

The Architecture of Compounding Advantage: Theoretical Foundations of the Kaivant Score

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Abstract

The dominant frameworks for measuring AI adoption are measuring the wrong thing. Deployment rates, productivity gains, and technology utilisation scores show whether organisations are using AI. They do not show whether organisations are built for it. This distinction matters because the main constraint on organisational performance in the AI era is structural, not technological. The underlying AI capabilities are widely accessible. First-mover advantages from early adoption are shrinking. The question that will determine competitive outcomes over the coming decade is not which organisations deployed AI first. It is which organisations have restructured themselves around what AI makes possible, while also developing the human capital those redesigns depend on.

The Kaivant Score is built around this two-axis claim. Leverage Architecture measures what the organisation's structural design has produced: how far coordination overhead has been reduced, how quickly decisions are made, and how much workflow runs without close oversight. Organisational Capital measures what the organisation is building towards: the learning infrastructure, human judgement capacity, capability development, and human dignity conditions under which leverage gains hold up over time. You cannot trade one axis off against the other. The instrument is constructed so that an organisation cannot average its way to a high score.

A third claim completes the theory. The two axes do not reinforce each other on their own. The compounding between them holds only where the organisation runs a deliberate loop around its use of AI: it governs AI, finds new value with it, changes the way it works, and measures, keeps and spreads the gains. Without that loop, gains on either axis come in episodes and fade.

A companion instrument, Kaivant-I, applies the same structural logic at the individual level. Its central tension is different: for an organisation, increasing AI-driven workflow autonomy is straightforwardly positive. For an individual, the same dynamic raises an augmentation-substitution question that output metrics cannot answer. Kaivant-I is designed to surface it.

This paper sets out the theoretical foundation for both instruments: the causal model, the two-axis architecture, the bridge dimension, the managed loop, the individual-level augmentation-substitution mechanism, the way the instruments move from a free, self-reported first reading to a verified Kaivant Score, and the two-layer design that separates the framework's stable intellectual claims from its versioned measurement layer.

I. The Measurement Problem

The most telling finding in enterprise AI research in 2026 is not how much organisations have invested in AI. It is the gap between that investment and its measurable consequences. A survey of nearly 6,000 senior executives in the United States, the United Kingdom, Germany and Australia found that 69 per cent of firms use AI, yet around nine in ten report no impact of AI on employment or productivity over the previous three years (Yotzov et al., 2026). Research based on the CFO Survey, run by Duke University with the Federal Reserve Banks of Richmond and Atlanta, documents what its authors call a productivity paradox: perceived productivity gains are larger than measured ones, which they link to a likely delay before the gains show up in revenue (Baslandze et al., 2026). Economic history points to a deeper reason. General-purpose technologies pay off only after organisations make large complementary investments in new processes, skills and structures, and while those investments are being made, measured productivity understates what is being built (Brynjolfsson, Rock and Syverson, 2021).

These findings do not describe an implementation failure. They describe a measurement failure. Organisations are investing at scale in tools, training, and transformation programmes while using measurement frameworks that cannot detect whether any of it is working. The metrics in circulation were designed for a different technological era and are being applied, largely uncritically, to a fundamentally different transition.

The problem runs deeper than outdated metrics. Industrial-era productivity frameworks measure input efficiency: output per unit of input, holding the nature of the work constant. AI does not merely change how efficiently work is done. It changes which work needs to be done at all, which coordination mechanisms are still necessary, and which human capabilities become more or less valuable as a result. Measuring AI impact through the lens of task-level efficiency is like measuring the impact of the industrial revolution through the lens of hand-tool productivity. The right question is not whether any given task is faster. It is whether the organisation has restructured itself around what AI makes possible, and whether it has done so in a way that builds rather than depletes the human capability on which sustained performance depends.

The KAIVANT instruments are built around these two questions. This paper provides their theoretical foundation.

II. The Two-Axis Claim

The theoretical foundation of the Kaivant Score rests on a single structural claim: durable advantage in the AI era requires two conditions operating at the same time, and neither is enough without the other.

The first condition is architectural redesign: the systematic reduction of coordination overhead, decision latency, and workflow friction through AI deployment against organisational structure, not just individual tasks. Organisations that do this generate real, measurable leverage gains. Those that have not will face redesign under competitive pressure, which is more expensive and more disruptive than redesign by choice.

The second condition is human capital investment: the deliberate development of the judgement, learning capacity, and capability resilience that makes architectural redesign sustainable over time. Organisations that reduce coordination overhead without developing human capital generate gains

that are real and structurally fragile. They have optimised for the competitive environment of today while reducing their capacity to adapt to the competitive environment of tomorrow.

The claim is not simply that both conditions matter. It is that they build on each other, and that neither does so effectively without the other. This relationship is the theoretical heart of the framework, and it is what the non-compensatory scoring formula reflects. A low score on either axis is not a trade-off to be managed. It is a structural risk that builds below the surface of output metrics until it is no longer small.

The Kaivant-O operationalises these two conditions as Leverage Architecture and Organisational Capital. Adaptation Architecture (AA) is the bridge dimension: the mechanism through which the two axes reinforce each other, and the measure of whether that reinforcement is working or stalling.

III. Leverage Architecture

The foundational insight behind Leverage Architecture comes from organisational economics. Ronald Coase's 1937 analysis of the firm established that every form of coordination carries a cost. Oliver Williamson extended this across decades of research on how governance structures are chosen and what they cost. Jay Galbraith's information processing theory of organisations identified the internal mechanism: organisational structure exists to process information under uncertainty, and every coordination mechanism, from management layers to approval workflows to status reporting, is an information-processing device whose cost is proportional to the volume of information it must process.

What AI changes is not the uncertainty of the environment. It is the cost of processing information within it. When AI systems make organisational data continuously visible and interpretable, the information-processing cost that coordination mechanisms were designed to address falls materially. The appropriate response is not to maintain those mechanisms at reduced cost. It is to redesign them around what has changed.

