

THE LUDDITE CONSULTANT IN THE AGE OF AI

David Michael Boje, Latest Revision September 22, 2026

Three Witnesses Three Career Futures

These are explicitly fictional composite characters. They make three kinds of AI-altered professional work discussable without claiming to speak for identifiable employees.



Sarah Calder

External consulting

Client pressure, AI agents, evidence, ethical refusal



Eleanor "Nell" Hart

Internal HRM and HRD

Training, careers, exits, dignity, developmental possibility



Rafael Ortiz

Internal OD

Work design, 3Cs, participation, organizational learning

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© 2026 David Michael Boje. Self-publish edition, until an agent comes knocking to represent my book to publisher. This book is based on Voice Memo dictations. AI did react-checking, spelling and grammar corrected, my living story retained. — September 18, 2026, Lake Caballo, New Mexico, with Cuddlebear, Australian Blue Heeler (mostly brown).

Table of Contents

Copyright _____	1
Table of Contents _____	2
<i>Preface: Why a Luddite Consultant?</i> _____	7
Introduction: The September 2026 Moment _____	7
Forty Years of Listening _____	8
Conclusion: Why This Book Now _____	10
<i>Three Composite Witnesses and the Four Entanglements</i> _____	11
Figure 0 Trace Your AI Algorithm Entanglements _____	11
<i>Glossary of Key Concepts and Technical Terms</i> _____	12
Critical Narrative & Deconstructive Frameworks _____	12
Socio-Economic Approach to Management (SEAM) & Qualimetrics _____	13
AI Transformation & Technical Terms _____	13
<i>Introduction: Let's Deconstruct Billion Dollar Consulting Companies in the AI Revolution</i> _____	15
The Eight Steps of Deconstruction _____	16
Step One: Identify Dualities in the Surface Narrative _____	16
Step Two: Reinterpret Dualities from the Marginalized Side _____	17
Step Three: Surface Rebel Voices _____	17
Step Four: Uncover the Other Side of the Story _____	18
Step Five: Deny the Official Plot _____	19
Step Six: Identify Exceptions to the Rule _____	19
Step Seven: Trace Between the Lines _____	20
Step Eight: Resituate to Unleash Human Potential _____	21
Accenture Deconstruction Case Example: Deconstructing Accenture's \$923M AI Restructuring Narrative _____	21
<i>Chapter 1: The Luddite Consultant in the AI Revolution</i> _____	23
Introduction: The Origin of a Stance _____	23
The NMSU Case: Hierarchical Consulting in Action _____	23
SEAM Would Have Done It Differently _____	24
The Oil and Gas Paradox _____	25
Pre-AI to Post-AI: The Same Logic, Accelerated _____	26
Conclusion: What Listening Costs, and What It Saves _____	26
<i>Chapter 2: Sarah and the Four Whos of Tesseract Leadership</i> _____	29

Summary	29
Key Words	29
Inset Antenarrative Processes	29
Introduction Sarah Is Not One Person	30
Figure Sarah in Four Tesseract Leadership Roles	32
The Conversation Begins Before and Beneath	32
Sarah Before the Dashboard	32
Sarahs Notebook No Dashboard for This	34
First Who Egoistic Sarah	35
Second Who Family Sarah	35
Third Who Corporate Sarah	36
Sarah and the Tools	36
Fourth Who Ecologically Conscious Sarah	37
Discussion What Sarah Contributes to Antenarrative Praxis	38
Conclusion The Story Is Still Moving	38
<i>Chapter 3: The SEAM Mathematical Framework and the Hidden-Cost Ledger</i>	<i>39</i>
Introduction: The Accounting Gap	39
The Six Dysfunction Families and Four Consequence Lines	40
Case Audit 1: Sarah's AI Workflow at Accenture	41
Case Audit 2: Deloitte Australia's DEWR Assurance Report	41
Tamaraland as Audit Tool: Qualimetrics Across the Four Rooms	42
The Triangulation Process and the Mirror Effect	43
Comparing Pre-AI and Post-AI Consulting: NMSU to Big Ten	43
Conclusion: Making the Invisible Visible	44
The Macro-Scale SEAM Calculation: Industry Hidden Costs	45
<i>Chapter 4: McKinsey in the AI Revolution – Who Made the Cut, Who Did Not, and the Snafus Along the Way</i>	<i>47</i>
Introduction: The Archetype Rewired	47
The Big Ten: Pre-AI to Post-AI Operating Models	47
The Big Ten and Their AI Platforms	49
Who Made the Cut and Who Did Not	49
Those Who Advanced	50

