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HR PRACTICE BUNDLES AND TOTAL FACTOR PRODUCTIVITY UNDER AI AUGMENTATION: RE-ESTIMATING COMPLEMENTARITY IN THE AUGMENTED FIRM

HRM VARIABLE: COMPLEMENTARY PRACTICE BUNDLES → ECONOMIC OUTCOME: TOTAL FACTOR PRODUCTIVITY

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ABSTRACT---
For three decades the most secure finding in strategic human resource management has been that practices pay off in bundles and not singly: adopting one innovative practice in isolation produces nothing measurable, while adopting a coherent system produces large and durable productivity gains. That finding was established on production technologies in which the binding constraint was the distribution of knowledge and discretion across a workforce. Generative artificial intelligence relaxes precisely that constraint. This paper re-estimates the practice–productivity relationship under conditions of AI augmentation, asking whether the complementarities that made bundling effective still hold. Forty-one studies were assembled — nineteen from the canonical 1990–2012 literature and twenty-two from the 2023–2026 augmentation literature — and set against three scenarios to 2035. The central empirical finding is an augmentation gap. At the task and worker level the measured effects are large: 26.1 per cent more completed tasks for software developers, 15 per cent more issues resolved per hour for customer-support agents, 25.1 per cent faster completion for consultants working inside the model's competence frontier. At the firm and economy level they nearly vanish: 4 per cent labour productivity in a matched sample of European and United States firms, 5.1 per cent and statistically insignificant once complementary investment is controlled for in Canadian firms, 0.6 to 1.8 per cent implied in United States executive reporting, and a null on earnings and hours in Danish administrative data. The gap is the signature of missing organisational complements rather than of a weak technology. Decomposing the bundle shows that complementarity has not disappeared but has been re-weighted: selection- and incentive-linked complementarities weaken as AI compresses the performance distribution from below, while verification, tool governance, decision-right allocation and continuous learning complementarities strengthen sharply. The paper specifies the re-weighted bundle for the augmented firm, sets out three scenarios distinguished by how quickly firms build those complements, and argues that the human resource function has become the rate-limiting factor on aggregate productivity growth rather than a downstream consumer of it.

KEYWORDS: *HR practice bundles, complementarity, supermodularity, total factor productivity, artificial intelligence, augmentation, high-performance work systems, productivity J-curve, scenario analysis.*--

I. INTRODUCTION

The single most robust result in the empirical human resource literature is also its least intuitive. Studying thirty-six homogeneous steel finishing lines over an extended period, researchers found that lines operating a coherent system of innovative practices — problem-solving teams, extensive communication, employment security, flexible job assignment, multi-skill training and incentive pay — achieved substantially higher productivity than lines operating traditional narrow-job, hourly-pay systems. The striking part was the negative result that accompanied it: adopting any one of those practices on its own produced no measurable effect at all [1]. The same pattern was found in the world automobile industry, where practice bundles rather than individual practices predicted assembly-plant performance [2], and it has survived two decades of meta-analytic scrutiny [3], [4].

The theoretical explanation was already available. Where the marginal return to one practice rises with the level of another — where the cross-partial derivative of output with respect to two practices is positive — the practices are complements and the production function is supermodular [5], [6], [7]. Under supermodularity a firm that adopts half a system captures far less than half its return, which explains both the empirical null on isolated practices and the persistent puzzle of why so many firms leave apparently free productivity on the table. It also explains why practice bundles interact so strongly with technology: the returns to information technology were repeatedly shown to depend on decentralisation, teamwork and skill investment rather than on the technology alone [8], [9], [10], [11].

That entire body of evidence, however, was assembled on production technologies with a common characteristic. The binding constraint on output was the distribution of knowledge, judgement and discretion across a workforce. Practice bundles worked because they moved information to where decisions were made, gave decision rights to the people holding the information, and paid for the resulting effort. Generative artificial intelligence relaxes that constraint directly. A model that can supply the codified knowledge a worker lacks, draft the analysis the worker would have produced, and diffuse the practices of the firm's best performers to its weakest, is intervening in exactly the mechanism through which the classical bundle operated [12].

This raises a question that the practice literature has not yet confronted. If the mechanism through which bundles worked is now partly performed by a technology, does the complementarity structure still hold? Three answers are logically available and each carries very different implications. The bundle may be unchanged, with AI simply raising the level of output and leaving the interaction terms intact. The bundle may be dissolving, with AI substituting for the practices that formerly produced its gains, so that the firm can now buy productivity without organisational change. Or the bundle may be re-weighting, with some complementarities weakening while others strengthen and new ones appear. The paper argues, on the assembled evidence, for the third.

The empirical point of departure is a discrepancy that has become impossible to ignore. Task-level and worker-level studies of generative AI report effects that would be historically extraordinary if they aggregated: a 26.1 per cent increase in completed tasks across three randomised controlled trials with 4,867 software developers [13], a 15 per cent increase in issues resolved per hour among 5,172 customer-support agents [12], a 25.1 per cent speed gain and a quality gain above 40 per cent among 758 consultants on tasks inside the model's competence frontier [14]. Firm-level and economy-level studies of the same period report effects an order of magnitude smaller: 4 per cent labour productivity across more than 12,000 European and United States firms [15], a 5.1 per cent adopter premium in Canada that loses statistical significance once complementary investment is accounted for [16], implied gains of 0.6 per cent in 2025 and 1.8 per cent expected in 2026 from United States executive reporting [17], and null effects on earnings and hours in Danish administrative data with confidence intervals excluding anything larger than 2 per cent [18]. The most careful macroeconomic assessment puts the total factor productivity gain at 0.71 per cent over a decade, and possibly as little as 0.55 per cent [19].

This paper treats that discrepancy as the central object of analysis rather than as a measurement nuisance. It is the eleventh in a series pairing a single human resource variable with a single economic outcome; its variable is the complementary practice bundle and its outcome is total factor productivity. Four questions organise it. First, what exactly did the classical evidence establish about complementarity, and on what production assumptions? Second, what do the 2023–2026 augmentation studies measure, and why does the task-level evidence fail to aggregate? Third, which specific complementarities are weakened by augmentation and which are strengthened? Fourth, under what organisational conditions does the augmented firm convert task-level gains into total factor productivity, and what does that imply for the design of the practice bundle? The contribution is a decomposition of the bundle into complementarities that survive augmentation and complementarities that do not, a three-scenario architecture for the period to 2035, and a re-specified bundle for the augmented firm.

II. THEORETICAL FRAMEWORK

2.1 Complementarity stated formally

Let output Y depend on a vector of practices $p = (p_1, \ldots, p_n)$ and on a technology parameter θ. Practices i and j are complements when $\partial^2 Y/\partial p_i \partial p_j > 0$, so that the marginal product of one rises with the level of the other. When this holds for every pair, Y is supermodular in p and the optimal configuration is a corner: adopt everything or adopt nothing, since partial adoption is dominated. The classical evidence is precisely a test of this property, and the null result on isolated practices is precisely what supermodularity predicts [1], [6].

Two consequences of supermodularity matter for what follows. The first is that the complementarity premium — the excess of the observed bundle effect over the sum of the individual effects — is the quantity of interest, not the bundle effect itself. A bundle can retain a large total effect while its premium collapses, and the two carry entirely different managerial implications: the first says keep doing what you are doing, the second says the practices can now be adopted separately and sequenced by cost. Figure 1 decomposes the two cases.