A distinction is essential here. Not all coordination is overhead. Coordination as information transfer (moving status, decisions and context across the organisation to enable action) is the primary target for reduction. Coordination as judgement application (the deliberate use of human reasoning on consequential, ambiguous or novel problems) is not overhead. It is work that AI cannot reliably perform and that the organisation must be designed to preserve and concentrate. This distinction runs through the entire framework: the Leverage Architecture dimensions measure the first kind; the Human Judgement Utilisation dimension of Organisational Capital measures the second. The two are complementary targets, not competing ones.

Leverage Architecture has four dimensions. Coordination Efficiency (CE) measures the current state of coordination overhead: how much of the organisation's time and structure exists for information transfer rather than judgement application, and how far that overhead has been reduced. Decision Velocity (DV) measures elapsed time from problem identification to solution implementation, achieved through better information rather than bypassing governance. Autonomous Workflow Percentage (AW) measures the proportion of routine workflow running with genuine autonomy: AI orchestration that maintains context across tasks without continuous human re-intervention at handoff points. Leverage Trajectory (LT) is the financial fingerprint of cumulative

architectural improvement: whether the ratio of output to coordination overhead is growing, flat, or declining, and at what rate.

AI applied to organisational design, rather than individual tasks, reduces coordination cost through five mechanisms. Information asymmetry reduction removes the need for infrastructure that exists to manage the gap between what decision-makers know and what they need to know: status meetings, reporting layers, and approval chains that are largely information-transfer mechanisms. Decision latency compression shifts the threshold at which decisions can be made without escalation, as the information cost of individual decisions falls. Workflow autonomy reduces handoffs not by executing tasks but by maintaining context across them, removing the need for human re-orientation at each transition. Adaptive capacity changes the economics of organisational redesign, because AI systems can be reconfigured without the formal change management overhead that makes traditional structural change expensive and disruptive. Verification compression reduces audit, review, and sign-off requirements as AI decision records become more legible and auditable, which matters most in regulated environments.

Klarna's disclosures between 2022 and 2024 illustrate what Leverage Trajectory improvement can look like at scale. The company reported approximately 5,527 full-time employees at the end of 2022, 4,352 at the end of 2023 and 3,422 at the end of 2024, a reduction of roughly 21 per cent in each year, which it attributed to a strategic decision to reduce headcount and drive efficiency by leveraging AI (Klarna Group, 2025). Over the twelve months to mid-2024, average revenue per employee rose by 73 per cent, from SEK 4.0 million to SEK 7.0 million, while revenue in the first half of 2024 was 27 per cent higher than a year earlier (Klarna, 2024). The case shows that the scale of leverage improvement the LT dimension is designed to track is observable in practice. It does not establish that architectural redesign was the cause; the financial record alone cannot separate the factors behind Klarna's performance. Critically, it speaks only to what LT measures. It says nothing about whether those gains are sustainable, which is precisely what the Organisational Capital axis assesses.

IV. Organisational Capital

An organisation that reduces coordination cost without also developing human capital is not building on gains. It is using up a stock. This is the theoretical foundation of the second axis, and it requires as rigorous a case as the coordination cost argument. The four dimensions of Organisational Capital are not softer considerations or ethical additions. They are the conditions under which Leverage Architecture gains hold up over time rather than eroding.

Learning Velocity. James March's foundational analysis of exploration and exploitation establishes the core tension: organisations that exploit existing knowledge at the expense of exploration eventually find their competencies obsolete; organisations that explore continuously without exploiting accumulate knowledge they never apply. Reducing coordination cost expands the experimentation budget, because more experiments can run in the same period when overhead falls. But expanded experimentation is only valuable if the organisation has the infrastructure to capture what experiments produce. Cohen and Levinthal's absorptive capacity research establishes the mechanism: the ability to recognise, assimilate, and apply new knowledge depends on the existing stock of related knowledge, and each increment of learning strengthens the capacity to absorb subsequent learning. Learning Velocity (LV) measures both: experimentation frequency captures exploration; feedback infrastructure and knowledge codification rates capture

whether exploration is converting into durable organisational knowledge rather than local and temporary improvement.

Human Judgement Utilisation. The primary risk of extensive AI deployment is not that the organisation will make mistakes. It is that it will eliminate the human capacity to catch them. Every AI system operates within the range of situations reflected in its training. At the edges of that range, in situations that diverge from training in ways the system cannot recognise, output quality is uncertain and the system itself cannot reliably signal that it is outside its competence. This is a structural property of systems that learn from historical data, not a temporary limitation of current technology. The question is not whether AI systems will encounter those edges. They will. The question is whether genuine human judgement remains behind the system, capable of detecting and correcting what the system cannot self-correct. Deci and Ryan's self-determination theory provides the mechanism through which nominal oversight becomes the default: genuine evaluation requires competence, and competence requires practice. Humans not regularly exercising judgement on challenging, consequential problems do not maintain the capacity to exercise it when it matters. Human Judgement Utilisation (HJU) measures the proportion of human working time engaged in work that genuinely requires human judgement: not as a cultural aspiration, but as a structural condition for AI deployment safety. The psychological safety sub-indicator within HJU, drawing on Edmondson's Team Psychological Safety Scale, measures the current social conditions under which that judgement can be exercised candidly. Psychological safety enters the framework in two distinct roles: HJU holds this current-state sub-indicator, while Human Dignity and Agency tracks the psychological safety trajectory as a lead indicator. The two are not duplicates; they measure a present condition and its direction of travel.

