

The 95% Problem

Why AI adoption stalls at the leadership layer, and the leadership behaviors that show up where AI investment pays.

Decode the signal. Develop the leader.

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Abstract

Enterprise AI adoption stalls at the leadership layer rather than the technology layer. Legacy competency frameworks were not designed to assess the AI-specific behaviors associated with whether AI investment converts into organizational value. The Signalead™ framework organizes three behavioral signals (Inner, Outward, and Grounded) across eleven named dimensions. Its underlying AI Leadership Battery measures thirty-six behavioral subdimensions through 108 items. The completed validation program combined expert content review with three development samples and three independently recruited validation samples, comprising 1,191 working leaders. The battery was supported by content-validity, exploratory and confirmatory internal-structure, reliability, separation from selected external measures, and criterion-related evidence across eight primary organizational and leadership criteria. The study also revealed four findings with implications for AI-era organizations. First, leaders in the validation reference samples reported help-seeking and candor about AI-driven change more readily than standing experimentation routines, scheduled capability review, and decisive provisional action under uncertainty. Second, within the 51-item validation sample, Team Learning Experiences had both the lowest construct mean and the strongest construct-level association with AI Adoption and Integration. Third, different constructs and subdimensions showed different criterion patterns, which is why the battery reports a profile rather than one overall score. Finally, in the largest criterion model, commonality analysis attributed 86% of explained variance uniquely to the AI-era behaviors, against 3% uniquely to the established measures. Decision Speed showed the weakest and least consistent relationships across the program. Together, these findings support profile-based developmental interpretation while preserving the distinction between concurrent evidence and causal or temporal prediction (AI Leadership Research Team, 2026; Akben & Coyne, 2026).

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Executive Summary: The Second Investment

Consider the organization that did everything the guidance asked of it. It bought the licenses and tracked activation. It ran the training and paid for the fluency certification. It wrote the acceptable-use policy and stood up a governance committee. Two years later, employees use AI most days, the adoption dashboards are green, and the finance team still cannot find the return. The technology worked, the people adopted it, but the work itself did not change.

This is the 95% problem – an external estimate drawn from MIT Project NANDA’s preliminary 2025 report, based on interviews, surveys, and a review of more than 300 publicly disclosed AI initiatives. The report estimated that 95% of organizations in its evidence base were getting zero return from generative AI, while 5% of integrated AI pilots were extracting millions in value. It called that split the GenAI Divide. The estimate is not a Signalead finding or a universal failure rate; it frames the gap between AI investment and realized value that this paper examines.

The result is a growing AI value gap. Organizations are deploying AI faster than they are converting it into operational and financial performance. Deloitte’s 2025 survey of 1,854 executives in Europe and the Middle East found that organizations typically expect technology investments to pay back within seven to twelve months, whereas respondents most often reported two to four years for a typical AI use case. Capital is moving faster than value realization.

RECORD INVESTMENT, MISSING RETURNS

\$285.9B

U.S. private AI investment in 2025
Stanford HAI, 2026

95%

Organizations in the preliminary MIT evidence base reporting zero return
MIT Project NANDA, 2025

2–4 yrs

Most commonly reported payback period for a typical AI use case
Deloitte, 2025

Three separate studies. Reported separately; not estimates of the same population rate.

There is precedent for a gap this wide, and it is more encouraging than it first appears. Electrification and computing each took decades to convert investment into measured productivity, and in both cycles the returns were concentrated in the organizations that made a second, largely invisible investment – reorganizing the work itself around the new technology (David, 1990; Brynjolfsson & Hitt, 2000). Factories that bolted electric motors onto the old shaft-and-belt layout captured little. Factories that redesigned the floor around what electricity made possible captured almost everything. Read against that record, today’s missing returns do not by themselves show that AI cannot pay. They suggest that many organizations may have made the first investment without yet making the second and, as this paper argues, that the second investment begins with leadership behavior that creates the conditions for teams to reorganize work around AI.

Three decades of implementation studies find that whether a new technology gets used consistently and skillfully depends on climate – the shared perception among employees that using it is expected, supported, and rewarded – and that this climate is assembled from what leaders visibly do rather than what they announce (Klein & Sorra, 1996; Klein, Conn, & Sorra, 2001). Recent evidence extends the pattern to AI. In a multisource, multi-wave study, Liu et al. (2026) found that leaders’ collaboration with AI was associated with team performance through two team-level conditions: how openly a team examines and revises the way it

works, and the shared confidence to take on broader responsibilities as roles evolve. Both conditions are shaped in part by observable leader behavior. This is why the constraint can be examined behaviorally rather than only attitudinally.

To address that gap and the executive need it leaves unmet, we developed Signalead™. It organizes those behaviors into three signals leaders send when working with AI. The **Inner Signal** reflects how a leader orients to AI and stretches their own thinking. The **Outward Signal** captures the people practices that enable teams to turn AI use into experimentation, collective learning, and adaptation. The **Grounded Signal** addresses the boundaries, calibration, and governance required for AI to scale responsibly. The underlying battery reports these behaviors through 11 construct composites and 36 subdimensions. It does not calculate one overall AI Leadership score, because the actionable information lies in the profile.

THE COMPLETED VALIDATION PROGRAM

1,191

working leaders
across development and validation

6

independent samples
analyzed separately

**86% unique / 11% shared / 3%
established**

of explained variance, by source
largest combined construct model

Samples are kept separate and never pooled across forms. Concurrent, same-source self-report.

We measured these behaviors in 1,191 working leaders across six separately recruited samples. The completed research program provides evidence across successive stages. Expert panels supported the content architecture; three development samples established the 108-item structure and reliability; three newly recruited samples confirmed the structure and separation from established comparison measures; and criterion analyses tested whether the behaviors added explanatory value beyond those measures. The increment was statistically significant in 19 of 21 construct-level models and 18 of 21 subdimension-level models, and when the models were tested on responses held out from estimation, adding the construct scores improved prediction in 18 of 21.