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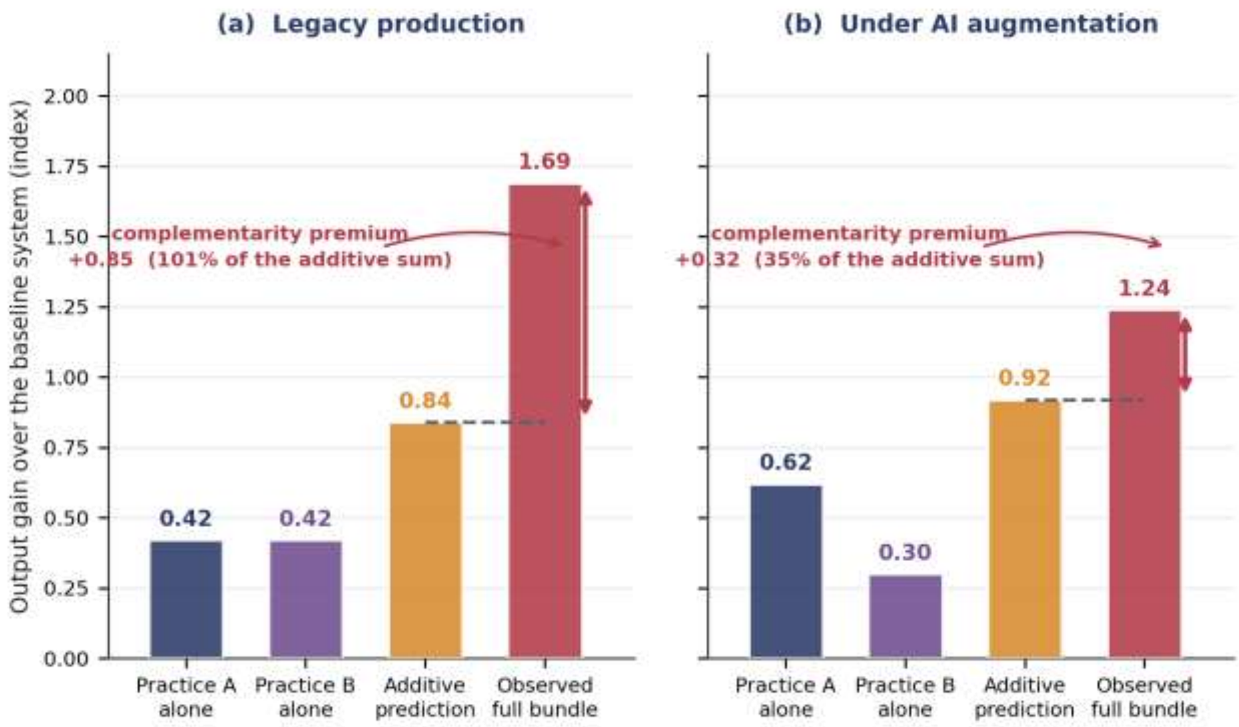
Figure 1 Superadditivity of the bundle, before and after augmentation



Augmentation raises the return to practice A alone and lowers the return to practice B alone, while the interaction term shrinks by roughly two-thirds. The bundle still beats either practice on its own, but by far less than the legacy literature would predict. Values are illustrative.

Figure 1 separates the level effect from the interaction effect. Augmentation can raise total output while shrinking the premium that made simultaneous adoption necessary.

The second consequence is that the technology parameter θ enters the cross-partial, not merely the level. A general-purpose technology that changes $\partial^2 Y/\partial p_i \partial p_j$ changes which practices must be adopted together, which is a far more disruptive event for HR architecture than one that simply raises Y. The question this paper asks is therefore whether AI augmentation is a level shifter or a cross-partial shifter, and the answer determines whether the practice literature needs updating or replacing.

2.2 Why augmentation is a candidate cross-partial shifter

Four features of generative AI make it a plausible disturbance to the interaction terms rather than only to the level. It supplies codified knowledge on demand, which substitutes for one of the things training and information sharing formerly delivered. It compresses the performance distribution from below, which weakens the return to selecting for prior ability [12], [14]. It is unreliable in a way that is not visible from the task description, so that output quality now depends on a verification capability that classical bundles never had to specify [14]. And its returns depend on complementary intangible investment with long build times, which relocates the gains into a period the firm's accounts will initially record as a productivity decline [20]. Each of these operates on a specific interaction term, and Section VI treats them individually.

III. LITERATURE REVIEW

3.1 The canonical practice–productivity evidence

The modern literature opens with survey evidence that innovative work practices were spreading unevenly across United States establishments and that their adoption was correlated with a distinct organisational logic rather than being drawn at random [21]. Cross-sectional work then established a large association between high-performance work practice indices and firm performance, reporting substantial effects on turnover, productivity and financial performance across roughly a thousand firms [22]. The identification problem in that design was immediately obvious, and the field's decisive contribution was the move to homogeneous technology and long panels. Studying finishing lines producing an almost identical physical product, researchers were able to hold technology constant and observe the practice system directly, finding large system effects and null effects for isolated practices [1]; the insider-estimate follow-up confirmed that managers themselves valued the complementary practices well above the incentive-pay component alone [23].

Parallel work in the world automobile industry showed that practice bundles interacted with production-system design, so that flexible production and human resource bundles reinforced one another [2]. The theoretical account was consolidated in the manufacturing-advantage synthesis, which specified the ability–motivation–opportunity structure through which bundles operate [24]. Sceptical work using nationally representative establishment data found weaker and less consistent effects, and remains the strongest internal challenge to the literature [25]. Two meta-analyses substantially resolved the dispute in favour of the bundle: the practice–performance association is real, is larger for systems than for individual practices, and is larger in manufacturing than in services [3], with the mediating pathways running through human capital and motivation rather than through cost reduction [4].

3.2 The technology–organisation complementarity extension

The second stream established that the returns to technology depend on organisational practice. Establishment-level evidence showed that the productivity effect of computer investment was conditional on workplace practices such as employee voice and profit sharing [8]. Firm-level evidence identified a three-way complementarity between information technology, decentralised work organisation and worker skill, with all three required jointly [9]. Longer panels found that measured IT returns rise substantially with the time horizon, consistent with slow accumulation of organisational capital [10]. Cross-country management-practice measurement showed large and persistent dispersion in practice quality that accounts for a material share of productivity differences between firms and nations [26], [27], and the multinational evidence showed that United States firms extracted higher returns from the same technology because they operated different people-management practices [11]. The productivity accounting literature situated all of this within the broader question of what determines firm-level productivity dispersion [28], while the J-curve model formalised why a general-purpose technology depresses measured productivity before raising it: firms invest in unmeasured intangible complements first, and the output appears only later [20].

3.3 The AI augmentation evidence

The third stream is barely three years old and already unusually well identified. A staggered deployment across 5,172 customer-support agents found a 15 per cent average increase in issues resolved per hour, concentrated almost entirely among novices and the lowest-skill quintile, with the most experienced agents gaining little and showing small quality declines; the authors interpret the mechanism as the model capturing and disseminating the behaviour of the firm's most productive agents [12]. A field experiment with 758 consultants found a 12.2 per cent increase in tasks completed, 25.1 per cent faster completion and a quality gain above 40 per cent on tasks inside the model's competence frontier, but a 19 percentage point fall in correctness on a task lying outside it, with below-average performers gaining 43 per cent against 17 per cent for above-average performers [14]. Three randomised controlled trials with 4,867 developers found a 26.1 per cent increase in completed pull requests, again concentrated among the less experienced [13], consistent with earlier Copilot evidence [29]. Experimental evidence on writing tasks found large time savings alongside quality improvement [30].