Capability Development Velocity. Gary Becker's human capital theory establishes the foundational framework: capabilities are assets that grow with investment and decline without it. Unlike physical capital, which depreciates towards a floor, human capabilities depreciate towards irrelevance when the threshold of valued work shifts beneath them. Autor, Levy, and Murnane's task-based framework establishes the directional mechanism: automation has historically replaced routine, codifiable tasks while complementing non-routine cognitive and interpersonal work. The precise applicability of this framework to current AI systems, which now reach into non-routine cognitive work, is actively contested. The directional insight holds; which specific capabilities retain and grow in value as AI capability expands must be treated as a question under continuous empirical review rather than a settled fact. Capability Development Velocity (CDV) indicators therefore sit in the indicator layer of the framework, subject to annual recalibration, rather than the stable conceptual layer. The obsolescence anxiety indicator merits particular attention: the proportion of employees who perceive their skills as declining is a leading indicator of disengagement and attrition, and a diagnostic signal that capability development investment is not keeping pace with automation investment. Obsolescence anxiety is not a psychological problem to be managed through communication. It is an accurate perception of a structural condition, and the appropriate response is structural redesign of capability development pathways.

Human Dignity and Agency. The case for Human Dignity and Agency (HDA) as a structural dimension rests on two arguments that converge on the same conclusion. The psychological argument: Deci and Ryan identify three basic needs whose satisfaction is necessary for sustained intrinsic motivation: autonomy, competence and relatedness. When these needs are consistently frustrated, predictable performance consequences follow: disengagement, reduced initiative, attrition, and capability stagnation. These accumulate below the surface of output metrics and crystallise in ways those metrics do not capture until the damage is significant. The structural

argument: Herzberg's two-factor research establishes that working conditions and basic dignity are hygiene factors whose absence generates active dissatisfaction, while their presence is merely the precondition for engagement rather than its driver. High Leverage Architecture built on degraded human dignity is not a stable position. The leverage gains appear in financial records before the HDA-related dissatisfaction appears in attrition and capability data, which is precisely why the lead indicators of HDA, psychological safety trajectory in particular, are designed to surface the condition while it is still addressable. The HDA floor reflects the asymmetric logic of this argument. It has two triggers: the HDA dimension score falling below its threshold, or the psychological safety that employees report falling below its own. Either one flags the Kaivant Score as a structural risk condition, whatever the composite. The score is still reported as calculated; the flag sits beside it and cannot be removed by strength elsewhere. HDA below threshold is a systemic risk indicator, not a dimension to be traded against. No leverage score offsets that condition. The thresholds themselves belong to the indicator layer and are maintained in the Measurement Specifications.

V. The Compounding Thesis

The separate theoretical cases for Leverage Architecture and Organisational Capital do not fully capture the most important claim of the KAIVANT framework. That claim is not that both axes matter. It is that they build on each other, and that neither does so effectively without the other.

Donald Reinertsen's application of queueing theory to knowledge work provides the mechanism through which coordination cost reduction compounds. Drawing on Little's Law, Reinertsen demonstrates that in knowledge-intensive organisations, high work-in-process creates non-linear increases in cycle time. The relationship is non-linear in a critical sense: small reductions in queue length produce disproportionately large reductions in cycle time, and reduced cycle time creates capacity for more improvement iterations per unit period. Applied to coordination overhead, the mechanism is: reduced coordination cost produces shorter approval queues and faster decision cycles, which enables more redesign iterations per period, which further reduces coordination cost per iteration. Each cycle creates the conditions for faster subsequent cycles. This is compounding, not linear improvement.

The Organisational Capital compounding mechanism runs in parallel. Cohen and Levinthal's absorptive capacity research establishes that each increment of organisational knowledge strengthens the capacity to acquire subsequent knowledge: existing knowledge stock is the primary determinant of learning rate, creating a self-reinforcing dynamic where richer organisations learn faster. The capability development literature establishes that expertise develops through sustained engagement at the challenge frontier. Organisations that design work so humans are consistently engaged at that frontier are organisations whose human capital is compounding. Those that allow AI to absorb the challenging work, leaving humans with residual execution tasks below their capability ceiling, are organisations whose human capital is declining, regardless of what output metrics show in the short term.

Neither compounding engine operates effectively without the other. Leverage Architecture without Organisational Capital produces gains that are real and structurally fragile. The organisation has built a system that produces output efficiently while depleting the capacity to maintain, redesign, or redirect it when conditions change. March's exploration-exploitation framework describes this

failure mode precisely: organisations that over-exploit existing capabilities at the expense of exploration eventually find those capabilities optimised for conditions that no longer exist.

Organisational Capital without Leverage Architecture is a different failure mode: the conditions for performance exist but the current architecture cannot express them. Human capability, learning infrastructure, and cultural conditions are producing output at the rate that coordination overhead permits, which is not stability. The unrealised leverage represents a widening competitive gap, because competitors who have redesigned their coordination architecture are building from a higher base while the high-OC, low-LA organisation improves slowly within its current structural constraints.

The non-compensatory composite formula reflects this argument precisely. The Kaivant Score floors at the lower of the two axis scores, with the higher axis able to contribute only a limited premium above a defined threshold. An organisation with a Leverage Architecture score of 90 and an Organisational Capital score of 20 is not in a strong position. It is generating strong current output while accumulating the structural fragility that limits its capacity to sustain or adapt it.

The compounding described in this section is a potential, not a certainty. Section VII sets out the condition under which it is realised.

VI. Adaptation Architecture: The Bridge Dimension

Adaptation Architecture (AA) occupies a structural position in the Kaivant-O that neither axis fully holds independently. It is the mechanism through which the two axes reinforce each other. High Leverage Architecture and high Organisational Capital produce compounding advantage only if the organisation has the structural capacity to identify opportunities for improvement and act on them at declining cost per cycle. Adaptation Architecture measures whether that capacity exists and whether it is growing.

The instrument architecture reflects this precisely. AA does not belong exclusively to either axis. It modulates both axis scores as a multiplier: a higher AA score allows each axis to express more of its own potential, and a lower AA score compresses both axes towards a floor, regardless of underlying axis strength. This is not an arithmetic device. It reflects the argument that coordination cost reduction and human capital investment reinforce each other only through the mechanism of implemented improvement. An organisation with high Leverage Architecture and high Organisational Capital that cannot translate those conditions into adaptive practice is an organisation whose compounding engine has stalled.