Four findings locate the gap and explain why it has stayed invisible

Leaders are open about AI and fewer are organized around it: in the validation reference samples, AI Help-Seeking and Vulnerability About AI-Driven Change had the highest average scores, while Structured AI Experimentation and Learning Routines, Decisive Provisional Action Under AI Uncertainty, and Systematic Applied Capability Review had among the lowest.

Within the 51-item validation sample, scarcity and consequence coincide: Team Learning Experiences had the lowest construct mean and the program's strongest construct-level association with AI Adoption and Integration. Its Systematic Applied Capability Review subdimension had the strongest subdimension-level association with the same criterion.

Different behaviors travel with different outcomes: AI Security and Risk Management and Customer and Stakeholder Response had different leading capability patterns, and the subdimension block added significant variance in 18 of 21 models. The battery therefore reports a profile rather than one overall score, and development targeting should begin with the outcome in view.

The AI-era behaviors added information beyond established measures: in the largest criterion model, 86% of the explained variance was attributable uniquely to AI Leadership, against 3% uniquely to the established measures.

Taken together, the findings point to a practical development opportunity: experiments run on a schedule, capability reviewed at intervals, and provisional decisions made before the evidence is complete. These structural practices can be specified, taught, reinforced, and measured again. Read together, the results describe development targets, not a fixed condition.

Section 1: The AI Value Gap and Its Causes

In the U.S. alone, private AI investment reached \$285.9 billion in 2025, a figure that places AI alongside the most capital-intensive technology cycles in history (Stanford HAI, 2026). Organizations are investing in technology, expecting to capture productivity gains and grow their businesses. Deloitte’s 2025 survey found that organizations typically expect technology investments to pay back within seven to twelve months, whereas respondents most often reported two to four years for a typical AI use case (Deloitte, 2025).

The pattern holds across research methods and industries. MIT Project NANDA, McKinsey, and Deloitte each document a gap between AI use or investment and enterprise-level return, although they use different samples and outcome definitions. MIT Project NANDA puts the most-cited number on it, and the most contested. The report is preliminary and its sampling has drawn scrutiny. By its estimate, 5% of integrated AI pilots were extracting millions in value. In IBM’s 2026 CEO Study, 83% of the 2,000 CEOs surveyed said AI success depends more on people’s adoption than on the technology itself (IBM Institute for Business Value, 2026).

EXHIBIT 1		
External indicators of the AI value gap		
MIT PROJECT NANDA · 2025	Organizations in its preliminary evidence base reporting zero return from generative AI	95%
MCKINSEY · 2025	Global survey respondents attributing any enterprise-level EBIT impact to AI	39%
DELOITTE · 2025	Most commonly reported payback period for a typical AI use case	2–4 years
STANFORD HAI · 2026	U.S. private AI investment in 2025	\$285.9B
Source. MIT Project NANDA (2025); McKinsey (2025); Deloitte (2025); Stanford HAI (2026). Status. Four separate studies with different samples, definitions and outcomes. These values are reported separately and are NOT estimates of the same population rate.		

Exhibit 1. The sources use different samples, definitions, and outcomes. The reported values should not be read as estimates of the same population rate.

EXHIBIT 2

Executive sponsorship is associated with reported generative-AI ROI

% of executives reporting ROI on at least one use case

Comprehensive C-suite sponsorship



Without comprehensive C-suite sponsorship



6 POINTS

Bars run the full 0–100% scale. Axis not truncated.

Source. Google Cloud / National Research Group, ROI of AI 2025 – 3,466 senior leaders across 24 countries. **Status.** Descriptive comparison between two groups of respondents. An association between reported sponsorship and reported ROI – not an effect of sponsorship, and not a measured return.

Exhibit 2. Google Cloud and National Research Group 2025 survey data. The comparison is descriptive.

The sponsorship data records an association. What it cannot show is the mechanism underneath: the daily leadership behavior that teams actually watch. AI creates value when teams change how work gets done. A recent multisource, multi-wave study (Liu et al., 2026) found that a leader's collaboration with AI was associated with higher team performance through two team-level mechanisms:

Team reflexivity is the degree to which teams openly reflect on, adapt, and revise how they work.

Team role-breadth self-efficacy is the shared belief among team members that they can take on a broader, more initiative-driven range of responsibilities.

Across two samples, the results centered on these team mechanisms rather than the leader's productivity alone. Leaders who visibly collaborate with AI can help create the everyday behavioral environment in which teams experiment, calibrate trust in AI outputs, and share what they learn.

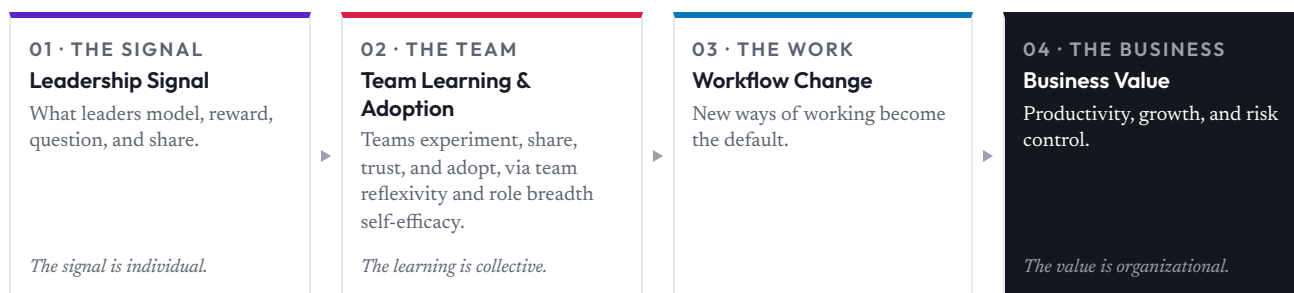
Why would a leader's visible behavior carry that much weight? Two research traditions supply the answer. Signaling theory (Connelly et al., 2011) describes how people read the observable choices of those in authority and adjust their own behavior without being told to. Social learning theory (Bandura, 1977) explains why the reading is so efficient. People learn by watching models, and models with status and credibility exert outsized influence on what observers adopt. Together, the two traditions predict what Liu et al. found. The team is the receiver. Leaders send signals through what they visibly do, and teams learn from those signals whether experimentation is safe, integration is expected, and transparency is the norm.

