

Evaluating the Triadic Alignment of AI-Driven Talent Assessment Tools on Skill Decay and Workforce Agility: A Multi-Sector Study in the Mumbai Metropolitan Region

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July 2026

Abstract

Organizations across the Mumbai Metropolitan Region (MMR) are rapidly embedding AI-driven talent assessment tools into recruitment, promotion, and continuous performance-evaluation cycles. While these systems promise consistency and efficiency, an emerging body of evidence suggests that heavy reliance on algorithmic decision support may carry an unintended cost: a gradual erosion of employee judgment, sometimes described as skill decay or “cognitive debt.” At the same time, organizations are investing heavily in workforce agility as a strategic capability for navigating volatile, technology-driven markets. This conceptual paper argues that the relationship between AI-driven talent assessment adoption and workforce agility is not direct but is instead conditioned by the degree of alignment across three interdependent actors: the assessment tool itself (its design and transparency), the individual employee (their trust, self-efficacy, and cognitive engagement), and the organization (its governance, feedback culture, and reskilling infrastructure). We term this the Triadic Alignment Model. Where alignment across the tool–individual–organization triad is weak, AI-driven assessment is proposed to accelerate skill decay and, counter-intuitively, undermine the workforce agility it is meant to support; where alignment is strong, the same tools may instead free cognitive capacity for higher-order tasks and reinforce agility. Drawing on task-technology fit theory, person-environment fit theory, and dynamic capabilities theory, this paper develops seven testable propositions and a detailed mixed-methods design for a future multi-sector empirical study spanning IT/ITES, BFSI, manufacturing, and healthcare organizations in the MMR. The paper closes with implications for HR practice and a research agenda for scholars examining human–AI collaboration in talent management.

Keywords: AI-driven talent assessment, skill decay, workforce agility, triadic alignment, task-technology fit, human resource management, Mumbai Metropolitan Region

1. Introduction

Artificial intelligence has moved from a peripheral experiment in human resource management (HRM) to a core infrastructure layer for how organizations screen, evaluate, and develop talent. Industry surveys indicate that AI adoption in HR functions roughly doubled between mid-2023 and early 2024, and the global market for AI-enabled HR technology is projected to expand at a compound annual growth rate of close to 25 percent through the end of the decade. Within this shift, a specific category of tool has drawn growing scrutiny: AI-driven talent

assessment systems that move beyond one-time resume screening toward continuous, structured evaluation of cognitive ability, technical skill, and behavioral fit.

Two streams of scholarship have developed largely in parallel around this shift. The first, rooted in cognitive and organizational psychology, examines whether reliance on AI assistance erodes the very skills it is meant to support — a phenomenon researchers have labeled skill decay or, in workplace contexts, “cognitive debt”: capability that atrophies each time an employee defers judgment to an algorithm rather than exercising it independently. The second stream, situated in strategic HRM, treats workforce agility — the capacity of employees to proactively adapt, absorb change, and remain resilient under uncertainty — as a critical organizational outcome in its own right, with its own validated measurement instruments and nomological network of antecedents and consequences.

What remains largely unexamined is the point at which these two streams intersect: the specific case in which the AI system is not merely a task-execution aid (as in AI-assisted coding or radiology) but is itself the evaluator that determines who is hired, promoted, or flagged for a skills gap. This is a materially different situation from AI-as-copilot, because the assessment tool simultaneously shapes what counts as a valued skill and how employees experience feedback about their own competence. Existing literature on AI adoption in Indian HRM contexts — for instance, work grounded in task-technology fit theory examining the pharmaceutical sector — shows that AI adoption remains highly uneven across industries even within the same country, with adoption rates as low as one quarter of firms in some sectors despite rapid growth elsewhere. This unevenness makes a multi-sector design essential: a single-industry study cannot capture how differing levels of AI maturity condition the skill-decay and agility outcomes this paper is concerned with.

The Mumbai Metropolitan Region (MMR) offers a particularly well-suited context for this inquiry. It combines a mature IT/ITES and BFSI (banking, financial services, and insurance) sector with high AI-tool penetration, alongside manufacturing and healthcare organizations where adoption is more nascent — allowing sector type to be examined as a genuine moderating condition rather than a constant.