Cohen and Levinthal's absorptive capacity concept is the primary theoretical anchor: the ability to apply new knowledge requires designed processes for doing so, and absorptive capacity is not automatically high in organisations with strong existing knowledge stocks. Teece, Pisano, and Shuen's dynamic capabilities framework establishes the strategic significance: in environments where the competitive landscape shifts continuously, the capacity to reconfigure organisational assets rapidly is a source of sustained competitive advantage that firms lacking it cannot replicate. AA operationalises this capacity at the level of working practice rather than strategic positioning.

The mechanism is deliberately indirect. Adaptation Architecture does not enter the composite as a third axis to be averaged with the other two. It is computed as its own score and then applied as a multiplier to both axis scores before the composite is formed, so that a strong Adaptation

Architecture allows each axis to express its full measured value while a weak one compresses both. A second feature reinforces the same logic: a large imbalance between the two axes is itself treated as a sign of an adaptation system under stress and reduces the Adaptation Architecture score, independent of how its own indicators read. An organisation can therefore record strong Leverage Architecture and strong Organisational Capital and still see both compressed, either because the capacity that converts them into implemented improvement is weak, or because the two axes have pulled too far apart. The exact multiplier range, the imbalance threshold, and the lag and lead weightings that produce the Adaptation Architecture score belong to the indicator layer and are maintained in the Measurement Specifications, where they are versioned as the evidence base develops.

The critical diagnostic implication of AA as a bridge dimension is the lag/lead gap. An organisation with high lag AA (effective adaptation in the past) and declining lead AA (a thinning pipeline of experiments and rising per-cycle adaptation cost) is at peak performance with a depleting adaptation engine. This is the most important AA signal: not the current level of adaptation performance, but the trajectory of the capacity that produces it.

VII. The Managed Loop: State and Practice

The first two claims describe what must be true of an organisation for AI-enabled advantage to compound: leverage and human capital built together, joined by a working bridge. They do not explain how an organisation keeps them true. The third claim closes that gap.

The managed-loop claim. The compounding between the two axes is sustained only where the organisation runs a deliberate improvement loop around its use of AI. Where that loop is missing, gains on either axis still occur, but they arrive in episodes, depend on individuals, and fade when those individuals move on or attention shifts. The loop is what turns a good position into a compounding one.

The claim rests on three bodies of research. The first concerns complementary investment. The returns to information technology have always depended on the organisational changes made around it: new processes, new decision rights, new skills (Brynjolfsson and Hitt, 2000). For general-purpose technologies these complementary investments are large, slow and largely invisible to conventional measurement, which is why measured productivity can lag behind what is being built (Brynjolfsson, Rock and Syverson, 2021). Complementary investment does not happen by itself. Someone has to decide it, fund it and check that it works.

The second concerns management practices. Large-scale research on management has found that the quality of basic practices, such as monitoring, target setting and incentives, is strongly associated with differences in productivity between firms (Bloom and Van Reenen, 2007). The same practices help explain why some firms gain far more from the same technology than others: the productivity advantage that US multinationals drew from information technology has been traced primarily to their people management practices (Bloom, Sadun and Van Reenen, 2012). The same technology, managed differently, produces different results.

The third concerns how capabilities are built. Dynamic capabilities do not appear by accident. They develop through deliberate learning mechanisms: accumulating experience, articulating what was learned, and codifying it so that it spreads (Zollo and Winter, 2002). Teece (2007) describes the underlying capacities as sensing opportunities, seizing them, and reconfiguring the organisation's

assets to match. The continuous improvement tradition makes the same point in operational terms. The cycle of plan, do, check and act that Deming carried into management, and the practice of kaizen, whose first character (改, change) KAIVANT carries in its name and mark, both treat improvement as a routine that is run, not an event that happens (Deming, 1986; Imai, 1986). Management system standards for AI, such as ISO/IEC 42001:2023, are built on the same logic of continual improvement.

The fourth body is the practice and research behind the GITO Approach itself (MindMagine Asia, 2026). Its starting observation is that organisations rarely lack good methods; they run them one project at a time. Linear change models close when the project closes, and the learning stops with them. Change efforts stall after the first steps and declare victory too soon. Organisations solve the same problem every few years because each fix addresses the symptom and leaves the system that produces it in place. New ways of creating value are judged by the criteria of the current model and quietly rejected. And the people side is the part most often left out: the unwritten expectations between people and their organisation, the conditions that sustain motivation and the safety to speak up decide whether a change is adopted or merely complied with. The GITO Approach answers these findings by joining governance, innovation, transformation and optimisation into one loop that runs continuously, with behaviour and culture at its centre and any proven method applied where it is needed. MindMagine has run that loop with organisations across Asia-Pacific for many years; the four elements of the managed-loop claim are its four elements.

The four elements of the loop. KAIVANT describes the loop in four elements, each read through four clusters of practice:

- **How the organisation governs AI:** who is accountable for AI outcomes, who can see what AI is doing, how oversight works in practice, and how the rules adapt as use grows.
- **How it finds new value with AI:** where ideas come from, the room to experiment, how pilots are judged and scaled, and whether AI use is tied to value.
- **How it changes the way it works:** the redesign of work and processes, support for people whose roles change, changes to structure, and how change is led and paced.
- **How it measures, keeps and spreads the gains:** how performance is measured, how feedback returns to decisions, how the portfolio of AI work is managed, and how good practice spreads and renews.

The elements work as a loop, and the loop is only as strong as its weakest element. An organisation that governs AI carefully but never measures what it gains cannot tell which of its rules are worth keeping. One that finds new value quickly but does not change the way it works collects pilots that never scale. The non-compensatory logic that governs the Kaivant Score applies here too: strength in one element cannot cover the absence of another.

State and practice. The loop has a precise place in the framework. The two axes and the bridge read the state of the organisation: where it stands and in which direction it is moving. The loop reads its practice: what the organisation actually does, week by week, to steer that state. A useful picture is a photograph and a film. A photograph can be accurate without showing whether the position in it is being managed. The practice reading adds the movement.