A leader who experiments openly with AI signals that experimentation is safe. A leader who shares what a model got wrong signals that transparency is expected. A leader who redesigns a workflow around AI output signals that integration is the norm, not the exception. Conversely, a leader who never references AI signals that it is optional. A leader who punishes a failed AI experiment signals that the risk is not worth taking. These signals operate through everyday, visible behavior, and they aggregate into the team's collective understanding of what is safe, expected, and rewarded.

The signal is the lever. The team, the multiplier. The work is where it lands. The business value follows.

EXHIBIT 3

The signal-to-value chain: how leadership behavior becomes AI value



The signal is the lever. The team, the multiplier. The work is where it lands. The business value follows.

Source. Klein & Sorra (1996); Lee & See (2004); Liu et al. (2026). **Transmission:** Connelly et al. (2011). **Status.** Mechanism described in the cited literature, not measured in this program.

Exhibit 3. The signal-to-value chain. The mechanism runs through the team: leader signals set the climate in which use is expected, supported, and rewarded (Klein & Sorra, 1996), that climate calibrates the team's trust in AI (Lee & See, 2004), and those conditions carry performance (Liu et al., 2026). Transmission: Connelly et al. (2011).

The stall point is visible in the broader transformation record. McKinsey's transformation research finds that roughly 70% of large-scale change efforts fall short, and the cause is typically organizational rather than technical: new ways of working fail to take hold (Robinson, 2019). Like the 95% estimate, this figure is widely cited and contested: it predates the AI era and its empirical base has been questioned. It indicates the direction of the transformation record, not a precise rate.

Leadership is where AI investment becomes team behavior, and team behavior is where it becomes business value. A stall at adoption is what it looks like when that first conversion fails.

Section 2: The Signalead™ Framework

If leadership behavior influences AI value through its effect on team learning, adoption, and workflow integration, the next question becomes clear. Which leadership behaviors matter most?

We reviewed the AI leadership literature, anchored by two recent systematic reviews: Sacavém et al. (2026), which analyzed 84 peer-reviewed studies, and Santiago-Torner et al. (2026). That research identifies the behavioral shifts AI-era leadership requires. Across this research, three behavioral clusters recur: how leaders adapt their own judgment when working with AI, how they build team capacity to learn and adopt it, and how they set clear guardrails around risk and ethical use. Decades of organizational research show that a company's choices reflect the judgment and values of its senior leaders (Hambrick & Mason, 1984), and a recent review across 31 leading journals finds this the dominant lens for understanding leadership in AI-enabled decisions (Bevilacqua et al., 2025). If leadership shapes how organizations absorb and scale AI, then leadership behavior is the logical place to intervene.

Building on that established science, the Signalead™ framework was designed to identify the specific behaviors most relevant to whether AI investment becomes organizational value. Behaviors were included only if they met three criteria. Each had to be uniquely relevant to an AI-transformed environment, demonstrably linked to how teams adopt and integrate AI, and observable and developable through practice or through deliberate changes to role, team, and decision flow.

Signalead™ names these three clusters the three signals:

01. Inner Signal (Mindset & Adaptability) How leaders adapt their own thinking, judgment, and learning as AI challenges expertise and introduces uncertainty.

02. Outward Signal (People Practices) How leaders create the conditions for teams to learn, experiment, share knowledge, and evolve together.

03. Grounded Signal (Judgment & Governance) How leaders establish trust, accountability, and governance as AI becomes embedded in work.

Together, the three Signals organize eleven named dimensions and thirty-six behavioral subdimensions. The dimensions provide the practitioner development language. The subdimensions preserve the score-level detail evaluated in the validation program. The validation program did not calculate Signal-level scores or test the Signals as higher-order factors.

Signal architecture and current dimension names

SIGNAL ARCHITECTURE

Signal architecture and current dimension names

SIGNAL	DEVELOPMENT FOCUS	CURRENT DIMENSIONS
INNER SIGNAL	Mindset and adaptability	Developmental Stretch; Adaptive Leadership; Outside-In Learning
OUTWARD SIGNAL	People practices	Team Learning Experiences; Role & Skill Evolution; Psychologically Safe Climate; Purposeful Communication; Proactive Transparency
GROUNDED SIGNAL	Judgment and governance	Ethical Guardrails & Accountability; Contextual Calibration; Change Discipline

Status. The table uses the current practitioner-facing terminology. The validation program did not calculate Signal-level scores.

The table uses the current practitioner-facing terminology. The validation program did not calculate Signal-level scores.

The eleven dimensions. Each signal is made up of specific, named dimensions – the level at which a leader is actually developed. Here is what each one measures.

Inner — Mindset & Adaptability

Developmental Stretch – using AI in ways that stretch one’s own capability, staying open when AI challenges your expertise or judgment, and improving from the evidence of working with it.

Adaptive Leadership – taking timely action on AI under incomplete information, then revising decisions and tactics when the evidence points to a better path.

Outside-In Learning – looking beyond the team’s usual domain for AI signals and practices, and translating what matters into learning the team can use.

Outward — People Practices

Team Learning Experiences – helping the team systematically turn AI-use experience into shared learning, better practices, and applied capability.

Role & Skill Evolution – developing capabilities, redesigning roles, and coaching critical AI discernment so people move into higher-value human work as AI changes the job.

Psychologically Safe Climate – creating a climate where people can speak up, experiment, ask for help, and raise concerns about AI – without fear of blame or embarrassment.

Purposeful Communication – making AI change intelligible and meaningful: supporting shared interpretation and preserving human purpose and role meaning as the work changes.

Proactive Transparency – openly explaining and documenting why AI is used, how it works, and how it shapes decisions – including the implications for those affected, even when the truth is uncomfortable.