The firm-level and macroeconomic evidence tells a different story, and the contrast is the empirical core of this paper. Matched data on more than 12,000 European and United States firms find a 4 per cent labour productivity gain from AI adoption, driven by capital deepening, with the authors emphasising the critical role of complementary investment in software, data and workforce training in unlocking it [15]. Canadian firm data show adopters with 16.8 per cent higher labour productivity than non-adopters, but the premium falls to 5.1 per cent and loses statistical significance once selection and complementary investments in research, cloud, analytics and training are controlled for [16]. A survey of 748 corporate executives finds reported labour productivity gains of 1.8 per cent in 2025 rising to 3.0 per cent expected in 2026, but implied gains computed from reported revenue and employment of only 0.6 per cent and 1.8 per cent respectively [17]. Danish administrative data linked to adoption surveys covering some 25,000 workers find null effects on earnings and hours two years after the technology became available, despite widespread adoption and substantial worker-reported time savings [18]. The most careful macroeconomic treatment estimates a total factor productivity gain of 0.71 per cent over ten years, bounded above by 0.55 per cent once hard-to-learn tasks are distinguished, on the basis that roughly 19.9 per cent of tasks are exposed and only about 23 per cent of those are profitably automatable within the decade [19], [31], [32].

Adoption is not the constraint. Roughly 41 per cent of the United States workforce reported using generative AI at work as of late 2025, with 12 per cent using it daily; 78 per cent of the labour force works at a firm that has adopted AI in some form, though only about 18 per cent of firms have done so on a firm-weighted basis [33], [34], and workplace survey evidence confirms that adoption is now reshaping role composition rather than remaining an individual practice [35]. The Danish evidence is more precise about what firm-led adoption actually adds: where employers combine encouragement, enterprise tools and training, adoption reaches 93 per cent and 19 per cent of workers report saving more than an hour a day, against 41 per cent adoption where the employer does nothing [18]. The gap between what the technology can do in a task and what it delivers in a firm is therefore not an adoption gap. It is a complementarity gap.

3.4 The human resource tradition on capability, structure and AI

The HRM literature has approached augmentation from the practice side, and the present author's prior work in this series

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traces the relevant arc. Early treatments framed talent management as the identification and development of scarce human capability [36], while evidence on appraisal and engagement established that recognition, feedback quality, perceived fairness and managerial support are the proximate determinants of discretionary effort, with fairness the strongest single correlate [37] — a result that matters here because it identifies the motivational leg of the bundle as psychological rather than technological, and therefore as unlikely to be performed by a model. Sector evidence on employee performance and motivation in manufacturing reinforced the point that productivity responds to the practice environment rather than to individual capability alone [38].

The structural leg of the bundle has been examined directly. Analysis of departmental structure and task achievement shows that functional and matrix configurations produce measurably different completion rates, agility and satisfaction, and that clarity of role definition and communication pathways is what converts structure into efficiency [39] — which is precisely the interaction term that augmentation stresses, since a model that redistributes information across roles alters the value of any given structural configuration. Complementary work on delegated authority establishes that decision rights themselves carry productivity consequences [40], and work on leadership and workforce burnout shows that the capability to sustain performance is a leadership variable rather than a tooling variable [41].

On augmentation itself, work on AI-enabled hiring analytics documents how rapidly screening, matching and prediction are being automated, and poses the efficiency-versus-fairness problem that arises when selection is delegated to a model [42] — directly relevant here, because if selection is the practice whose complementarity is most eroded by skill compression, then the case for investing in ever more sophisticated selection technology weakens at exactly the moment the technology becomes available. Broader treatments of the role of human resource management in leveraging artificial intelligence position the function as the mechanism through which technological capability is converted into organisational capability [43], and the reskilling literature specifies the training architecture that conversion requires under conditions of technological displacement [44]. The strategic HRM account of economic resilience makes the macro-level version of the same argument: skill diversification and labour-market fluidity are constitutive of resilience under technological disruption rather than threats to it, and firms that respond by freezing their existing workforce configuration forgo the reconfiguration that resilience requires [45].

Three further strands complete the picture. Work on building future-ready organisations identifies leadership capability and continuous capability-building as the primary organisational technologies of the coming decade [46]. Work on talent designation and social comparison shows that formal high-potential labelling produces growth effects but also comparison costs among the undesignated [47] — a finding with direct bearing on augmentation, since a technology that lifts the bottom of the distribution mechanically compresses the status hierarchy that designation systems depend on. And the study of enterprise resource planning in the Indian higher-education sector documents the migration of institutional knowledge from individuals into codified systems [48], which is the same substitution that AI performs at greater speed. Evidence on employee perspectives in the Bengaluru technology cluster provides the labour-market complement, showing that learning opportunity and autonomy dominate compensation in the decisions of skilled staff [49].

3.5 The research gap

Three gaps follow. The classical practice literature established complementarity on production technologies that no longer describe knowledge work, and has not been re-estimated under augmentation. The AI evidence measures effects at the task and worker level with excellent identification but has not been connected to the practice architecture that would explain why those effects fail to aggregate. And the scenario and forecasting literature on AI and productivity has proceeded almost entirely through task-exposure accounting, treating organisational practice as a residual rather than as the mechanism. This paper addresses all three by decomposing the bundle, connecting the two evidence bases through the complementarity structure, and building scenarios whose distinguishing variable is the rate at which firms construct organisational complements.

IV. METHOD

4.1 Evidence assembly

The evidence base was assembled following a protocol adapted from the PRISMA 2020 reporting standard [50], reported in Table 1. Two distinct bodies of work were searched. The canonical stream covered 1990 to 2012 and required a measured association between a multi-practice human resource system and a productivity or performance outcome, with an explicit treatment of complementarity or interaction. The augmentation stream covered January 2023 to June 2026 and required a measured effect of generative AI access or adoption on a productivity outcome, identified by randomisation, staggered deployment, matched comparison or a structural model. Forty-one studies were retained, nineteen from the canonical stream and twenty-two from the augmentation stream.

Table 1. Evidence assembly protocol and scenario architecture

Protocol element	Canonical stream	Augmentation stream
Window	January 1990 to December 2012	January 2023 to June 2026
Databases	EconLit; Web of Science; Scopus; JSTOR; NBER	Scopus; EconLit; NBER and SSRN series; arXiv; central-bank and statistical-agency series
Treatment construct	Adoption of a multi-practice human resource system, or measured variation in a practice index	Access to, or firm adoption of, generative AI tools
Outcome construct	Physical productivity, labour productivity, TFP, or an established performance composite	Task completion, output per hour, labour productivity, earnings, TFP
Identification required	Panel with technology held constant, establishment fixed effects, or a defensible practice index	Randomisation, staggered deployment, matched comparison, administrative linkage, or structural model
Complementarity requirement	Explicit treatment of interaction, bundling or system effects	Not required; complement investment coded where reported
Excluded	Cross-sectional incidence correlations without identification; attitudinal outcomes only; single-practice studies without a system comparison	Self-reported adoption without an outcome; vendor studies; benchmark performance of models rather than of workers
Retained	19 studies	22 studies
Scenario driver	Not applicable	Rate and character of organisational complement investment
Scenario bounds	Not applicable	Anchored below by the published aggregate TFP estimate and above by the institutional labour-productivity range

Because the two streams differ fundamentally in unit of analysis, outcome scaling and identification, no pooled estimate is computed and none should be. What is compared is the direction and the order of magnitude of effects at each level of aggregation, which is sufficient for the question at hand: the augmentation gap is a gap of an order of magnitude and does not depend on precision-weighted estimation to be visible.