The distinction from Adaptation Architecture matters, because the two can look alike. AA measures the capacity to adapt and what that capacity has produced: how quickly and at what cost the organisation has implemented improvement, and whether its pipeline is filling or emptying. The loop measures the routines that exercise that capacity on purpose. An organisation can show

strong AA for a while without a managed loop, carried by a few energetic individuals or by the momentum of an early programme. The claim predicts that such adaptation will not last. An organisation can also run a sound loop before its state shows it, because complementary investment takes time to appear in results.

This is why the most useful diagnostic signal of the third claim is disagreement between state and practice. When the state runs ahead of the practice, the position is not being managed and is at risk of eroding. One pattern deserves particular attention: a high share of AI-run work alongside weak accountability and decision rights. In plain words, AI decides more than the rules for who decides. When the practice runs ahead of the state, the organisation is building, and its results do not show it yet.

At the individual level the claim has a direct parallel that the framework already measures. Personal Adaptation Architecture reads the deliberate practice and reflection through which a person turns AI-assisted work into capability (Section VIII). The managed loop is the organisational counterpart of that discipline.

How the claim is measured. The loop is measured as its own reading, the steer and improve reading, drawn from the four elements, with the weakest element setting the result. It sits beside the Kaivant Score and never changes it. Keeping the two readings separate is deliberate. Folding practice into the score would let good intentions compensate for weak results, which is exactly the averaging the non-compensatory design exists to prevent. Separate readings keep the disagreement between state and practice visible, and that disagreement is the signal.

Evidence status. The managed-loop claim is grounded in practice as well as research. The four elements are the GITO Approach (Govern, Innovate, Transform, Optimise) developed by MindMagine, which has applied it in organisations across Asia-Pacific for many years, over successive waves of technology and operating-model change, and has seen the pattern the claim describes: improvement that lasts where the loop is run, and fades where it is not. That experience is the reason the loop is measured. What has not yet been done is to test the claim statistically against outcome data collected through the KAIVANT instruments themselves. Until it has, the claim is held to the same evidence standard as every other claim in the framework (Section IX): practice-proven and research-grounded, with predictive validity still to be established from KAIVANT data.

VIII. The Individual Instrument: A Structurally Different Problem

The Kaivant-I applies the same structural logic to the individual level. It is not the organisational instrument at a smaller scale. The two instruments face a fundamental structural asymmetry that defines the individual assessment's distinct theoretical character.

At the organisational level, increasing the proportion of AI-executed workflow is straightforwardly positive. The organisation benefits when AI absorbs execution work and concentrates human capacity in judgement work. The two axes of the Kaivant-O can in principle both be high simultaneously. There is no inherent tension between building Leverage Architecture and building Organisational Capital.

At the individual level, the equivalent dynamic creates a tension that has no organisational parallel. When an individual offloads cognitive work to AI, two outcomes are possible. In the augmentation

pattern, freed capacity is reinvested in higher-judgement work: output improves and capability develops in tandem. In the substitution pattern, the AI handles work that was developing the individual's judgement, and the capability that would have developed does not develop. The individual's output may improve while their capability stagnates or declines. These two patterns produce identical short-term output trajectories and divergent medium-term capability trajectories. This is what makes substitution difficult to detect and important to measure.

The Axis Structure

Personal Leverage Architecture (PLA) measures the structural conditions of the individual's AI use: how effectively it is increasing effective output, absorbing routine work, and whether leverage gains are building or plateauing. Its four dimensions are Personal Workflow Automation Rate (PWA), Personal Decision Velocity (PDV), Coordination Footprint (CF), and Personal Leverage Trajectory (PLT). PWA and PDV measure the current state of the individual's AI integration: how much routine work is genuinely automated and how quickly decisions are reached. CF measures the individual's coordination overhead: the time consumed by information-transfer work rather than judgement and output work. PLT is the trajectory signal: whether effective output per unit of time is growing, flat, or declining as AI integration deepens.

Human Capital Depth (HCD) measures whether the individual's independent capabilities are growing or declining as AI integration increases. Its four dimensions are Judgement Independence (JI), Cognitive Range (CR), Relational Intelligence (RI), and Capability Independence and Resilience (CIR). JI measures the quality of unassisted reasoning: not as a test of AI-free performance as a goal in itself, but as a periodic calibration of the capability that AI integration is meant to build on. CR measures the breadth and flexibility of cognitive engagement: whether the individual's work draws on an expanding or contracting range of cognitive demands. RI measures the interpersonal and collaborative dimensions of capability that AI cannot reliably replicate and that become more valuable as AI absorbs analytical execution work. CIR measures whether the individual's capability functions at material quality when AI tools are unavailable, and whether that baseline is stable or declining over consecutive assessment periods.

The Bridge Dimension

Personal Adaptation Architecture (PAA) is the mechanism through which PLA and HCD reinforce each other at the individual level, occupying an identical structural position to Adaptation Architecture in the Kaivant-O. It measures whether the individual is using AI in ways that build judgement and capability or substitute for them: the quality of learning infrastructure, deliberate practice patterns, and the reflection through which AI-assisted work is converted into genuine capability growth. PAA modulates both axis scores as a multiplier, in the same manner as AA in the Kaivant-O. The bridge is the compounding mechanism: without it, PLA and HCD accumulate independently rather than reinforcing each other.

The Capability Atrophy Mechanism

The foundational research on expertise establishes that capability develops through sustained engagement at the edge of current competence. The conservative and well-supported version of this claim, which the Kaivant-I relies upon, is that capabilities not regularly exercised decline, and habitual reliance on AI for tasks that would otherwise exercise those capabilities therefore carries a genuine atrophy risk. The mechanism is not controversial; it is the specific quantitative claims

about practice requirements and expertise timelines that remain contested. The Kaivant-I depends on the directional mechanism, not those contested specifics.

Csikszentmihalyi's challenge-skill calibration research provides the complementary mechanism: when challenge falls below skill, engagement moves towards boredom. An individual whose AI integration has consistently reduced work challenge will find themselves operating below their capability ceiling. Over time, skill adjusts towards challenge rather than the reverse.