1.1 Research Problem

Despite growing practitioner attention to both AI-driven assessment and workforce agility, no published study to date has modeled how the alignment (or misalignment) among the assessment tool, the individual employee, and the organization jointly determines whether AI-driven assessment helps or harms the workforce agility organizations are trying to build. This paper addresses that gap conceptually, as a precursor to empirical testing.

1.2 Research Objectives

This paper aims to: (1) synthesize the separate literatures on AI-driven talent assessment, skill decay, and workforce agility into a single integrative framework; (2) introduce and define the construct of Triadic Alignment (TA) as the missing conditioning variable between AI-driven assessment adoption and workforce agility outcomes; (3) develop a set of testable theoretical propositions specifying the direction and boundary conditions of these relationships; and (4) design a rigorous, sector-comparative, mixed-methods empirical study for the Mumbai Metropolitan Region that can validate or disconfirm the proposed model in future research.

1.3 Significance of the Study

For scholars, this paper offers a novel integrative construct — triadic alignment — that connects two previously disconnected literatures and extends task-technology fit and person-environment fit theorizing into the domain of algorithmic talent evaluation. For practitioners, particularly CHROs and HR technology leaders in the MMR, the paper offers an early diagnostic lens for evaluating whether an organization's current AI-assessment rollout is more likely to erode or enhance the workforce capabilities it depends on.

2. Literature Review

2.1 AI-Driven Talent Assessment Tools: From Screening to Continuous Evaluation

AI-driven talent assessment platforms have evolved considerably from early applicant-tracking keyword matching. Contemporary platforms combine cognitive-ability testing, structured skills challenges, behavioral and personality profiling, and AI-conducted interviews with adaptive follow-up questioning, often layered into a single continuous pipeline that extends from hiring into ongoing performance monitoring. This shift toward continuous, real-time skill measurement means that the assessment tool is no longer a discrete hiring gate but an ongoing feature of the employment relationship.

Adoption of these tools within the Indian context has been shown to depend heavily on perceived task-technology fit, organizational readiness, and technological preparedness, with substantial variation across industries; one study of the Indian pharmaceutical sector found that only a quarter of firms had adopted AI-enabled HR tools despite broader industry growth pressures. Parallel work on AI-driven recruitment across Indian corporate and allied sectors has identified algorithmic opacity — the difficulty candidates and employees face in understanding why an algorithm reached a given decision — as a persistent source of perceived unfairness and depersonalization, even when the underlying system reduces certain forms of human bias.

2.2 Skill Decay and Cognitive Debt in AI-Augmented Work

A growing theoretical literature distinguishes several related but conceptually separable phenomena that arise when humans work alongside AI systems: automation bias (accepting AI output without independent verification), automation-induced complacency (reduced vigilance during monitoring tasks), and skill decay proper (the degradation of cognitive capability through disuse). Critically, this literature — building on decades of aviation-automation research — emphasizes that AI assistance may impair users' cognitive skills in ways the users themselves cannot easily detect, since the same tool that erodes a capability also removes the everyday opportunities to notice that erosion. Commentators studying this dynamic in workplace settings describe the resulting accumulation as “cognitive debt”: capability that quietly erodes each time an employee lets an algorithm make a judgment call that would otherwise have required independent reasoning.

It is worth noting explicitly that this literature has developed primarily around AI as a task-execution aid — a radiologist assisted by an image-recognition system, a developer assisted by a code-completion model — rather than AI as an evaluator of the human. This is the central gap this paper seeks to address: does an AI system that assesses and scores an employee's competence produce the same decay dynamics as an AI system that assists the employee in performing a task? We argue the mechanisms are related but not identical, because assessment tools

additionally shape employees' beliefs about which skills are worth maintaining independently versus which are safe to offload.