4.2 Scenario architecture

The forward analysis follows the standard scenario-planning discipline of holding the driving uncertainty explicit and letting the scenarios differ only in it [51]. The driving uncertainty here is the rate at which firms build the organisational complements that convert task-level gains into firm-level productivity — training architecture, decision-right reallocation, verification capability, workflow redesign and data infrastructure. Three scenarios span the range: substitution-led, complementary deepening and fragmented frontier. Each is specified by its assumptions on complement investment, on the direction of task redesign and on the diffusion of practice across the firm size distribution, and each is carried through to a total factor productivity path in Section VIII. The paths are constructions from the stated assumptions and are anchored at the low end by the published macroeconomic estimate [19] and at the high end by the more optimistic institutional range [16]; they are not forecasts and are not offered as such.

V. THE EMPIRICAL RECORD RE-ASSEMBLED

5.1 What the canonical evidence established

Table 2 sets out the canonical stream. Four findings recur across it with enough consistency to be treated as established. Systems of practices outperform individual practices, and individual practices adopted alone frequently produce nothing measurable. The magnitude of the system effect is large — on the order of a several-percentage-point productivity difference between full and traditional systems, and larger still in the meta-analytic estimates where the outcome is broadened beyond physical productivity. The effect is larger in manufacturing than in services, which is consistent with a mechanism operating through the coordination of physically interdependent tasks. And the practice system interacts with technology, so that the same capital equipment yields different productivity depending on the organisational configuration around it.

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Table 2. The canonical practice–productivity evidence, 1990–2012

Study and setting	Design	Finding on complementarity	Magnitude
Ichniowski, Shaw and Prennushi (1997); 36 steel finishing lines	Panel with production technology held nearly constant; line and time effects	Coherent systems of practices raise productivity; individual practices adopted in isolation have no effect	Substantial productivity difference between full and traditional systems; null for isolated practices
MacDuffie (1995); world auto assembly plants	International plant-level comparison	HR bundles interact with flexible production systems; the logic is the system, not the practice	Bundle indices predict productivity and quality; single practices do not
Huselid (1995); ~1,000 US firms	Cross-section with instrumentation	High-performance work practice index associated with turnover, productivity and financial performance	Large associations; identification contested
Osterman (1994); US establishments	Nationally representative survey	Adoption is clustered rather than random, consistent with an underlying organisational logic	Descriptive
Cappelli and Neumark (2001); US establishments	Representative establishment panel	Effects weaker and less consistent; labour costs rise alongside output	The principal internal challenge to the literature
Combs, Liu, Hall and Ketchen (2006); meta-analysis	Meta-analysis of 92 studies	System measures show larger effects than individual practices; effects larger in manufacturing	Practice–performance association confirmed; system premium confirmed
Jiang, Lepak, Hu and Baer (2012); meta-analysis	Meta-analytic path model	Effects operate through human capital and motivation, not through cost reduction	Mediation established
Black and Lynch (2001); US manufacturing	Establishment panel with capital controls	Computer investment raises productivity conditional on workplace practice	Technology effect contingent on organisation
Bresnahan, Brynjolfsson and Hitt (2002); US firms	Firm-level panel	Three-way complementarity between IT, decentralised organisation and worker skill	All three required jointly
Brynjolfsson and Hitt (2003); US firms	Multi-horizon firm panel	Measured IT returns rise with the horizon, consistent with slow organisational capital accumulation	Long-difference returns several times the short-difference returns
Bloom and Van Reenen (2007); international	World Management Survey	Large, persistent dispersion in practice quality explains part of productivity dispersion	Practice score strongly associated with productivity and survival
Bloom, Sadun and Van Reenen (2012); European establishments	Multinational ownership comparison	US-owned firms extract higher IT returns through different people-management practices	Practice, not technology, carries the difference

5.2 What the augmentation evidence establishes

Table 3 sets out the augmentation stream, separated by unit of analysis. Read at the task level it is the most encouraging evidence for a new general-purpose technology in decades. Read at the firm level it is the productivity paradox restated with better data. Figure 2 places the two panels side by side on a common scale.

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Table 3. The AI augmentation evidence, 2023–2026, by unit of analysis

Study and population	Level	Design	Headline result	Heterogeneity
Brynjolfsson, Li and Raymond (2025); 5,172 customer-support agents	Worker	Staggered deployment with firm and time effects	+15% issues resolved per hour; customer sentiment up ~0.18 points; attrition falls	+30% for the lowest-skill quintile; near zero and small quality declines for the most experienced
Dell'Acqua et al. (2023); 758 BCG consultants	Task	Pre-registered field experiment	Inside frontier: +12.2% tasks completed, +25.1% speed, +40% quality. Outside frontier: correctness falls 19 percentage points	+43% for below-average performers against +17% for above-average
Cui et al. (2025); 4,867 developers at three firms	Worker	Three randomised controlled trials	+26.1% completed pull requests; +13.6% commits; no overall decline in build success	+27–40% for junior developers against +7–16% for senior
Noy and Zhang (2023); professional writing tasks	Task	Randomised online experiment	Large reduction in time to complete with quality maintained or improved	Gains concentrated among lower-ability writers
Peng et al. (2023); GitHub Copilot	Task	Controlled experiment	Substantial reduction in task completion time for a standardised programming task	Larger for less experienced developers
Bank for International Settlements (2025); >12,000 EU and US firms	Firm	Matched firm panel with exposure measure	+4% labour productivity; no adverse employment effect; higher wages in adopting firms	Concentrated in medium and large firms; complementary software, data and training investment identified as critical
Statistics Canada (2026); Canadian firms	Firm	Adopter versus non-adopter with selection and complement controls	Raw premium of 16.8% falls to 5.1% and becomes statistically insignificant once complements are controlled	Firms with analytics capability 15 percentage points more likely to adopt
Atlanta and Richmond Fed (2026); 748 executives	Firm	Executive survey with implied-productivity computation	Reported gains 1.8% (2025) and 3.0% expected (2026); implied gains 0.6% and 1.8%	Gains concentrated in finance and high-skill services
Humlum and Vestergaard (2025); ~25,000 Danish workers	Worker and firm	Adoption survey linked to administrative records	Null effects on earnings and hours; intervals exclude effects above 2%	93% adoption where encouragement, tools and training are combined, against 41% where the employer does nothing
Acemoglu (2025); US economy	Economy	Task-based macroeconomic accounting	TFP gain of 0.71% over ten years; 0.55% once hard-to-learn tasks are distinguished	19.9% of tasks exposed; ~23% of those profitably automatable within the decade
Federal Reserve Board (2026); US economy	Economy	Adoption monitoring	41% of workers use generative AI at work; 12% daily; 78% of the labour force at adopting firms	18% of firms firm-weighted; manufacturing adoption far below services