Sparrow, Liu, and Wegner's transactive memory research establishes a directly relevant empirical mechanism: the expectation of AI tool availability changes internal cognitive engagement before the tool is even used. When people expect access to an external system that performs cognitive work, they are less likely to engage in the internal processing that would develop that capacity themselves. The habit of cognitive offloading is not merely situational. It is architectural, reshaping how internal processing is engaged across contexts. Risko and Gilbert's cognitive offloading research extends this: habitual reliance on external tools for cognitive tasks reduces internal processing demand, with documented effects on reasoning engagement and metacognitive monitoring.

The CIR Floor

Capability Independence and Resilience is the systemic risk indicator of the Kaivant-I, occupying an equivalent structural position to Human Dignity and Agency in the Kaivant-O. When CIR declines over two consecutive assessment periods, the Kaivant-I Score is flagged regardless of its level. This reflects the asymmetric logic of the HDA floor: some conditions are systemic risks, not trade-offs to be averaged. An individual with high Personal Leverage Trajectory and declining CIR is building performance on an increasingly fragile foundation. The flag is reported as a structural risk condition, not a penalised score: its purpose is developmental.

A critical governance requirement follows directly from the measurement design. CIR benchmark results are private to the individual by default. If CIR data is accessible to employers as a performance signal, it generates precisely the behaviour it is designed to detect: performed AI-free work for measurement purposes rather than genuine engagement. Privacy here is not a policy choice. It is an architectural requirement for the instrument to produce valid data.

Cross-Validation Between Instruments

The two instruments validate each other in ways that make each more credible than either alone. The organisational claim that humans are deployed in judgement work (HJU) is validated or contradicted by whether those humans have the judgement capacity to do it (aggregate JI scores from Kaivant-I). An organisation with high HJU and declining aggregate JI has a structural problem it does not know it has: it believes its humans are doing judgement work; their judgement capacity is declining; the gap between organisational claim and individual reality is a systemic risk accumulating silently.

The organisational claim that capability development investment is producing results (CDV) is validated or contradicted by aggregate HCD trajectories. If the organisation is investing in capability development but individual HCD scores are not improving, the investment is not reaching the individuals it is designed to serve. Each cross-validation relationship identifies a potential gap between the architecture the organisation has designed and the experience the organisation is producing, and that gap is where the most important diagnostic and design interventions lie.

IX. From Self-Report to Verified Score: How the Instruments Are Used

The spot inspection model. The KAIVANT instruments are designed as diagnostic spot inspections, not longitudinal prediction engines. The distinction matters for how results are interpreted and how the instruments are used.

A spot inspection provides two readings at the same moment. The lag reading describes the current state of the architecture, derived from historically observable indicators. The lead reading describes the trajectory the architecture is on, derived from investment patterns, pipeline activity, and directional trends. Neither reading predicts an outcome. Together they answer the question: where is this organisation or individual now, and in which direction are they moving?

The lag/lead gap is the primary diagnostic output. A high lag score with a declining lead score is the most important signal the instrument produces: it identifies current performance that is not being sustained by the investments and design choices that would maintain it. The converse, a low lag score with a rising lead score, identifies an organisation or individual whose current performance understates their trajectory. Both signals are more actionable than a composite score that averages them away.

Two free ways in. Most people first meet the framework through one of two free tests on kaivantscore.com.

The Kaivant-I Starter is the short form of the individual instrument: fifteen questions across the same nine dimensions, taking about 10 minutes. It places the person in one of five patterns (Compounding, Substitution Risk, Underleveraged, Early Stage and Mixed Signals) and gives a written read of that pattern. The result is private to the person who takes it, for the reason set out under the CIR floor in Section VIII.

The Leadership Pulse is the short form of the organisational instrument, answered by one senior leader about their own organisation in about twenty-five minutes. Part one reads the state: twenty-seven questions, three for each of the nine dimensions, two looking back and one looking ahead, the lag and lead model in a lighter form. Part two reads the practice: fifty questions across the four elements of the managed loop. Part one produces the Pulse reading; part two produces the steer and improve reading. A closing question asks how many of the leader's answers their employees would agree with. It is not scored. It names the limit of any single view.

A mirror, not a measurement. Both free tests show how one person sees things. Nothing in them is checked, each uses a few questions where the full instruments use a full set of indicators, and each is one point in time. The HDA floor cannot run in the Pulse, because it needs a psychological safety measure that one leader's self-report cannot provide. For these reasons a free test never produces a Kaivant Score. Its results are always called by their own names (the Starter pattern, the Pulse reading and the steer and improve reading), so that a first reading is never mistaken for a verified one.

The full Kaivant-O. The Kaivant Score comes only from the full Kaivant-O, led by a Certified Kaivant Practitioner. Its design follows from a simple observation: the input most prone to optimism is a leadership team rating its own organisation. The instrument therefore draws on three sources and checks the one that is weakest.

- **The leadership team** takes the same Leadership Pulse, both parts, through its own link. Leaders give their role level but not their names, and no single leader's answers are shown. Their averages, and the range between them, form the leadership view.
- **The employees** take the full Kaivant-I through a separate link, including a psychological safety scale drawn from Edmondson's work. The people side of the organisation (learning, use of human judgement, capability growth, and voice and agency) is read from them, not from the leaders.
- **The practitioner** validates. On the work side (coordination, decision speed, AI-run work, output per person and the ability to change) and on the four elements of the loop, the practitioner starts from the leaders' average and confirms it or sets a new score, recording the evidence behind it: an interview, a document, a metric or an observation. A note is required even when the leaders' score is kept, because a number already on the screen is easy to accept.

The Kaivant Score is computed from the validated work side and the employees' people side. The leaders' view of the people side is kept as a comparison. Where it differs materially from the employees' view, the report names the gap as a difference in view, not an error. It is often the most useful finding of the engagement. Both HDA floor triggers can run, because the employees' psychological safety is measured directly.