2.3 Workforce Agility as a Strategic Outcome

Workforce agility has been conceptualized behaviorally as observable performance consisting of three core dimensions — proactivity, adaptability, and resilience — and has more recently been operationalized through a validated ten-dimension taxonomy encompassing accepting change, decision-making, creating transparency, collaboration, reflection, user-centricity, iteration, testing, self-organization, and learning. Empirical work using this multidimensional measure has demonstrated that workforce agility relates positively to task performance, innovative performance, organizational citizenship behavior, job satisfaction, and employee well-being, and negatively to job exhaustion.

A comprehensive systematic review of 74 peer-reviewed workforce agility studies drawn from Scopus and Web of Science found that the field's antecedents, mediators, and moderators remain fragmented across more than twenty-five underlying theories, and that organizational characteristics and human-resource-management practices — including technology-mediated practices such as AI-driven assessment — remain insufficiently investigated as antecedents of workforce agility. The same review explicitly calls for future research employing mixed-methods designs, broader cultural samples, and conceptual models that examine mediating and moderating mechanisms, which is precisely the gap this paper's proposed design is built to fill.

2.4 Toward a Triadic Lens: Tool, Individual, and Organization

Three established theoretical traditions provide the building blocks for the framework proposed here. Task-technology fit theory holds that a technology will only be adopted effectively, and will only produce positive performance outcomes, to the extent that its functionality matches the tasks it is meant to support — a lens already applied productively to AI-HRM adoption in the Indian context. Person–environment fit theory, and its more specific person–organization fit variant, holds that individual outcomes depend on the congruence between an individual's characteristics (here, trust, self-efficacy, and cognitive engagement) and the demands of their environment. Dynamic capabilities theory, at the organizational level, holds that a firm's capacity to sense, seize, and reconfigure resources — including its governance structures and reskilling investments — determines whether it can convert technological change into sustained advantage rather than disruption.

Existing empirical studies typically isolate a single node of this triad: a study of tool adoption drivers, a study of individual cognitive decay, or a study of organizational agility outcomes — rarely all three within one model. We argue that this fragmentation is precisely why the literature has not yet been able to explain the counter-intuitive finding implicit across several of the sources reviewed above: that AI tools introduced to build workforce capability can, under certain conditions, erode the very capability they are meant to support. We propose that the missing variable is the degree of alignment across all three nodes simultaneously, rather than any single node in isolation.

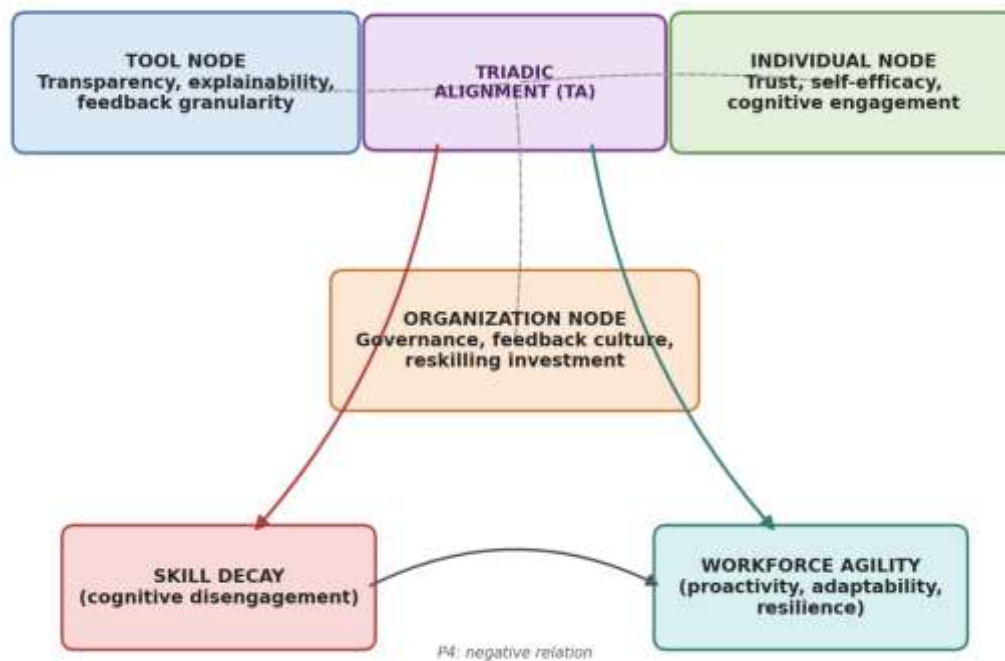
3. Conceptual Framework: The Triadic Alignment Model