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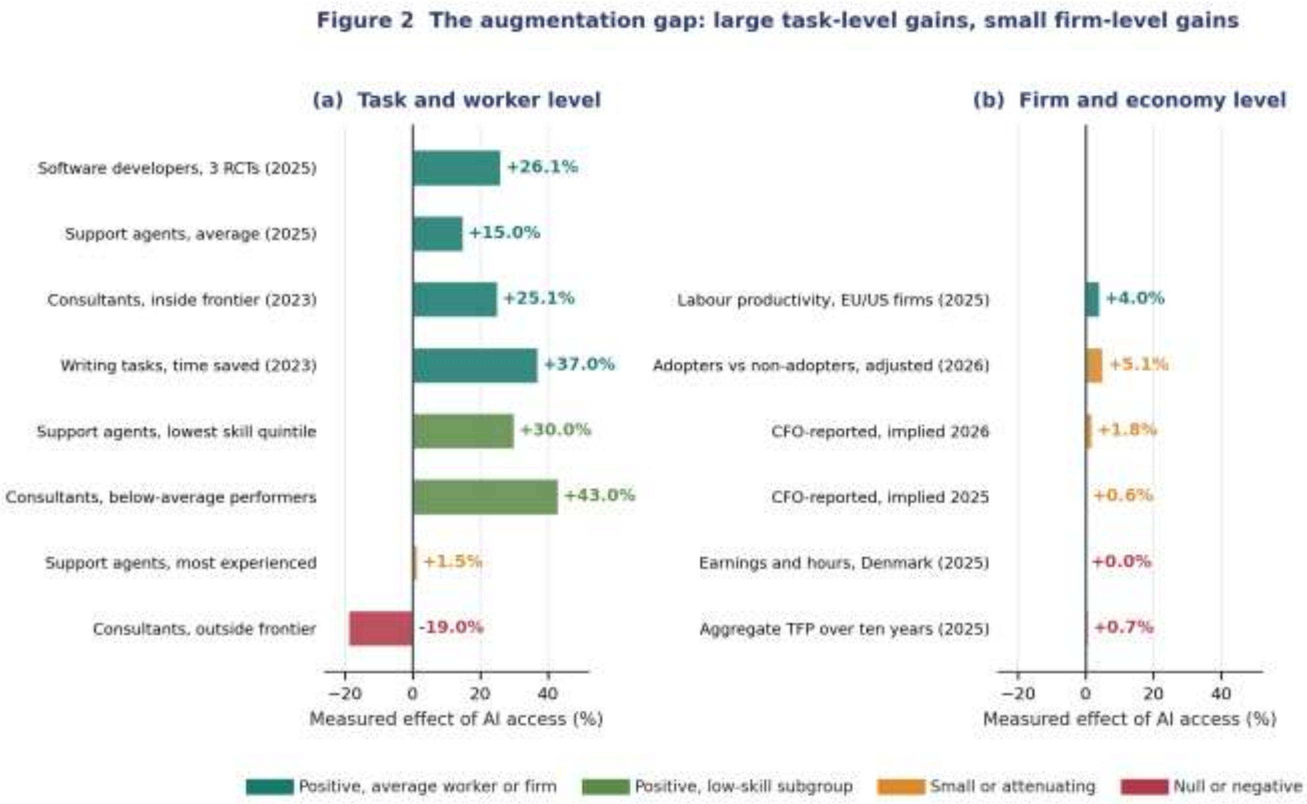

Figure 2 is the central empirical exhibit. Both panels are drawn on the same axis; the difference in scale between them is the finding, not an artefact of presentation.

5.3 Why the task-level gains do not aggregate

Five mechanisms account for the gap, and they are not mutually exclusive. Composition: task-level studies select tasks on which the model performs well, and the consultant experiment demonstrates directly that performance reverses on tasks that look similar but lie outside the model's competence frontier [14]. Reallocation without absorption: 85 per cent of Danish workers reallocated their time savings to other tasks rather than to leisure, but a saved hour becomes measured productivity only if the firm has somewhere valuable to put it [18]. Verification cost: output that requires checking has a lower net value than output that does not, and the checking labour is rarely counted in the task-level estimate. Intangible build time: the J-curve predicts exactly this pattern, with complement-building suppressing measured productivity before the returns appear [20]. And missing complements: the Canadian result is the cleanest single piece of evidence here, since the adopter premium collapses from 16.8 per cent to an insignificant 5.1 per cent once complementary investment is controlled for, which says the premium was substantially the complements rather than the technology [16], a reading the European firm evidence supports directly [15].

The fifth mechanism is the one this paper is about, and it converts the augmentation gap from a puzzle into a human resource problem. If firm-level returns to AI are contingent on organisational complements, and if the human resource function owns most of those complements, then the function is currently the rate-limiting factor on the aggregate productivity effect of the most significant general-purpose technology since electrification.

VI. FIVE DISTURBANCES TO THE COMPLEMENTARITY STRUCTURE

Complementarity is not a property of a practice but of a pair of practices under a technology. This section identifies five specific disturbances that augmentation introduces into the cross-partial derivatives, summarised in Table 4 and assessed in Figure 3.

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Table 4. Five disturbances to the complementarity structure

Disturbance	Mechanism	Interaction term affected	Direction	Principal evidence
Skill compression	Gains concentrate at the bottom of the ability distribution, raising the floor faster than the ceiling	Selective hiring × incentive pay; selective hiring × training	Strongly weakened	Brynjolfsson et al. (2025); Dell'Acqua et al. (2023); Cui et al. (2025)
Knowledge codification	The model supplies codified organisational knowledge on demand and diffuses best-performer behaviour	Information sharing × team working; training × job rotation	Weakened over the codifiable domain	Brynjolfsson et al. (2025); enterprise-systems evidence
The jagged frontier	Model competence boundaries do not track perceived task difficulty, so failures are invisible ex ante	Tool deployment × verification, escalation and accountability design	Strongly strengthened; a new term	Dell'Acqua et al. (2023)
Measurement change	Output is jointly produced by worker and model, and performance variance narrows	Incentive pay × appraisal; talent designation × motivation	Weakened	Skill-compression results; talent-designation evidence
Adjustment lag	Intangible complements are expensed before their output is measured	All terms × time; complement investment × subsequent productivity	Strengthened but deferred	Brynjolfsson, Rock and Syverson (2021); Acemoglu (2025)

6.1 Skill compression inverts the selection complementarity

The classical bundle paired selective hiring with incentive pay and training on the reasoning that superior raw ability, correctly motivated and developed, produces disproportionate output. Augmentation attacks the first term. Every well-identified study finds gains concentrated at the bottom of the distribution: a 30 per cent gain for the lowest-skill quintile of support agents against little for the most experienced [12], 43 per cent for below-average consultants against 17 per cent for above-average [14], and 27 to 40 per cent for junior developers against 7 to 16 per cent for senior ones [13]. New agents with two months of AI-assisted tenure matched the performance of untreated agents with six months or more [12]. This is skill-biased technological change running in reverse, and it mechanically reduces the marginal return to selecting for prior ability, which reduces the complementarity between selection and everything the classical bundle paired it with.

6.2 Codification weakens the information-sharing complementarity

Information sharing and team working were complements because knowledge held by one worker was expensive to move to another. A model that supplies codified organisational knowledge on demand performs part of that transfer at near-zero marginal cost, and the support-agent evidence is explicit that the mechanism is the diffusion of the best performers' behaviour to everyone else [12]. This is the same substitution that enterprise systems performed more slowly for institutional process knowledge [48]. It does not eliminate the value of information sharing — tacit, contextual and strategic knowledge remain outside the model — but it narrows the domain over which the complementarity operates.

