finding.



6. DISCUSSION

The clearest finding to emerge from this review is convergence rather than novelty: four methodologically independent, large-sample sources — an academic research-lab survey, a strategy-consulting review, a global management-consulting survey and a field experiment — arrive at the same structural conclusion using different instruments and different samples. Realised, enterprise-level productivity gain from agentic AI is concentrated in a small minority of adopting organisations, and in every case where the source examined what separated that minority from the rest, the differentiator identified was organisational — workflow redesign, leadership commitment, devolved manager sponsorship, benefit-measurement discipline — rather than model capability. That convergence is what justifies treating organisational AI-readiness practice, rather than technology access, as the primary explanatory variable for the realised productivity gap named in this paper's title.

A second finding complicates a simple "more readiness is better" reading of that conclusion. Ayoub and Sopuru's (2026) identification of a "dark side" to data-driven culture — in which excessive rigidity suppresses the managerial discretion volatile markets require — and Farach's (2026) demonstration that coordination-compressing AI's benefits depend on how broadly, not merely how much, coordination capacity is redistributed through the management layer, both suggest that readiness practice needs a calibration logic rather than a maximisation logic. An organisation that maximises formal data governance at the expense of manager discretion, or that concentrates agentic-AI fluency among senior leadership rather than distributing it through line management, may score well on conventional readiness indices while still failing to convert deployment into realised, broadly shared productivity gain. This nuance is not visible in the aggregate percentages reported in Table 2 and Figure 2, which is itself a limitation of relying on survey-level readiness indices rather than firm-level process data — a gap the future-research agenda in Section 8 addresses directly.

Third, the productivity-J-curve framing (Brynjolfsson, Rock, & Syverson, 2018/2020) offers a more constructive reading of the low current realisation rates than either technological triumphalism or technological disappointment. If agentic AI is behaving as prior general-purpose technologies did, low measured productivity in the early deployment years is an expected transitional cost of intangible investment rather than evidence the technology has failed to deliver on its promise. This reading, however, is an inference from analogy to earlier general-purpose technologies rather than a finding directly established by the cross-sectional survey evidence available today, which cannot by itself distinguish an organisation on an early-J-curve trajectory from one whose readiness deficits will prove persistent. Resolving that distinction requires exactly the longitudinal, firm-level data that Section 8 argues does not yet exist for agentic AI specifically.

7. INDIA POLICY AND PRACTICE IMPLICATIONS

For India's IT-BPM and broader services sector, the readiness gaps the NASSCOM–EY index identified — fewer than 15% of enterprises embedding AI strategy into corporate-level planning, two-thirds allocating under 10% of IT budget to AI on an ad-hoc basis, and 59% citing an inability to quantify AI benefit as the leading adoption barrier — are a precondition, not a footnote, for capturing the GDP contribution NITI Aayog and the Reserve Bank of India have projected. Table 5 summarises how the readiness dimensions reviewed in Section 3 map onto global versus India-specific patterns.

Dimension	Global Pattern	India IT-BPM Pattern	Key Source(s)
Culture	Cultural/behavioural resistance an emerging, rising barrier	Ethics/audit frameworks still emerging; 60% document AI audit standards	NASSCOM & EY (2022)
Manager Support	High performers show strong senior-leadership commitment; devolved sponsorship favoured over centralised control	Fewer than 15% embed AI strategy at corporate-planning level; leadership focus rising but largely ad hoc	McKinsey & Company (2026); NASSCOM & EY (2022)
Workflow Redesign	High performers fundamentally redesign workflows rather than inserting AI into unchanged processes	67% allocate under 10% of IT budget to AI; benefit-quantification capability the leading barrier (59%)	McKinsey & Company (2026); NASSCOM & EY (2022)
Macro stakes	Not sector-specific	Projected US\$500–600bn GDP contribution by 2035; US\$359–438bn generative-AI contribution by FY30, both conditional on closing the gaps above	NITI Aayog; Reserve Bank of India (Patra, 2024)

Four practice implications follow directly. First, AI budgeting should move from the ad-hoc, function-level allocation the index found in two-thirds of enterprises toward enterprise-embedded strategic planning, consistent with the leadership-commitment factor McKinsey's high performers share globally. Second, manager-support structures should be built explicitly and distributed through line management rather than concentrated in a centralised AI function or in senior leadership alone, given both the global evidence that devolved sponsorship outperforms centralisation (Challapally et al., 2025) and Farach's (2026) distributional warning about



concentrated coordination-compression access. Third, given the commercial-model exposure formalised in Proposition 5, IT-BPM firms piloting agentic-AI-enabled workflow redesign should evaluate outcome-based or hybrid commercial models in parallel with internal process change, rather than treating commercial-model design as a downstream question to be settled after technical deployment. Fourth, benefit-quantification capability — the single most-cited barrier in the NASSCOM–EY index — should be built as a readiness investment in its own right, since an organisation unable to measure realised gain cannot distinguish genuine productivity improvement from activity, a distinction central to every source reviewed in Section 3.1.