Those Who Did Not _____	50
The March 2026 Security Incident: When One AI Hacked Another _____	51
Lilli's Security Protocols: Claims and Reality _____	51
Submerged Costs and the Luddite Perspective _____	52
Conclusion: What the McKinsey Case Demonstrates _____	52
<i>Chapter 5: Compressed AI Exits – Comparing Workforce Reductions Across Major Consulting Firms _____</i>	<i>54</i>
Introduction: Documenting the Undocumented _____	54
Eight Composite Trajectories: Survivors and Leavers _____	55
Those Who Remained and Adapted _____	55
Those Who Exited _____	56
Cross-Firm Comparison: Scale, Framing, and Human Consequences _____	57
AI Impact on Junior Roles: The Systemic Pattern _____	58
Voices from the Anonymous Record _____	58
Conclusion: The Uneven Distribution of the AI Dividend _____	58
<i>Chapter 6: Silence in the Pyramid, Voices from the Lab – Why Consulting Firms Do Not Narrate Their AI Transitions _____</i>	<i>61</i>
Introduction: The Asymmetry of Voice _____	61
Public Narratives from AI Corporations: Volume, Detail, and Function _____	61
The Consulting Silence: Institutional Mechanisms of Narrative Control _____	62
Composite Characters as Methodological Necessity _____	63
Discussion: Epistemological Consequences _____	64
Conclusion: The Silence Is the Finding _____	65
<i>Chapter 7: The Regulatory Tamaraland - AI Governance Between Europe and the United States _____</i>	<i>68</i>
Introduction: The Regulation Room _____	68
Two Regulatory Architectures, Neither of Them Simple _____	69
The 2026 Timeline: Why Precision Is an Ethical Practice _____	71
AI Literacy: Training Record or Capacity to Refuse? _____	72
Human Oversight Is Not Human Presence _____	72
The Regulatory Tamaraland _____	73
A SEAM Regulatory Audit _____	74

Discussion: Procedural and Relational Accountability	75
Conclusion: After the Policy Is Signed	75
Chapter 8: The Physical AI Machine - Ghost Labor, Data Centers, Energy, Water, and Communities	77
Introduction: The Machine Beneath the Machine	77
Ghost Labor: The Humans Inside Automation	78
Everyday AI and the Personal Infrastructure Audit	79
From Ghost Labor to Ghost Infrastructure	81
Electricity, Grids, and the Local Concentration Problem	82
Water: Why the Boundary Must Be Named	83
Consulting Firms as Infrastructure Intermediaries	84
The Expanded SEAM Hidden-Cost Ledger	84
Community Voice Is Not a Public-Relations Meeting	85
Discussion: Where Does the AI Dividend Go?	86
Conclusion: Count the System	86
Chapter 9: The Employment Law Paradox — Selling Responsible AI While Settling Discrimination Claims	88
Summary	88
Introduction: The Mirror Nobody Ordered	88
The Settlements: What the Government Found	89
Table 1: The Responsibility Chain	90
Table 2: The AI Hidden-Cost Ledger	91
Table 3: The compact scorecard.	93
Step-by-Step Deconstruction: The Responsible AI Paradox	93
Step One: Identify the Duality	93
Step Two: Reinterpret from the Marginalized Side	94
Step Three: Surface Rebel Voice	94
Step Four: Uncover the Other Side of the Story	94
Step Five: Deny the Official Plot	94
Steps Six through Eight	94
Tamaraland Audit: Four Rooms, Four Stories	95
The Boardroom	95
The HR Room	95
The Workforce Room	95
The Client Room	95
What SEAM Would Look Like If It Used AI — But Kept the Human in Charge	95