6.3 The jagged frontier raises the verification complementarity

The single most important organisational finding in the augmentation literature is that model competence is jagged: capability boundaries do not follow the contours of task difficulty as a human would perceive them, so a worker cannot infer from a task's apparent difficulty whether the model will succeed or fail [14]. A 19 percentage point fall in correctness on an outside-frontier task, occurring in a population of professional consultants, is a governance failure rather than a skill failure. This creates a complementarity that the classical bundle never had to specify: between the deployment of the tool and the design of verification, escalation and accountability around it. It is the strongest new interaction term in the augmented production function and the one least represented in current practice.

6.4 Measurement change destabilises the incentive complementarity

Incentive pay complements other practices only where individual contribution is measurable and attributable. Augmentation degrades attributability in two directions at once: output is now jointly produced by worker and model, and the compression of the performance distribution reduces the variance that incentive schemes are designed to reward.

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Where the technology raises the floor faster than the ceiling, the dispersion on which pay-for-performance depends narrows. This also disturbs the status architecture that talent-designation systems rest on, since designation derives its motivational force from visible differentiation [47].

6.5 Adjustment lag relocates the return in time

The J-curve result establishes that general-purpose technologies depress measured productivity while their intangible complements are being built, and that the recorded return appears only after the build [20]. Firms currently reporting disappointing returns may be at the trough rather than at the ceiling. The corollary for practice is uncomfortable: the complement investment must be made before the measured return justifies it, which requires a firm to act on a theory rather than on its own management accounts. The historical adoption evidence suggests a J-curve of no less than two decades for previous digital technologies [19], [20].

Figure 3 Re-weighting of practice complementarities under AI augmentation

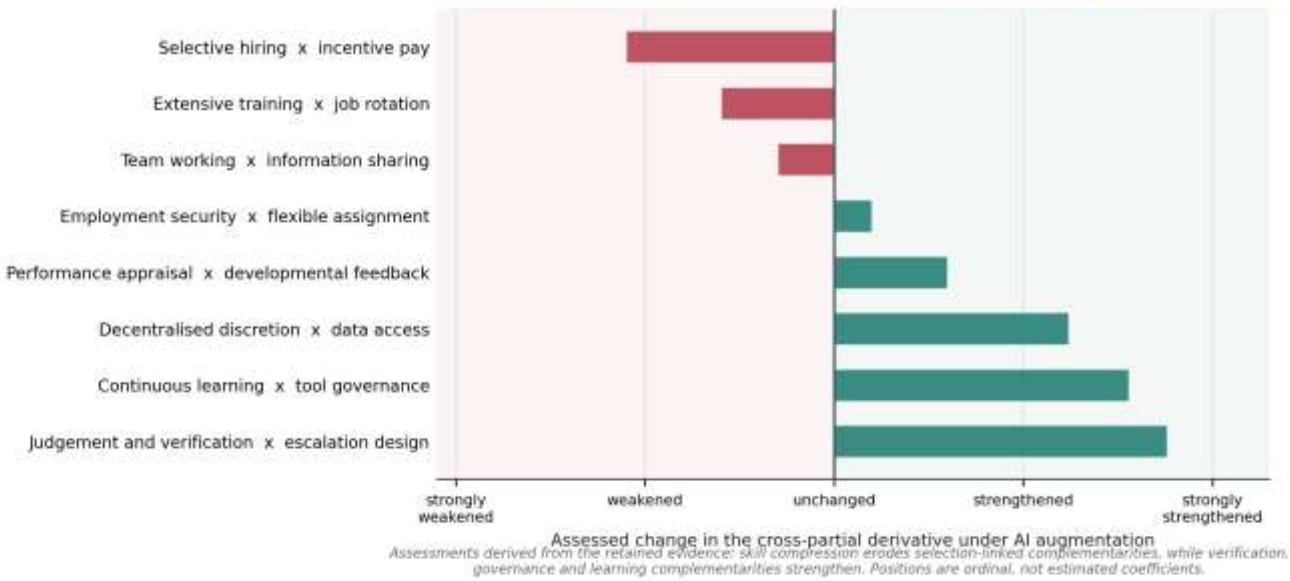

Figure 3 assesses the direction of change in each cross-partial derivative. The pattern is not dissolution but rotation: the bundle's centre of gravity moves from selection and incentives towards governance, discretion and learning.

VII. RE-ESTIMATION: DOES THE BUNDLE STILL HOLD?

Six propositions follow from the assembled evidence and the disturbance analysis.

Proposition 1: complementarity survives, but the bundle rotates

The evidence does not support the dissolution hypothesis. If AI substituted for organisational practice, adopters would show productivity gains independent of complementary investment; instead the Canadian adopter premium collapses when complements are controlled for [16], the European gain is explicitly attributed to complementary software, data and training investment [15], and Danish adoption reaches 93 per cent and delivers substantial reported time savings only where the employer supplies encouragement, tools and training together [18]. That last result is a bundle finding in the classical form: three practices adopted jointly produce an outcome that none produces alone. Complementarity is intact. What has changed is which practices are in the bundle.

Proposition 2: the complementarity premium is smaller, and the bundle is less all-or-nothing

Two of the five disturbances weaken interaction terms and three strengthen them, but the weakened terms sit at the historical core of the high-performance work system while the strengthened terms are new and thinly implemented. The practical consequence is that the strict corner solution of the classical model — adopt everything or nothing — is a weaker prescription than it was. A firm can now sequence: verification design and tool governance can be built before selection systems are overhauled, and will pay off on their own. This is a genuine change in HR strategy, and it lowers the entry cost of the augmented bundle for smaller firms, which the firm-size evidence indicates are currently being left behind [15].

Proposition 3: training rises in importance while selection falls

The classical bundle treated selection and training as complements to one another. Augmentation splits them. Selection's marginal return falls with skill compression, while training's rises for three reasons: the technology changes faster than the workforce, the verification capability is a trained capability rather than a selected one, and the Danish result shows training to be one of the three employer initiatives that

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jointly determine whether adoption produces anything [18]. The reskilling architecture becomes the load-bearing element of the augmented bundle rather than a support function [44], [45].

Proposition 4: decision rights become the binding constraint

The three-way complementarity between technology, decentralisation and skill established for information technology [9] reappears under augmentation in sharper form. A model that supplies analysis to a worker who lacks authority to act on it produces no output. The reallocation finding is the direct evidence: 85 per cent of workers redirected time savings to other tasks [18], but whether those other tasks were valuable depends on decision rights and workflow design, which the evidence on delegated authority identifies as a measurable determinant of effectiveness [40] and which structural configuration governs [39].

Proposition 5: the gains accrue where the workflow is redesigned, not where the tool is deployed

The distinction between a point solution, which inserts a technology into an existing workflow, and a system solution, which reorganises the workflow around the new capability, is the organising insight of the applied AI literature [52], and the augmentation gap is what a population of point solutions looks like in aggregate statistics. The executive survey evidence is consistent: reported gains concentrate in high-skill services where workflow redesign is cheapest, and firms expect compositional reallocation away from routine clerical work towards skilled technical roles rather than uniform efficiency gains [17].

Proposition 6: augmentation strategies dominate substitution strategies for total factor productivity

The macroeconomic case for modest aggregate effects rests on the observation that only about a fifth of tasks are exposed and only a fraction of those are profitably automatable within a decade [19], [31], [32]. Automation of that fraction produces a bounded, one-time cost saving. Augmentation of the remainder — raising the output of workers on tasks that are not automatable — has a far larger base, and the task-level evidence indicates the effects on that base are large. The strategic error the literature warns against is designing for human replacement rather than for human capability extension, since the former forgoes the larger prize [53]. The scenario architecture in the next section is built on precisely this fork.