Grounded — Judgment & Governance

Ethical Guardrails & Accountability – setting clear ethical boundaries for AI use, holding them under pressure, and accepting accountability for the outcomes.

Contextual Calibration – interpreting, questioning, and calibrating AI output against context, situation, and future implications before relying on it.

Change Discipline – structuring AI implementation with discipline: paced to the team's capacity, coordinated across stakeholders, governed by clear criteria, and sustained through setbacks.

Section 3: Leadership Science Didn't Change; the Work Did

Most organizations already use well-established tools to measure leadership potential, personality, competencies, and effectiveness, and those assessments remain valuable. Hogan, Korn Ferry, DDI, and their peers provide important insights into how leaders think, interact, and perform. The issue is not that these instruments are wrong. They were built and validated for broader leadership questions, not specifically for leadership behavior in AI-enabled work.

These assessments tend to focus on traits, leadership styles, and broad competencies, and they capture characteristics associated with effective leadership in general. A newer and more specific set of behaviors is relevant to whether AI investment becomes organizational value. The established comparison measures used in this study were not designed to isolate those AI-specific behaviors. They say less about how a leader adapts judgment when AI challenges expertise, how teams experiment and learn alongside machines, how isolated AI wins become repeatable workflows, or how leaders set the boundaries that responsible AI use requires.

The research literature points in the same direction. Aziz et al.'s (2025) systematic review describes AI-powered leadership as an emerging, fragmented literature and names the long-term impact of AI leadership on organizational outcomes among its most pressing research gaps. That agenda remains open, and the instrument gap it implies is what this paper begins to address. Without that measure, the behaviors that may shape the outcome go unwatched: whether teams adapt how they work, whether they build the confidence to take on broader responsibilities alongside AI, and whether those changes compound into lasting workflow improvement.

EXHIBIT 4

Established measures and AI-specific behavioral measurement answer different questions

ESTABLISHED LEADERSHIP MEASURES

Broad leadership interpretation

- Personality, leadership styles, and broad competencies
- General leadership and organizational criteria
- Broad leadership interpretation
- Used as comparison measures in the validation models

AI LEADERSHIP BATTERY

Behavioral profiles for AI-enabled work

- Observable, developable behavior in AI-enabled work
- AI-era adoption, work, performance, growth, customer, and risk criteria
- Construct and subdimension profiles for targeted development
- Tested for incremental contribution beyond the comparison measures

COMPLEMENTARY LAYERS • NOT SUBSTITUTES

Status. The two layers are complementary. The appendix reports the incremental evidence.

Exhibit 4. The two measurement layers are complementary. The Appendix summarizes the incremental evidence.

Appending AI-themed questions to legacy instruments does not close the gap. Those instruments do many things well, but because they were validated before AI began shaping performance outcomes, isolating and developing the behaviors that distinguish high-performing AI adopters falls outside what they were designed to do.

Signalead™ is built to complement these instruments, not replace them. It focuses on the observable signals a leader sends when a team adopts AI, learns from it together, and scales it into practice. Read alongside a leader's existing profile, it extends the picture into AI-specific leadership behavior and gives leaders a more actionable basis for development.

Section 4: The Three Signals

The Signalead™ framework organizes AI-era leadership behavior into three practical Signals: Inner, Outward, and Grounded. The completed validation program tested eleven constructs and thirty-six subdimensions through three separate survey forms; it did not calculate aggregate Signal, form-level, or overall AI Leadership scores. The empirical results below use the current construct names and identify the independent validation sample for each result.

Adapt → Adopt → Scale · *The signal is individual · The learning is collective · The value is organizational*

EXHIBIT 5

The three signals every leader sends

	INNER SIGNAL	OUTWARD SIGNAL	GROUNDING SIGNAL
DOMAIN	Mindset & Adaptability	People Practices	Judgment & Governance
WHAT IT CAPTURES	How a leader adapts and orients to AI.	How a leader helps the team learn, experiment, share, and turn AI use into shared practice.	How a leader sets trust, accountability, and boundaries so AI can scale responsibly.
SHAPES	The leader	The team	The organization
MOTION	ADAPT	ADOPT	SCALE

Status. The behavioral architecture behind AI adoption, productivity, and responsible scale. No aggregate Signal score is calculated.

Exhibit 5. The behavioral architecture behind AI adoption, productivity, and responsible scale.

Inner Signal: Mindset and Adaptability

The Inner Signal is where AI leadership begins. It captures what a leader does when AI challenges familiar expertise. Some leaders defend the old boundary of competence. Others stretch their judgment past it.

Leaders set the cultural tone for AI adoption through the behavior their teams can see. A guarded leader can be trained on every tool in the stack and still signal that AI is not really how work gets done here. A leader who tests, learns, and adjusts in the open gives the team permission to do the same. Part of that stretch points outward. Leaders who scan how AI is being used beyond their own walls and translate what applies, supply the reference points their team's trust is calibrated against. Without that intake, the team decides in a vacuum.

Outward Signal: People Practices

The Outward Signal measures the routines a leader builds so the team can experiment, share, and learn together. This is where individual AI use becomes team adoption. AI creates little value when knowledge stays trapped in individuals. Productivity gains become organizational gains only when teams share learning, codify discoveries, and build shared workflows. Decades of research on team learning and psychological safety place leaders at the center of those conditions. Without them, AI wins stay individual and never compound.

Grounded Signal: Judgment and Governance

The Grounded Signal measures how leaders calibrate trust, exercise judgment, and establish boundaries so AI can scale responsibly. As AI systems increasingly influence decisions, the leader's role shifts from making every call personally to designing how calls are evaluated, challenged, and governed. Researchers describe this as a movement from direct execution toward decision architecture. Grounded Signal behaviors help leaders determine where AI should be trusted, where human judgment remains essential, and how to scale without creating unacceptable risk. Governance, done well, is the architecture that makes scaling safe, not a brake on adoption.

The validation program evaluated constructs in three independently administered forms and did not calculate Signal-level scores. The findings are therefore summarized by validation sample. They should not be read as statistical tests or comparisons of the three Signals.