The route from a free test to the full instrument follows from this design. A free test raises the question that only the full instrument can answer: do the leadership team and the wider organisation see the same picture, and does the evidence support it?

The validation principle. The framework separates two kinds of claim. Grounding concerns the conceptual architecture, and rests on the research this paper sets out and on the practice behind it. Predictive validity concerns whether scores reliably predict organisational and individual outcomes over time, and it can only be established with outcome data. KAIVANT makes no predictive claim until the evidence supports it. The samples and follow-up periods that each level of claim requires are fixed in advance in KAIVANT's validation programme, and its current standing is published at kaivant.org/validation. This is not a weakness to be managed. It is the standard any credible assessment instrument should meet, and one that many commercial frameworks in this space do not state.

X. Interaction Risks

The eight axis dimensions of the Kaivant-O, and the Adaptation Architecture bridge that links them, do not operate independently. The most diagnostically important signals the instrument produces are often patterns of imbalance between dimensions rather than individual dimension scores. Ten cross-dimensional interactions have specific theoretical grounding and are worth examining as a set.

High Coordination Efficiency, Low Human Dignity and Agency. Coordination mechanisms can be removed in ways that increase autonomy or in ways that reduce it: eliminating unnecessary approvals versus removing roles without redesigning for agency. CE improvement that simultaneously reduces HDA is not the target state of the framework. It is the failure mode in which efficiency gains are purchased at the cost of the psychological conditions that sustain productive contribution.

High Decision Velocity, Low Human Judgement Utilisation. Eisenhardt's research on fast decision-making establishes that speed and quality are positively correlated when speed is achieved through better information and clearer priorities, not when it is achieved by bypassing deliberation. High DV achieved by shortcutting analytical engagement may improve throughput while reducing the depth of human oversight. High DV achieved by improving information quality is the target.

High Autonomous Workflow Percentage, Low Capability Development Velocity. The interaction risk is specific: when automation removes work categories that were developing the judgement required for exception handling, the organisation is simultaneously increasing workflow efficiency and reducing the human capability required to manage the failure modes of those workflows. Not all routine work is developmentally important; the risk is real when the automated work was the substrate through which consequential competence was maintained.

High Leverage Trajectory, Low Human Dignity and Agency. High leverage gains achieved through workforce reduction without transition investment, or through efficiency without agency, activate the Herzberg dissatisfaction mechanism in the remaining workforce. The leverage gains appear in financial records before the dissatisfaction appears in attrition and capability data, which is precisely why HDA's lead indicators are designed to surface the condition while it is still addressable.

High Learning Velocity, Low Adaptation Architecture. An organisation that generates learning at high velocity but lacks the structural capacity to act on what it learns produces knowledge that accumulates without changing practice. The competitive advantage from learning is not realised. This is the organisational equivalent of intensive research without a path to application.

High Leverage Architecture Composite, Low Organisational Capital Composite. The master interaction risk. The dynamic capabilities literature establishes that competitive advantage in environments of continuous change requires not just the ability to perform well in the current configuration but the ability to reconfigure when conditions shift. The organisation is performing well in its current configuration while reducing its capacity to change it. The lead indicators of Organisational Capital (psychological safety trajectory, skill trajectory distribution and experimentation pipeline depth) are specifically designed to surface this condition before it reaches the performance layer.

High Organisational Capital Composite, Low Leverage Architecture Composite. The mirror failure mode. The conditions for performance exist but the current architecture cannot express them. Unrealised leverage builds over time as competitors who have redesigned their coordination architecture generate returns from a structurally superior configuration. This pattern is common in organisations that have invested heavily in culture, capability, and learning while leaving coordination structures intact.

High Adaptation Architecture, Low Learning Velocity. The organisation is efficient at implementing change and increasingly short of meaningful improvement to implement. The adaptation engine is operating; the pipeline that feeds it is emptying. High lag AA combined with declining lead LV indicators is the specific signal of this condition.

High Human Judgement Utilisation, Low Autonomous Workflow Percentage. Humans are correctly deployed in judgement work, but the execution work that AI should handle is still consuming significant human capacity. This is an opportunity risk, not a harm risk: unrealised

leverage that is often invisible in organisations whose culture correctly values human judgement without having redesigned around what AI can absorb.

High Capability Development Velocity, Low Leverage Trajectory. Human capital investment is constrained by architectural inertia. The organisation is developing the capacity to operate differently without having built the system that would operate differently. Unlocking the return on CDV investment in this configuration requires not more capability development but Leverage Architecture work: specifically the workflow redesign and authority restructuring that allows developed human capability to generate leverage rather than accumulate as unrealised potential.

XI. The Two-Layer Architecture

The KAIVANT framework is designed to remain credible and useful across a 10-to-20 year horizon in an environment where AI capability is shifting rapidly. Achieving this requires separating two layers of the framework that operate on fundamentally different timescales.

The conceptual layer contains the theoretical architecture: the two-axis compounding thesis, the non-compensatory composite logic, the bridge dimension design, the managed-loop claim, the augmentation-substitution distinction, the lag/lead gap as primary diagnostic output, and the cross-validation relationship between the Kaivant-O and Kaivant-I. These claims operate at a level of abstraction that sits above specific AI capabilities. They do not depend on AI being unable to perform any particular task. They depend on the structural relationship between coordination cost, human capital, and compounding advantage, which holds regardless of where the AI capability frontier sits at any given moment. The conceptual layer is treated as a stable intellectual asset. Changes to it require a formal revision process with documented rationale. No empirical evidence has been presented that refutes the two-axis compounding thesis, the managed-loop claim or the augmentation-substitution mechanism, and the conceptual layer is expected to hold for at least a decade.