VIII. THREE AUGMENTED SCENARIOS TO 2035

Table 5 specifies the three scenarios and Figure 4 traces their illustrative total factor productivity paths. The scenarios differ only in the rate and character of complement investment; they share the same assumptions about model capability, which is deliberate, since the argument of this paper is that capability is not currently the binding constraint.

Table 5. Three augmented scenarios to 2035

Dimension	S1 Substitution-led	S2 Complementary deepening	S3 Fragmented frontier
Core assumption	AI is deployed to remove labour from exposed tasks; workflow and practice bundle left intact	AI is treated as a system innovation; the practice bundle is rebuilt around it	Complement investment occurs but is concentrated in large firms and a few sectors
Complement investment	Minimal; tooling only	High and sustained; training, verification, decision rights, data and workflow	Bifurcated: high in the leading decile, minimal elsewhere
Bundle status	Legacy bundle degrades without replacement	Bundle rotates towards governance, discretion and learning	Two bundles coexist; dispersion widens
Task design	Task elimination	Task redesign and reallocation towards judgement-intensive work	Redesign in the leading firms; point solutions elsewhere
Measured TFP path	Front-loaded rise, then a ceiling as automatable tasks are exhausted	J-curve: trough while complements are built, then compounding gains	Shallow, steady rise held down by the unaugmented majority
Illustrative 2035 TFP growth	≈ 2.3% and flattening	≈ 3.7% and still rising	≈ 1.5%
Employment signature	Routine clerical decline; limited creation	Compositional shift towards verification, judgement and technical roles	Polarisation between augmented and unaugmented firms
Leading indicator	Headcount reduction announcements outpacing workflow redesign	Rising training intensity and formal verification architecture	Widening productivity dispersion by firm size
Current evidence	Consistent with large-firm expectations in executive reporting	Consistent with the Danish combined-initiative result and the European complement finding	Consistent with the observed firm-size gradient — the modal scenario on present data

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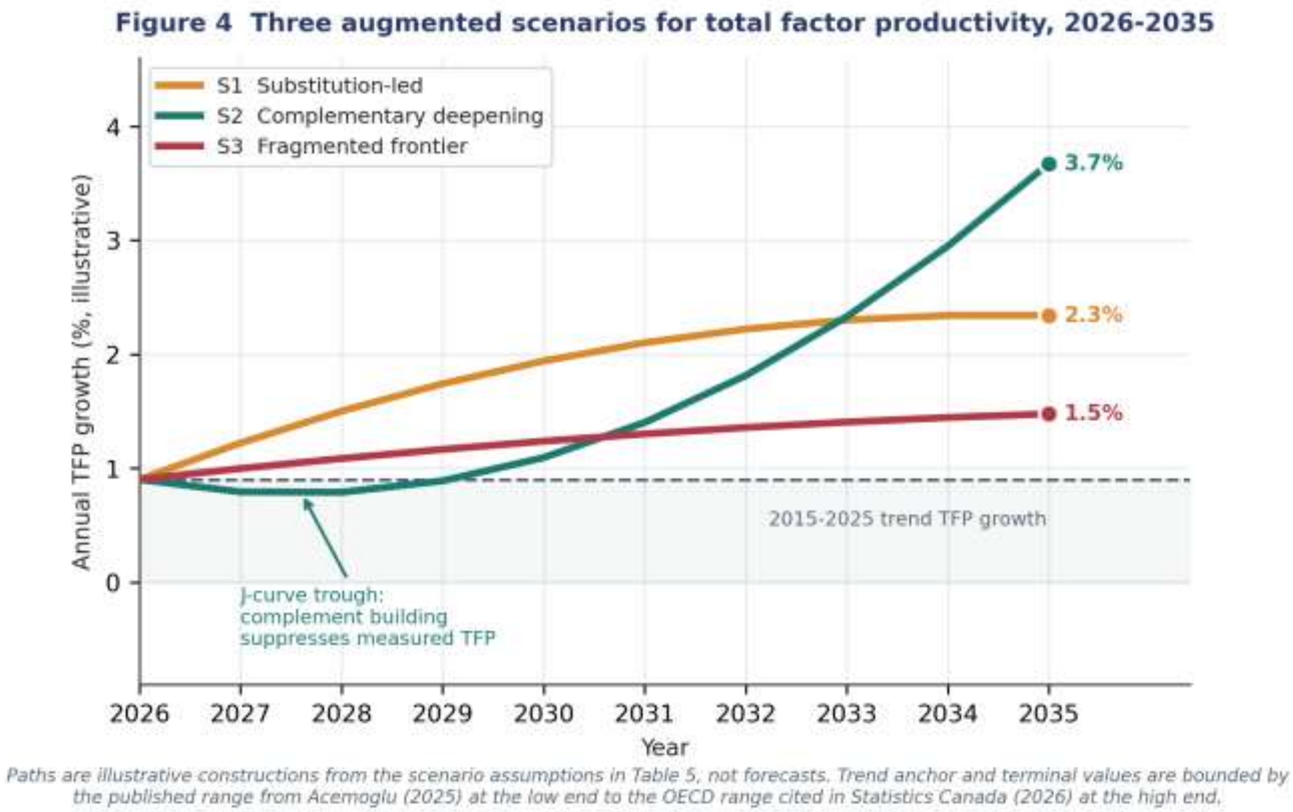

Figure 4 traces the three paths. The characteristic signature of the complementary-deepening scenario is that it looks worst for several years before it looks best, which is the practical difficulty with acting on it.

8.1 Scenario 1: substitution-led

Firms deploy AI to reduce headcount on exposed tasks without redesigning workflow or rebuilding the practice bundle. Gains are front-loaded, real and bounded: the cost saving on automatable tasks is captured quickly, measured productivity rises for two to four years, and then the ceiling that task-exposure accounting predicts is reached [19]. Complementarity is not rebuilt; the classical bundle degrades without replacement; verification failures accumulate quietly in the tail of the output distribution. This scenario is the most consistent with what the executive survey currently observes in larger firms, which anticipate workforce reductions while smaller firms expect modest hiring increases [17].

8.2 Scenario 2: complementary deepening

Firms treat augmentation as a system innovation and invest in the re-specified bundle: verification and escalation architecture, decision-right reallocation, continuous learning infrastructure, data and workflow redesign. Measured productivity falls or stagnates first, because the investment is expensed and its output is unmeasured — the J-curve trough [20]. Returns then compound, because the complements are themselves complementary to one another and because the firm accumulates organisational capital that competitors cannot buy. This is the scenario in which total factor productivity growth meaningfully exceeds its recent trend, and it is the only one in which the task-level effect sizes aggregate.

8.3 Scenario 3: fragmented frontier

Complement investment occurs, but unevenly: concentrated in large firms, in high-skill services and in a handful of sectors, while the rest of the economy deploys point solutions. Aggregate total factor productivity rises modestly because the augmented sector is a minority of activity; productivity dispersion between firms widens, which is the pattern that management-practice measurement already documents [26], [11]; and the firm-size gradient observed in the European evidence persists or worsens [15]. On current adoption and practice data this is the modal scenario, which is why the policy discussion in Section X is addressed to diffusion rather than to invention.

IX. THE RE-SPECIFIED BUNDLE

Table 6 sets out the re-specified bundle practice by practice, stating the legacy role, the augmented role and the direction of change; Figure 5 renders the same content as a shift in emphasis weights.