EXHIBIT 6

The validated constructs divide the outcome space

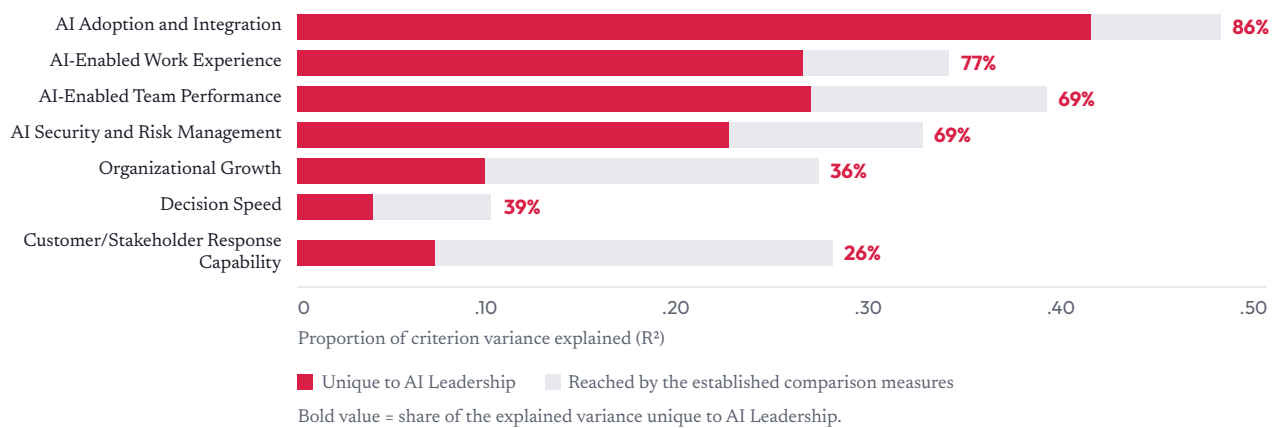
INDEPENDENT SAMPLE	LEADING CAPABILITY PATTERN	SELECTED CONCURRENT ASSOCIATIONS
First (n = 198)	Developmental Stretch led six of the eight primary criteria; Ethical Guardrails & Accountability led AI Security and Risk Management.	Developmental Stretch with AI-Enabled Work Experience, $r = .57$; Ethical Guardrails & Accountability with AI Security and Risk Management, $r = .51$.
Second (n = 202)	Team Learning Experiences led five primary criteria.	AI Adoption and Integration, $r = .66$; AI-Enabled Work Experience and AI Security and Risk Management, $r = .56$; AI-Enabled Team Performance, $r = .55$.
Third (n = 201)	Adaptive Leadership, Change Discipline and Outside-In Learning led different criteria.	Adaptive Leadership with AI-Enabled Team Performance, $r = .45$; Change Discipline with Customer and Stakeholder Response and AI-Enabled Work Experience, $r = .44$; Outside-In Learning with AI Security and Risk Management, $r = .48$.

Source. Technical report, Ch. 6. **Status.** Concurrent, same-wave associations – not causal effects or temporal prediction. Samples were analyzed separately; no form-level total or overall AI Leadership score was calculated.

Exhibit 6. Final validation results from three independent samples. Correlations are concurrent, same-wave associations and do not represent causal effects or temporal prediction. The samples were analyzed separately; no form-level total or overall AI Leadership score was calculated. Constructs are grouped by the form in which they were administered, not by Signal.

WHERE THE EXPLAINED VARIANCE COMES FROM

The established measures reach almost none of it



What this shows. Every criterion defined in terms of AI shows a higher unique AI Leadership share than every criterion defined without reference to it, and the gap between the two groups is 30 percentage points. Where the outcome concerns AI-enabled work, the established comparison measures provide almost none of the explained variance on their own.

Source. Technical report, Table 6.5 and Figure 6.5. 51-item administration, $n = 202$. Bars share a common scale to 0.55. **Status.** The unique segment is the construct-composite ΔR^2 over the five established comparison measures; the remainder is the established-measures R^2 , which combines shared variance with established-only variance. For AI Adoption and Integration that remainder divides 11% shared and 3% established-only. Concurrent, same-wave; never pooled across administrations.

A Behavioral Architecture

The numbers deserve one caveat, made once: these are self-reported, concurrent associations from three independently administered forms, and the Appendix reports their limits in full. They establish that the validated constructs and subdimensions carry differentiated criterion information. They do not constitute a direct statistical comparison of three signal totals, because the validation program neither pooled the samples nor calculated form-level scores.

The three signals are not a competency checklist. They form an architecture for measuring the AI-era leadership behaviors targeted by the framework:

The Inner Signal shapes how leaders personally adapt.

The Outward Signal shapes how teams learn and adopt.

The Grounded Signal shapes how organizations scale responsibly.

The behaviors originate with the leader, take hold through collective behavior, and relate to organizational outcomes. Because the validated constructs and subdimensions carry different criterion patterns rather than collapsing into a single score, the framework supports targeted development.

The goal is not to measure leadership excellence. The goal is to measure leadership behaviors associated with how organizations adopt, govern, and derive value from AI.

Section 5: From Diagnosis to Behavior Change

Measurement locates the signal. Development targets it. Reassessment asks whether it moved.

Awareness alone rarely changes behavior. Leadership development research keeps finding the same pattern: leaders gain insight and fail to act on it. The barriers are well documented: too many priorities at once, too little deliberate practice, weak accountability, thin manager reinforcement, and no follow-up measurement once formal learning ends (Goldsmith & Morgan, 2004; Gollwitzer & Sheeran, 2006; Lacerenza et al., 2017).

If leadership behavior is part of how AI becomes organizational value, then development has to do more than build self-awareness. It has to produce measurable change in what leaders do, how teams work, and how deeply AI embeds in everyday workflows.