We define Triadic Alignment (TA) as the degree of congruence among three interdependent nodes surrounding any AI-driven talent assessment deployment:

- **Tool Node** — the transparency, explainability, and feedback granularity built into the assessment system itself.
- **Individual Node** — the employee's trust in the system, self-efficacy regarding the assessed skill domain, and active (versus passive) cognitive engagement with assessment feedback.
- **Organization Node** — the governance policies, feedback culture, and reskilling infrastructure the organization builds around the tool.

The central theoretical claim of this paper is that TA does not simply add to the direct effect of AI-driven assessment adoption on outcomes; it conditions that effect. Specifically, we propose that TA moderates the relationship between AI-driven assessment use and skill decay (weak alignment strengthens the decay effect; strong alignment weakens it), and that TA mediates the relationship between AI-driven assessment adoption and workforce agility (adoption improves agility only when it flows through a high-TA context). Figure 1 depicts the full model.

Figure 1. The Triadic Alignment Model of AI-Driven Talent Assessment, Skill Decay, and Workforce Agility



4. Research Propositions

Based on the framework above, the following seven propositions are advanced for empirical testing:

P1. Tool-node transparency (explainability of AI-driven talent assessment outputs) is positively associated with individual-node trust in the assessment system.

P2. Higher behavioral reliance on AI-driven talent assessment tools, with correspondingly lower active cognitive engagement in the assessment process, is positively associated with employee skill decay over time.

P3. Triadic alignment (TA) negatively moderates the relationship between AI-driven talent assessment use and skill decay, such that the positive relationship in P2 is weaker when TA is high.

P4. Skill decay is negatively associated with workforce agility, with the strongest negative effects on the proactivity and adaptability dimensions.

P5. Triadic alignment positively mediates the relationship between AI-driven talent assessment adoption and workforce agility, such that adoption is associated with higher agility only when TA is high, and with lower agility when TA is low.

P6. Sector type (IT/ITES, BFSI, manufacturing, healthcare) moderates the strength of the TA → skill decay and TA → workforce agility relationships, reflecting uneven AI-maturity levels across sectors in the Mumbai Metropolitan Region.

P7. Organizational investment in structured reskilling and feedback mechanisms (a component of the organization node) buffers the negative relationship between skill decay and workforce agility.

5. Proposed Methodology for Future Empirical Validation

As a conceptual paper, this work does not report primary data. This section instead specifies, in detail, the research design through which the propositions above can be tested in a future multi-sector study across the Mumbai Metropolitan Region (MMR), so that the model is falsifiable rather than purely speculative.

5.1 Overall Design

A sequential explanatory mixed-methods design is recommended: an initial quantitative phase to test the structural relationships among TA, skill decay, and workforce agility, followed by a qualitative phase to explain and contextualize the quantitative patterns through practitioner narratives.

5.2 Phase 1 — Quantitative Survey

Population and sampling: Full-time employees and HR business partners at organizations using AI-driven talent assessment tools, drawn from four sectors present in the MMR — IT/ITES, BFSI, manufacturing, and healthcare — selected because they represent markedly different levels of AI-assessment maturity documented in the sector literature reviewed above. A stratified proportional sampling approach across these four sectors is recommended, with organizations recruited through HR-industry bodies and professional networks operating in Mumbai, Navi Mumbai, and Thane. A target sample of approximately 400–450 respondents is suggested, based on standard guidelines for structural equation modeling with a model of this complexity (a minimum ratio of roughly 10 respondents per estimated parameter).