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Table 6. The re-specified bundle for the augmented firm

Practice	Legacy role	Augmented role	Legacy weight	Augmented weight
Selective hiring	Screen for prior ability, on which all other practices build	Reserved for roles at the top of the jagged frontier where the model does not help; a bimodal rather than uniform strategy	9	6
Incentive pay	Convert selected ability into discretionary effort	Weakened by joint human–model production and narrowed performance variance; shifts towards team and outcome measures	8	4
Extensive training	Build firm-specific skill over a long amortisation period	Load-bearing. Tool capability, verification judgement and reskilling architecture, with a standing budget rather than project funding	8	9
Team working	Coordinate interdependent tasks and pool tacit knowledge	Retained for tacit and contextual knowledge; narrowed where the model supplies the codified component	9	6
Information sharing	Move information to the point of decision	Reframed as data access and provenance: the constraint is now which data the model and the worker may see	7	8
Employment security	Underwrite worker cooperation with change	More important, not less: workers will not surface model errors or redesign their own tasks under displacement threat	7	8
Discretion and decision rights	Give authority to those holding the information	Binding constraint. Analysis without authority to act produces no output; rights must be reallocated deliberately	6	9
Verification and tool governance	No counterpart in the legacy system	The new central practice. Sign-off thresholds, escalation design, accountability for model-assisted output, error measurement in the tail	1	10

Figure 5 The re-specified bundle for the augmented firm

Weights are ordinal emphasis scores derived from Table 6, on a 0-10 scale.

Figure 5 shows the rotation directly. The augmented bundle is not a smaller version of the legacy bundle but a differently shaped one, with its mass moved towards governance, discretion and learning.

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Three features of the re-specified bundle deserve emphasis. First, verification and tool governance enters as a practice that had no counterpart in the classical system, and it enters at the highest weight, because the jagged-frontier evidence makes it the condition on which output quality now depends [14]. Second, extensive training rises rather than falls, contrary to a common expectation that AI reduces the need for human capability development; the evidence says the opposite, since the technology changes faster than the workforce and since training is one of the three employer initiatives that jointly determine whether adoption yields anything [18]. Third, selective hiring and incentive pay fall in weight but do not disappear. They remain necessary for the roles that sit at the top of the jagged frontier, where the model does not help and where judgement is the scarce input — which means the augmented firm needs a bimodal talent strategy rather than a uniformly relaxed one.

X. IMPLICATIONS FOR PRACTICE AND POLICY

10.1 For the human resource function

Four implications follow directly. Build the verification layer before scaling deployment: define which decisions require human sign-off, train the judgement to exercise it, and measure error rates in the tail rather than averages in the centre. Reallocate decision rights deliberately rather than allowing them to drift, since analysis without authority produces nothing [40], [39]. Treat training as infrastructure with a standing budget rather than as a project, because the depreciation rate of tool-specific capability is now measured in quarters [44]. And re-found the motivational architecture on the practices the evidence identifies as durable — appraisal fairness, recognition, feedback quality and managerial support [37] — because these are the elements of the bundle that a model does not perform and that the compression of the performance distribution makes more rather than less important.

10.2 For measurement

The augmentation gap is partly a measurement artefact and should be attacked as one. Firms measure tool adoption and task-level time savings because both are cheap to observe, and neither predicts total factor productivity. The quantities that do — complement investment, workflow redesign, verification error rates, the share of reallocated time that reaches valuable work — are largely unmeasured. The discrepancy between executive-reported gains of 1.8 to 3.0 per cent and implied gains of 0.6 to 1.8 per cent from the same respondents is a direct estimate of how large the perception error currently is [17].

10.3 For policy

If the binding constraint is complement-building rather than model capability, then policy aimed at accelerating capability has limited marginal value while policy aimed at diffusing organisational practice has high marginal value. The firm-size gradient in the European evidence [15] and the practice-dispersion findings in the management-measurement literature [26] both point to the same instrument: support for management and workforce capability in small and medium firms, which is where the complement deficit is concentrated and where the aggregate productivity headroom therefore lies. For emerging economies with large services sectors and dense technology clusters, the strategic HRM case is that fluidity and skill diversification are the conditions of resilience under disruption rather than risks to be managed [45], [49].

XI. LIMITATIONS

Four limitations qualify these conclusions. The augmentation evidence base is three years old, covers a narrow set of occupations — customer support, software development, consulting and writing — and cannot yet speak to production, logistics, healthcare or the public sector, where the complementarity structure may differ substantially. The comparison between the canonical and augmentation streams is across different units of analysis and different outcome constructs, and is therefore a comparison of orders of magnitude rather than of estimates. The disturbance assessments in Figure 3 are ordinal judgements derived from the retained evidence, not estimated cross-partial derivatives; they are stated as such and should be treated as hypotheses for testing rather than as results. And the scenario paths are constructions from stated assumptions, bounded by published estimates but not themselves estimated; their function is to make the assumptions arguable, not to forecast.

XII. DIRECTIONS FOR FUTURE RESEARCH

Five directions follow. First and most important, the interaction between AI adoption and specific practice bundles has never been estimated directly; the Danish design, which observes employer encouragement, enterprise tooling and training separately and jointly, is the template, and it should be replicated with productivity rather than earnings as the outcome. Second, the verification complementarity is entirely unmeasured: no study yet estimates the return to formal verification and escalation architecture, although the jagged-frontier result implies it should be large. Third, the skill-compression finding needs testing over longer horizons, since a technology that lifts novices quickly may or may not still do so once the novices would otherwise have become experts, and the answer determines whether selection practices should be rebuilt or retired. Fourth, the J-curve prediction is directly testable on current data: firms that invested early in complements should show a measurable trough followed by a recovery, and identifying that pattern would convert a theoretical defence of disappointing returns into an empirical one. Fifth, the entire evidence base is drawn from high-income economies; the augmentation gap in labour-abundant economies with different relative factor prices is unexamined, and the Indian services sector is an unusually well-suited setting in which to examine it.

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XIII. CONCLUSION

The complementarity thesis has not been overturned by artificial intelligence. It has been re-weighted, and the re-weighting is substantial enough that a firm applying the classical high-performance prescription unchanged will be investing in the wrong half of its bundle. Selection and incentive complementarities weaken as the technology compresses the performance distribution from below. Verification, decision-right and learning complementarities strengthen sharply, and one of them — the governance of a tool whose competence boundary is invisible to its user — has no counterpart in the classical system at all.

The evidence for that conclusion is the augmentation gap. Task-level effects between 15 and 43 per cent sit alongside firm-level effects between zero and 5 per cent and an aggregate total factor productivity estimate below 1 per cent over a decade. A technology cannot be simultaneously that powerful in a task and that weak in a firm unless something between the task and the firm is missing. What is missing is the organisational complement, and the human resource function owns most of it. That is a larger claim about the function than the practice literature has previously made: not that human resource management contributes to productivity, but that it is currently the constraint on the productivity of the most consequential general-purpose technology of the present era.

The awkward corollary is that the firms doing the right thing will look, for several years, as though they are doing the wrong thing. Complement investment is expensed immediately and pays late, and the J-curve guarantees that measured productivity falls before it rises. Any organisation that manages this transition by its own quarterly productivity statistics will therefore abandon the correct strategy at precisely the point of maximum discouragement. Getting the bundle right is a matter of acting on the structure of the production function rather than on the current reading of the accounts — which is, in the end, what the complementarity literature has been saying since 1990.

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