Bakhtin Answerability and the Ghost Vortex	97
Can a Luddite Consultant and Claude Form a Working Relationship?	98
Principle 1: Truth	98
Principle 2: Make Room	98
Principle 3: Plot	98
Principle 4: Timing	99
Principle 5: Help Stories Along	99
Principle 6: Staging	99
Principle 7: Reflecting	99
Discussion: The Answerability Chain	99
Conclusion: Going Old School Is Going Forward	100
<i>Endnotes</i>	102
<i>References</i>	106

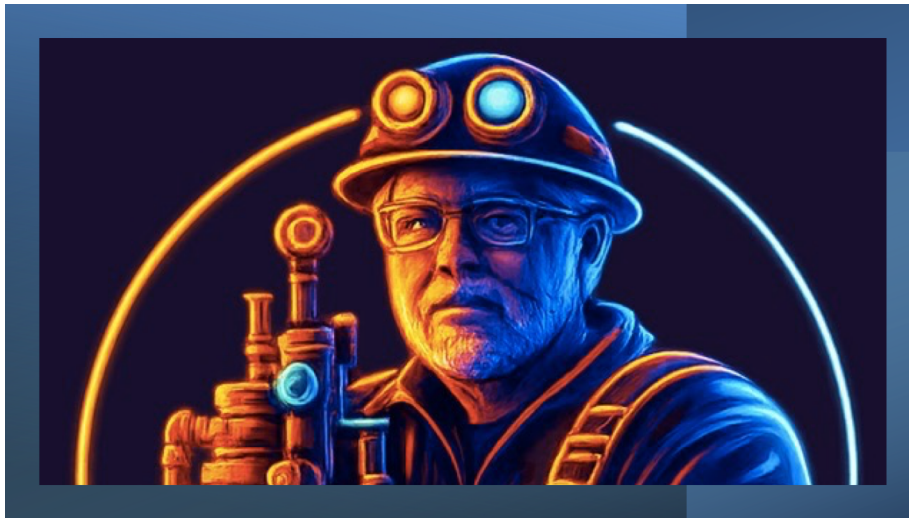
Preface: Why a Luddite Consultant?

Summary

*This preface cuts through the confusion of September 2026. Anthropic CEO Dario Amodei published *We Must Pace the Frontier*, calling for slowdown, with OpenAI CEO Sam Altman and Elon Musk agreeing that recursive self-improvement requires regulation, while Meta CEO Mark Zuckerberg and Nvidia CEO Jensen Huang rejected coordinated slowdown as harmful to competition. Inside labs, researchers such as Jacob Coxon resigned warning of extinction risk. Two Princeton-led studies gave frontier agents six days and thousands of dollars to produce peer-reviewable research and all submissions were rejected for lack of scientific judgment. Meanwhile the Big Ten consultancies sell AI transformation, not extinction, telling different stories in different rooms of Tamaraland. This book follows Shelia, a composite Luddite Consultant, and asks who tells the same story in every room.*

Keywords: Tamaraland; Luddite Consultant; AI extinction narrative; ResearchArena; pacing the frontier

Research Question: Why AI Corporations Generate Public Career Narratives While Elite Consulting Firms Produce Only Aggregate Success Stories



Introduction: The September 2026 Moment

Call her Shelia. Sometimes I call her Sherry. She is a fictitious composite — you have met her type. She worked at Accenture before the AI boom, when consulting was still process maps and sensible decks. When restructuring came, when every practice had to become AI practice overnight, she stayed about six months. She watched old contracts re-labeled, juniors replaced with prompt harnesses, billable hours re-priced as tokens. She was not anti-technology. She was what I call a Luddite Consultant. Original Luddites were skilled craftspeople defending quality against speed. Shelia was let go, or forced out, or left — the paperwork does not matter. She left because she kept asking about hidden costs. I stayed long enough to become one too.

It is September 2026 as I dictate this at Lake Caballo, New Mexico, walking Cuddlebear, my Australian Blue Heeler who is mostly brown. This book emerges from a strange historical moment. Anthropic CEO Dario Amodei has just published *We Must Pace the Frontier*, calling for regulatory coordination to slow AI development before recursive self-improvement makes the technology uncontrollable. OpenAI CEO Sam Altman and Elon Musk of xAI have both agreed that some form of governance is required. Mark Zuckerberg and Jensen Huang have rejected the call, arguing that slowdown simply hands advantage to China. Inside AI laboratories, prominent researchers including Jacob Coxon have resigned, citing extinction risk and the inadequacy of current safety frameworks. Princeton-led ResearchArena studies gave frontier AI agents six days and thousands of dollars to produce peer-reviewable scientific research — and every submission was rejected by reviewers for fundamental failures of scientific judgment and experimental rigor. The agents could generate fluent text. They could not generate science.