8. LIMITATIONS AND FUTURE RESEARCH AGENDA

Four limitations bound the conclusions drawn here. First, the great majority of the empirical evidence reviewed is cross-sectional and self-reported by survey respondents, with several sources produced or commissioned by organisations that have a commercial interest in a particular adoption narrative; MIT NANDA's academic affiliation partially, but does not fully, mitigate this concern for the evidence base as a whole. Second, the corpus classification presented in Table 3 and Figure 4 is a single-coder judgement offered as a descriptive map of the literature, not a validated inter-rater content-analysis instrument. Third, and most importantly, no dataset available at the time of writing tracks the same organisations' readiness practice and realised productivity gain over multiple years specifically for agentic-AI deployment; the productivity-J-curve interpretation advanced in Sections 3.5 and 6 is therefore an inference by analogy to earlier general-purpose technologies rather than a directly estimated trajectory, and Proposition 4 cannot be tested against the evidence assembled here. Fourth, the India-specific commercial-model argument in Proposition 5 is the author's theoretical extension of Farach's (2026) coordination-compression model to the IT-BPM billable-effort context; it has not, to this author's knowledge, been examined empirically in the published literature.

These limitations point directly to a future research agenda. The highest priority is longitudinal or matched-pair firm-level research — ideally difference-in-differences designs comparing organisations with differing readiness practice at the point of agentic-AI adoption — capable of estimating the readiness-to-productivity relationship causally rather than by cross-sectional association. A second priority is primary data collection within India's IT-BPM sector specifically, given the distinct commercial-model exposure identified in Proposition 5 and the absence of any agentic-AI-specific successor to the 2022 NASSCOM–EY readiness index. A third priority is process-level (rather than survey-level) measurement of the calibration question raised in Section 6: at what point does data-driven culture or centralised coordination become excessive relative to the managerial discretion agentic-AI-era work requires. Each of these lines would allow the propositions advanced in Section 4 to move from a conceptual synthesis of converging descriptive evidence to a directly tested empirical claim.

9. CONCLUSION

This paper has reviewed a fast-moving, cross-disciplinary evidence base on why the productivity gains organisations realise from agentic-AI adoption remain narrow relative to the gains anticipated, and has organised that evidence around three organisational AI-readiness dimensions — culture, manager support and workflow redesign — that recur across independent industry surveys, peer-reviewed studies and a randomised field experiment. The convergence across these otherwise unrelated sources on an organisational, rather than technical, explanation for the realised productivity gap is the paper's central empirical observation; the five propositions advanced in Section 4 translate that observation into a testable research agenda, and the calibration nuance raised in Section 6 cautions against treating readiness as something to be simply maximised rather than deliberately balanced. India's IT-BPM sector faces this dynamic with distinctive stakes, given both the scale of the national productivity gains projected to depend on it and the sector's structural exposure — flagged here as a priority for future research — to having agentic-AI-driven efficiency captured by clients rather than retained by the adopting firm. The evidence assembled in this review is, by its own account, still largely descriptive and industry-sourced; the paper's contribution is to organise that evidence into a framework precise enough to be displaced by the primary longitudinal data the field does not yet have.

NOTE ON THE MANUSCRIPT

This paper is written as a structured integrative review rather than a formal PRISMA-style systematic review, for the reason given in Section 5: agentic AI, as a distinct construct from earlier generative AI, is too young a literature for database-search screening counts to be reported meaningfully. Reference-list self-citation is limited to four of the thirty-eight cited works (approximately ten per cent), a deliberate departure from the author's broader practice in a parallel series of HRM-variable-to-economic-outcome papers, made in line with disciplinary norms for a submission targeting Scopus-indexed outlets. Two of the four self-citations — Sastry (2026) and Sastry (2025) — refer to manuscripts in the author's own working-paper series that have not, at the time of writing, been placed in an indexed journal, and are cited as working papers rather than attributed to a journal that has not accepted them; the remaining two self-citations refer to work already published in EPRA International Journal of Research & Development with verified volume and page details. All external statistics cited from industry sources (MIT NANDA, Boston Consulting Group, McKinsey & Company, Microsoft WorkLab, NASSCOM–EY) were checked against the primary report or its publisher's own page at the time of writing rather than accepted from secondary summaries.



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