The managed loop in the conceptual layer. The loop is stated as a claim of the conceptual layer, not only as a measure, for three reasons. First, the framework measures and teaches the practice of steering AI, through part two of the Leadership Pulse and in practitioner training; a measure without a stated theory invites misreading. Second, the practice experience behind the GITO Approach and the research on complementary investment, management practices and deliberate learning give the claim a firm base. Third, the claim is consistent with the other two: it explains how their compounding is sustained without changing what they assert. The measurement of the loop sits in the indicator layer and does not change how the Kaivant Score is calculated.

The indicator layer contains specific metrics, thresholds, benchmarks, and measurement instruments within each dimension. These are expected to have a useful life of three to five years at most and are formally versioned from launch. The indicator layer is under annual review, triggered by any material shift in what AI systems can reliably perform, by accumulation of sufficient dataset evidence to challenge a threshold or weighting assumption, or by the scheduled annual review regardless of trigger events. Each version release includes a change log specifying which indicators were modified, added, or retired; the rationale for each change; a transition protocol for organisations in longitudinal tracking; and an effective date after which old and new version scores are reported separately.

This explicit separation is not a qualification of the framework's confidence. It is the design feature that makes the KAIVANT framework a living instrument rather than a static publication: one that responds to a genuinely changing world rather than pretending the world is stable.

XII. Scope, Calibration and Cultural Context

Launch Scope

The KAIVANT instruments are designed for knowledge-work organisations and knowledge workers. The framework's theoretical architecture (coordination cost, Human Judgement Utilisation, cognitive capability development) applies specifically to environments where cognitive work and its organisation are the primary sources of value. The framework is designed for knowledge work wherever it sits. In a manufacturer or a retailer, the engineering, planning, commercial and management functions are in scope; production lines, store operations and other roles without meaningful cognitive AI integration are not. This is a precision statement, not a limitation. Publishing scope explicitly is a credibility signal: the framework makes claims about what it measures and the conditions under which those claims hold.

The Kaivant-O applies to organisations with a minimum of approximately 30 employees. Below this threshold, personal trust relationships substantially replace formal coordination mechanisms, and the framework's structural indicators lose diagnostic resolution. The free Leadership Pulse is open to organisations of any size, and a Pulse reading for a very small organisation should be read with this threshold in mind. Sector comparisons cover eleven sectors, from financial services, technology and professional services to manufacturing, healthcare, education and government. Until a sector has enough real assessments, its comparison is a research-based estimate, labelled as such.

Norm Development

Calibration norms develop as the dataset builds, and the method for building them was defined before the first assessment. Until a sector reaches a minimum group of assessments, its comparison is a research-based estimate built from published sector indicators and clearly labelled as an estimate. Once the minimum is reached, measured data replaces the estimate. Saying plainly when a comparison is an estimate is part of the framework's credibility, not a limit on it.

Cultural Calibration

Most of the research the framework draws on was developed in Anglo-American, low power-distance organisational contexts, while KAIVANT is developed in and used across Asia-Pacific as well as elsewhere. Several assumptions therefore require explicit acknowledgement and staged adaptation.

The psychological safety indicators (the current-state sub-indicator within HJU and the trajectory tracked under HDA) are the most culturally context-dependent. Edmondson's psychological safety construct was developed in low power-distance settings. The behavioural expression of psychological safety, such as speaking up, challenging authority and escalating concerns, varies materially across cultural settings with different norms around hierarchy, dissent, and face-saving. The underlying need is structurally universal: conditions under which concerns can be raised without destructive consequences. The appropriate measurement approach is not.

Hofstede's cultural dimensions framework and Trompenaars' cross-cultural research provide the primary conceptual anchors for adaptation work. Power distance is the most significant dimension for HDA calibration. Uncertainty avoidance bears on how DV and AA thresholds are interpreted. Individualism-collectivism bears on how HJU and CDV individual contribution framing is applied.

The staged approach: at launch, the cultural scope is explicitly acknowledged and high power-distance adaptations are flagged as in development. In Year 2, cultural calibration modules will be developed in partnership with researchers in at least two non-Anglo-American markets. From Year 3, context-specific norm sets will be released where sufficient dataset depth exists.

XIII. Why This Framework, Why Now

AI capability has crossed the threshold of organisational relevance. The most capable systems available in 2026 maintain context across complex workflows, can be deployed against coordination mechanisms rather than only individual execution tasks, and reduce the information cost of decisions in ways that directly affect organisational structure. The organisations that have already redesigned around these capabilities are building their advantage. Those that have not will face redesign under competitive pressure: a more expensive and more disruptive path than redesign by choice.

The existing measurement landscape does not address the question this creates. Most AI maturity and readiness models in use are adoption-curve instruments. They measure whether an organisation, or in some cases a national economy, has the inputs associated with AI deployment: strategy, talent, data, technology and a culture open to digital tools. Many are well designed for the questions they address. They are not designed to measure whether the organisational architecture has been redesigned to generate leverage from those inputs, and they do not address whether the human capital conditions for sustaining that leverage are being built or depleted. The productivity paradox data suggests this is the more important question. The KAIVANT instruments address it.

The KAIVANT instruments are also designed with a different intent. Assessment products produce scores. Growth instruments produce development pathways. The KAIVANT framework's diagnostic logic is designed to generate specific, actionable design interventions, not to produce a number to be reported or compared. The interaction risk architecture in Section X is not a list of warnings. It is the foundation of the intervention library that provides concrete, evidence-grounded responses to each failure mode the instrument identifies.

The long-term value of the framework builds with use. Each assessment improves calibration norms. Each longitudinal track generates evidence towards the validation condition. Each cross-validation between Kaivant-O and Kaivant-I data refines both instruments. The framework is designed to get more useful over time, for the organisations and individuals using it, and for the broader question of what AI-native architecture actually looks like in practice.

That question will still matter in 2036. The specific indicators used to answer it will have changed. The claims at the foundation are designed to outlast them.

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This paper is the theoretical foundation of the KAIVANT platform and the Kaivant Score. It constitutes the conceptual layer of a two-layer framework architecture and is published as a statement of theoretical standing and methodological intent. The indicator layer (specific metrics, thresholds, and measurement instruments) is maintained separately and versioned annually.

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