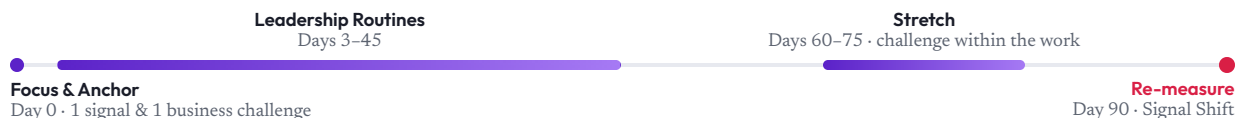
The Signalead™ Signal Sprint™ was designed around the conditions research most consistently links to lasting behavior change, and each element of its design answers one of the barriers above. A leader works on one signal and one live business challenge, because a single, relevant goal is what turns intention into follow-through (Gollwitzer & Sheeran, 2006). Success is defined not by completing a program or improving a score, but by observable changes in leadership behavior that show up in how work gets done.

EXHIBIT 7

The 90-Day Signal Sprint™: Three roles, ninety days, one destination

● Leader track ● Manager reinforcement ● Observer feedback ● Day 90 destination

LEADER TRACK — RUNS THE REPS



MANAGER REINFORCEMENT — FIVE MOMENTS



OBSERVER FEEDBACK — RE-READS THE SIGNAL



Behavioral re-measurement

Day 90 · self and observer pulse · change and recognition

Source. Signal Sprint™ program design, as published on signalead.ai. **Status.** Illustrative. Dates shift with the start date and any pauses. A description of the program, not a finding and not evidence of improvement.

Exhibit 7. Three roles move in parallel for ninety days. The leader runs the repetitions, the manager reinforces them, and observers provide an additional perspective at Day 90, when behavior is assessed again. Timeline as published on signalead.ai, illustrative. Dates shift with the start date and any pauses.

The practice itself happens in real work, not in isolated learning events. A leader draws on a library of more than twenty subdimension-specific Leadership Routines. These are structured practices built for repetition, such as a pre-decision disclosure protocol for Proactive AI Role Disclosure or a pre-committed stop-criteria template for Ethical AI Boundary Setting. Transfer-of-training research identifies this kind of applied, repeated practice as what makes development hold (Lacerenza et al., 2017).

Not every behavior responds to coaching in the same way. Some priorities are best addressed through direct practice; others require changes to roles, team routines, or decision flows that make the desired behavior easier to sustain. The Sprint therefore pairs behavioral practice with structural changes when the work context is part of the barrier.

Stakeholder FeedForward steps supply the accountability. The leader makes the development goal visible to others and returns to it in repeated conversations about progress. In Goldsmith and Morgan's (2004) study of 11,480 leaders, continuing interaction and follow-up with colleagues emerged as the central factor associated with perceived improvement.

Manager reinforcement sustains momentum without turning development into an evaluation. The Signalead™ Coach Report gives the leader's manager a focused account of what the leader is working on and why it matters for team performance. It also maps five brief touchpoints across the ninety days, each anchored to a conversation the manager is already having. In Goldsmith and Morgan's (2004) study, leaders who received follow-up from people around them improved more often than leaders who worked without reinforcement.

The Sprint is designed to close with two connected assessments. The leader retakes the assessment, and observers provide a separate perspective on whether the intended behavior is visible. These paired readings are part of the Sprint's development design; test-retest stability, observer agreement, and sensitivity to change remain to be established. Together, the two readings are intended to reveal the signal gap: the distance between the signal a leader intends and the signal others experience. Did the signal actually move?

Measurement locates the signal. Development targets it. Reassessment, from the leader and from those around them, asks whether it arrived.

Section 6: The Signalead™ System

The argument of this paper reduces to one premise. Tools create possibilities. Leadership behavior influences whether those possibilities become organizational value.

Take that premise seriously and three requirements follow. An organization needs to see the signals its leaders are sending, develop the ones holding value back, and reassess whether they moved. Signalead™ was built around exactly those three requirements, one pillar for each: Signal Measurement, Leader Development, and Organizational Value.

01 • Signal Measurement: The Signal Profile™ The Signal Profile™ answers the seeing problem. It maps a leader's observable behavior across eleven dimensions and thirty-six behavioral subdimensions, each selected for its relevance to AI-era leadership and organizational criteria. The output is a picture of what the team is already watching: where the leader stretches, where they hold back, where they clear the way for adoption, and where risk-management signals may need attention. It is not a verdict on whether a leader is AI-ready.

02 • Leader Development: The Signal Sprint™ The Signal Sprint™ answers the development problem. One signal, one behavior priority, one business outcome, ninety days. The leader practices in real work, the manager reinforces at five set moments, and observers report whether the intended signal is visible. The design includes reassessment rather than assuming change.

03 • Organizational Value: Analytics & Advisory Analytics & Advisory addresses enterprise-level interpretation. A single profile describes one leader's reported behavior. Aggregated Signal Profile™, Signal Profile 360™, and Sprint results can be examined for patterns in adoption-related behavior, development priorities, and risk-management signals. Those organizational applications require continuing multisource and longitudinal evidence. Signalead™ advisors use the resulting map with executive teams to inform leadership-team design, AI governance, and investment priorities.

Each seat at the executive table will ask something different of this system.

For CHROs and CLOs, the question is developmental. Which reported behaviors are associated with stronger AI adoption, and which should become development priorities? Awareness programs and fluency certifications cannot answer that alone. Behavioral measurement can add evidence, as can development tied to a specific behavior, a specific outcome, and reassessment at the close.

For CEOs and operating leaders, the question is execution. Organizations capture AI value when teams collectively change how work gets done, not when individual employees happen to use AI tools. Leaders influence that change through what they test, what they reward, what they let spread, and what they stop. The signal a leader sends becomes the norm a team follows.

For CFOs and risk leaders, the question is accountability. If leadership behavior contributes to AI returns, then leadership development can no longer be justified by participation rates and satisfaction scores. It has to show movement in behaviors associated with adoption, productivity, growth, and risk control. Measurement is investment discipline.

The organizations that capture AI value will not be the ones with the most tools or the largest training budgets. They will be the ones that know what signals their leaders are sending, where those signals are weak, and whether they moved.