Instruments: (a) Workforce agility should be measured using the validated ten-dimension multidimensional workforce agility scale; (b) the tool node should be measured using an adapted task-technology fit instrument; (c) the individual node (trust, self-efficacy, cognitive engagement) should draw on established trust-in-automation and self-efficacy scales adapted to the talent-assessment context; (d) skill decay should be measured through a combination of a self-report cognitive-offloading scale and, where organizational records permit, an objective proxy such as pre- and post-adoption competency assessment scores. Because no validated skill-decay

scale specific to algorithmic talent assessment currently exists, scale development and validation should be treated as a necessary sub-contribution of the empirical phase, following standard psychometric development procedures (item generation, expert review, pilot testing, exploratory and confirmatory factor analysis).

Analytical approach: Partial least squares structural equation modeling (PLS-SEM) is recommended given the model's combination of formative and reflective constructs and its moderated-mediation structure; bootstrapped confidence intervals should be used to test the significance of the TA moderation (P3) and mediation (P5) paths, and multi-group analysis should be used to test the sector-moderation proposition (P6).

5.3 Phase 2 — Qualitative Interviews

Semi-structured interviews with approximately 15–20 CHROs, HR technology leads, and senior HR business partners across the same four sectors should follow the quantitative phase, focused specifically on explaining any unexpected or sector-divergent quantitative findings. Interview data should be analyzed using thematic analysis, with themes mapped back onto the three nodes of the triadic model to preserve theoretical coherence between phases.

5.4 Ethical and Regulatory Considerations

Any future data collection involving employee performance and assessment records must secure institutional ethics clearance, obtain informed consent, and ensure anonymization of organization- and employee-identifying information. Given that assessment data of this kind may qualify as personal data under India's Digital Personal Data Protection Act, 2023, the study design should build in data-minimization and consent-management protocols from the outset rather than retrofitting compliance after data collection.

5.5 Anticipated Limitations of the Proposed Design

A cross-sectional quantitative phase can establish association but not causal direction between skill decay and workforce agility; a longitudinal extension (repeated measurement across at least two AI-assessment cycles) is recommended as a follow-on study once the cross-sectional model is validated. Findings would also be geographically bounded to the MMR and would require replication in other metropolitan and rural Indian labor markets before broader claims about the triadic alignment model could be made.

6. Theoretical and Practical Implications

6.1 Theoretical Contributions

This paper extends task-technology fit and person-environment fit theorizing into the specific domain of algorithmic talent evaluation, and it offers the workforce agility literature — which recent systematic reviews describe as still under-theorized with respect to HR-technology antecedents — a concrete, testable mechanism (triadic alignment) linking a specific technology-adoption context to agility outcomes. It also bridges the skill-decay literature, previously concentrated on AI-as-task-aid contexts such as radiology and software development, into the HRM domain of AI-as-evaluator.

6.2 Practical Implications

For HR and technology leaders deploying AI-driven talent assessment, the model suggests that tool selection alone is insufficient: organizations should audit alignment across all three nodes before and during rollout — verifying that the tool is explainable, that employees are given avenues to build trust and remain cognitively engaged with assessment feedback rather than passively accepting scores, and that reskilling and feedback infrastructure is in place to convert assessment data into development rather than mere sorting. Sector-specific rollout pacing may also be warranted, given the uneven AI-maturity levels documented across Indian industries.

7. Limitations and Future Research Directions

As a conceptual paper, this work's principal limitation is the absence of empirical data; all propositions remain theoretical until tested through the design proposed in Section 5. Future research should also explore whether the triadic alignment construct generalizes beyond talent-assessment contexts to other algorithmic HR decisions (compensation, scheduling, and involuntary separation), and whether individual-difference variables such as AI literacy or algorithm aversion moderate the strength of the individual node's contribution to overall alignment.

8. Conclusion

As AI-driven talent assessment becomes a standard feature of HR infrastructure across the Mumbai Metropolitan Region and beyond, organizations risk treating adoption as a simple efficiency upgrade rather than a triadic governance challenge. This paper has argued that the true determinant of whether such tools build or erode workforce capability lies not in the tool alone, but in the alignment achieved among the tool, the individual employee, and the organization around it. The Triadic Alignment Model and its accompanying propositions offer a starting point for the empirical work needed to test this claim, and, if supported, a practical diagnostic that HR leaders can use to steer AI-driven assessment toward its intended purpose: a more agile, not a more dependent, workforce.

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