Appendix: The Instrument and the Evidence

This appendix summarizes the completed validation program directed by Dr. Mustafa Akben. The program proceeded in stages so that content was defined before items were tested, the item set was fixed before independent confirmation, and criterion evidence was evaluated only after the measurement structure had been established. The complete methods, tables, figures, appendices, and reproducibility records are documented in the *AI Leadership Battery Technical Report* (AI Leadership Research Team, 2026). A peer-facing account of the development and validation studies is available as a preprint (Akben & Coyne, 2026).

THE COMPLETED VALIDATION PROGRAM

The program began with 180 candidate items written to 36 definitions fixed in advance. Twelve definition-matching surveys asked doctoral-level expert judges to compare every item with its intended definition and with established neighboring constructs. Three independent development samples of working leaders then supplied the exploratory evidence used to select three items per subdimension and fix the battery at 108 items. Three newly recruited validation samples supplied the confirmatory, discriminant, criterion-related, and reference-distribution evidence. Each leader completed one of three survey forms, and the samples were analyzed separately rather than pooled.

EXHIBIT 8

The completed validation program at a glance

199 doctoral-level expert judges · 1,191 working leaders in six samples · 108-item final battery

EVIDENCE STAGE	ANALYTIC SAMPLE	FINAL RESULT
Content validation	Doctoral-level expert panels across twelve definition-matching surveys	174 of 180 candidates met all three content criteria; every subdimension retained at least three
Exploratory structure and reliability	590 records from 589 working leaders across three development samples	Parallel analysis supported the specified factor count for all 11 constructs; 108 items selected across all 36 subdimensions
Independent confirmation and discriminant validity	601 working leaders across three new samples	All three prespecified models admissible; all 142 comparisons met the discriminant-validity criteria; the marker-variable check changed no classification
Criterion-related validity	The same three independent validation samples	Increments significant in 19 of 21 construct-level and 18 of 21 subdimension-level models; held-out prediction improved in 18 of 21; largest increment $\Delta R^2 = .436$ over a baseline R^2 of .071

Source. Technical report, Ch. 3–7; Akben & Coyne (2026). Status. Samples are kept separate and never pooled across forms. Concurrent, same-source self-report.

Exhibit 8. The development samples contributed 590 records from 589 leaders (one leader completed two development forms). The validation samples contributed 601 leaders, none of whom took part in development. The six samples are analyzed separately and not pooled.

WHAT THE COMPLETED PROGRAM ESTABLISHES

The completed program supports the content and structure of the instrument. 174 of the 180 candidate items met all three content-validity criteria, and every subdimension retained sufficient content coverage. In the development samples, parallel analysis and scree inspection supported the theory-specified factor count for all 11 constructs. Every selected item loaded most strongly on its intended factor, and all 36 three-item subdimensions passed the prespecified reliability review.

Independent confirmation then evaluated the fixed 108-item battery rather than an earlier candidate version. All three prespecified confirmatory models converged and were admissible without item removal, cross-loadings, correlated residuals, or model-driven revision. The 30-item model showed robust CFI = .95, robust TLI = .93, robust RMSEA = .058, and SRMR = .061. The 27-item model showed robust CFI = .98, robust TLI = .98, robust RMSEA = .033, and SRMR = .042. The larger 51-item model produced acceptable robust RMSEA (.062) and SRMR (.059), while robust CFI (.89) and TLI (.87) were lower.

Table A1 · Confirmatory model fit across three independent forms

TABLE A1

Confirmatory model fit across three independent forms

FORM	SAMPLE N	ROBUST CFI	ROBUST TLI	ROBUST RMSEA	SRMR
30-ITEM FORM	198	.95	.93	.058	.061
51-ITEM FORM	202	.89	.87	.062	.059
27-ITEM FORM	201	.98	.98	.033	.042

Source. Technical report, confirmatory factor analyses. Values as published by Dr. Akben, 2 September 2026. Status. All models were prespecified correlated-factor models. The 51-item model had acceptable RMSEA and SRMR but lower CFI and TLI than the other two, and estimated more parameters.

Table A1. All models were prespecified correlated-factor models. The 51-item model had acceptable RMSEA and SRMR but lower CFI and TLI than the other two models. It also estimated more parameters. Every subdimension met the loading, composite-reliability, and average-variance-extracted benchmarks. All 142 tested comparisons used selected three-item representations of 11 established leadership and organizational measures. Each comparison met the prespecified HTMT, bootstrap, and focal-side variance criteria. A marker-variable sensitivity analysis changed no classification.

The criterion results support the central practical claim that the profile carries information beyond established comparison measures. All 88 construct-composite associations with the eight primary criteria were positive, and 84 were statistically significant ($p < .05$, uncorrected). The AI Leadership increment was statistically significant in 19 of 21 construct-level models, and in repeated cross-validation, adding the construct scores improved prediction on held-out responses in 18 of 21. Team Learning Experiences correlated .66 with AI Adoption and Integration, the largest construct association in the program; Systematic Applied Capability Review had the corresponding largest subdimension association, .62. For that criterion, the second sample's five construct composites added $\Delta R^2 = .436$ beyond the five established measures (baseline $R^2 = .071$), the full subdimension block added $\Delta R^2 = .522$, and 86% of the variance explained by the combined construct model

was unique to AI Leadership. On held-out responses, explained variance for this criterion rose from .009 with the established measures alone to .430 with the construct scores added.

The results also show why the battery reports a profile. Developmental Stretch and Ethical Guardrails & Accountability carried the largest contributions in the first sample. Team Learning Experiences carried the largest contribution for five of the six eligible criteria in the second sample. Adaptive Leadership, Change Discipline, and Outside-In Learning carried the largest contributions for different criteria in the third sample. Construct composites provide an organizational summary, while the 36 subdimensions preserve the behavioral detail required for targeted feedback and development planning. Reference distributions from the three validation samples, totaling 601 respondents, provide a descriptive empirical anchor for every construct and subdimension score.

WHAT THE CURRENT EVIDENCE DOES NOT ESTABLISH

The evidence should be read with discipline. The criterion results are self-reported, concurrent, and same-wave. They establish association and incremental explanatory contribution within the validation samples, not temporal prediction or causal effect. The validation program administered three separate forms to three separate samples. It did not pool the samples, model all 108 items in one linked administration, calculate three form-level totals, or calculate an overall AI Leadership score. Some subdimensions within the same form are closely related. The largest latent correlations were .85, .81, and .79, all among learning and adaptation behaviors, so how distinct these subdimensions are from one another remains to be tested.

The reference distributions are empirical anchors from research-panel samples, not population norms. The current program does not yet establish measurement invariance across demographic or organizational groups, test-retest stability, response-process evidence, or predictive validity based on multisource, behavioral, objective, or longitudinal criteria. It also does not establish that the Signal Sprint™ itself causes behavioral or organizational change. Those questions require evidence from the continuing program rather than inference from the present concurrent findings.

INTENDED USE

Intended use. The AI Leadership Battery and its Signal Profile reporting application are intended for leader self-development, coaching, team and organizational development, and research. They are not designed or validated for hiring, promotion, compensation, cut scores, automated ranking, or any other employment decision. Scores describe self-reported behavior for developmental interpretation against published reference distributions; they are not population norms and carry no pass/fail threshold.

What Comes Next

The next research stages are specified in the technical report as a sequenced program. They include a full-architecture linked administration of all 108 items, measurement-invariance testing, test-retest reliability, response-process interviews, focused replication of the closest subdimension relationships, population-based normative work, and multisource, behavioral, and longitudinal criterion studies. That sequence will determine whether the current score interpretations extend to group comparisons, population benchmarking, stable change measurement, and temporal prediction.

The Evidence Standard

The standard for an instrument like this is easy to state and hard to meet. It must measure the intended behaviors reliably and distinctly, relate to relevant criteria beyond what established measures already explain, and eventually demonstrate that score changes correspond to observable changes over time. The completed program now establishes the first two parts of that standard. The continuing instrument program will extend the linked, multisource, and longitudinal evidence; a separate intervention evaluation will be needed to test whether the Signal Sprint™ changes behavior and organizational outcomes.

Table A2 · Edge-to-Signal concept mapping

TABLE A2

Edge-to-Signal concept mapping

PREVIOUS EDGE	PREVIOUS DIMENSION	CURRENT SIGNAL	CURRENT DIMENSION
Inner Edge	Frontier Readiness	Inner	Developmental Stretch
Strategic Edge	Adaptive Action	Inner	Adaptive Leadership
Strategic Edge	AI Scout	Inner	Outside-In Learning
Human Edge	Deliberate Transparency	Outward	Proactive Transparency
Human Edge	Capability Choreography	Outward	Role & Skill Evolution
Human Edge	Learning Orchestration	Outward	Team Learning Experiences
Human Edge	AI Psychological Safety	Outward	Psychologically Safe Climate
Human Edge	Purposeful Narrator	Outward	Purposeful Communication
Inner Edge	Contextual Judgement	Grounded	Contextual Calibration
Inner Edge	Ethical Backbone	Grounded	Ethical Guardrails & Accountability
Strategic Edge	Change Architecture	Grounded	Change Discipline

Status. The regrouping was not a rename. Dimensions moved between groupings, so the two structures do not correspond one to one – Inner Edge dimensions appear under both the Inner and Grounded Signals. Provided for readers working from the technical report.

Table A2. The earlier Edge grouping and its dimension names, mapped to the current Signals. The regrouping was not a rename: dimensions moved between groupings, so the two structures do not correspond one to one. Provided for readers working from the technical report.

About the Authors

Leslie Coyne is the Founder & Principal Advisor of Signalead™ and the designer of its AI leadership framework. As an executive talent strategist, she has spent over 20 years developing assessment, succession, and leadership development systems for enterprise organizations. Her past client experience includes work with General Electric, United Technologies, Honeywell, Jabil, and LivaNova. She holds graduate degrees in Human Resources from the University of South Carolina and in Communication (focusing on Industrial-Organizational Psychology) from the University of Georgia. She holds certifications in Hogan assessments, Korn Ferry Learning Agility, and the Leadership Versatility Index.

Mustafa Akben, PhD, is the Director of Artificial Intelligence Integration and an Assistant Professor of Management at Elon University. His research focuses on how generative AI influences workplace cognition and decision-making. He holds a PhD in Business Administration from Temple University's Fox School of Business and an MS in Organizational Dynamics from the University of Pennsylvania. His research integrates organizational behavior with machine learning techniques, such as using neural networks to screen survey responses and classify leadership skills. He has published his research in the *Journal of Applied Psychology*. Dr. Akben directs the psychometric validation and statistical analysis of the Signalead™ instrument.

About Signalead™

Signalead™ is the AI-native system for AI-era leadership, licensed and delivered through Jack Ryan Advisory. It organizes AI-era leadership into three behavioral signals (Inner, Outward, and Grounded) across eleven dimensions and thirty-six behavioral subdimensions. That behavioral profile is paired with a manager-anchored 90-day Signal Sprint™ that concludes in behavioral reassessment. The system is built around three connected stages (Signal Measurement, Leader Development, and Organizational Value) and includes the free Signal Pulse™, the Signal Profile™ and Signal Profile 360™, the 90-day Signal Sprint™, and organizational analytics and advisory. Learn more at signalead.ai.

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Current figures reflect the completed multi-stage validation program directed by Dr. Mustafa Akben (Elon University). Criterion findings are self-reported, concurrent associations and incremental explanatory contributions, not causal effects or temporal predictions. Full methodology and results are documented in the AI Leadership Battery technical report and in the preprint Akben & Coyne (2026), arXiv:2609.17965. Hogan Assessments® is a registered trademark of Hogan Assessment Systems, Inc.; it has not endorsed or approved Signalead™. Korn Ferry and DDI are trademarks of their respective owners.

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