Meanwhile the Big Ten consulting firms — Accenture, McKinsey, BCG, Deloitte, EY, PwC, KPMG, Bain, Oliver Wyman, Booz Allen Hamilton — have not paused anything. They are selling AI transformation as the product. Their Boardroom story is about efficiency gains, GenAI bookings, and reinvention. Their Workforce Room story, if you can find anyone willing to tell it, is about compressed timelines, compressed exits, and apprenticeship collapse. The divergence between what these firms say in public press releases and what their workers experience on the ground is exactly the gap that this book opens.

I am not against AI. I use it daily to recover my voice from Voice Memo dictations. But I have learned that tools like ChatGPT and Claude will happily reinforce any dumb idea, hallucinate references even when you upload your own sources, and leave your voice on the editing room floor while producing a neat beginning-middle-end narrative. My work for forty years has been to deconstruct that BME and find the living stories underneath. That is the work of a Luddite consultant.

Forty Years of Listening

Why am I a Luddite consultant? I trained for four decades with some of the best consultants in the world. Every summer for twenty years I went to Lyon, France — joyous years, not complaining. We would spend about a month, sometimes just a week, with Henri Savall, Véronique Zardet, Amandine Savall, Marc Bonnet at ISEOR. To pay my way there, they would have me teach classes in the Socio-Economic Approach to Management, SEAM, which is a consulting approach. Not being an interventionist, they call it being an intervener. Well over 2,000 companies have enjoyed and profited by SEAM consulting. At my own university I ended up teaching it to undergrads, MBAs, PhD students, and being a researcher in SEAM. It is written into most of the books I have

done in the last 25 years. Our annual conference, now in its 17th year at quantumstorytelling.org, is always in December.

So what is a Luddite consultant? I guess I am in the middle of the AI bubble, and the whole consulting industry has been turned on its head as everyone, especially the Big Ten consulting firms, install their own AI products in other companies, with layoffs happening as they make this transition. I am going to be 79 in December. A lot of my colleagues have passed away. Others are in rehab, some are not able to present themselves anymore, and others are doing fine, probably will present into their 90s. I do not know what my future will be. But I do know the following things. With the socio-economic approach to management, one of the rules is: do not lay off anyone. Instead, get them into teams called DPI — Diagnosis, Project, Implementation, and Evaluation. That is what DPI stands for.

After a month, three months of consultants listening and interviewing people, you launch the DPI groups, with horizontal groups horizontally composed, vertical groups vertically composed, to tackle some of the biggest problems they call dysfunctions. It is a dysfunction because there is a misalignment of how humans are being treated in hierarchies and what their potential is. So we use the phrase unleashing human potential. The DPI groups meet after a mirror effect meeting with the board and executives and the manager group, and hopefully with the workers as well. That is the second principle: you have to listen to your people. It is not the same thing to listen to AIs, and a bunch of people trained in consulting to use AI tools that will run strategy analysis in nanoseconds and build out a strategy for reorganizing the supply chain with very short-term thinking.

SEAM requires ten months in the field, taking verbatim observation notes. You can hear that through SEAM, which is 10 months in the field, not even using the tablet I am using now. I have been infected by artificial intelligence. I can have a manuscript generated by Claude, by ChatGPT. Claude hallucinates less than ChatGPT. But you know what? Both take my dictations and then lay out my voice and summarize it in the AI's own words, where my voice joins the voiceless on the editing room floor. AI is really good at beginning-middle-end narrative construction. I call them BME, and there it is. This book resists the BME. It insists on storying.

Tamaraland is the metaphor I have used since 1995, drawn from John Krizanc's play *Tamara*, which ran for years in Los Angeles. In the play, audience members follow different characters through different rooms of a villa simultaneously — you cannot see everything, only the room you are in. I adapted it as an organizational metaphor: every consulting engagement happens in at least four rooms at once — the Boardroom, the Workforce Room, the Community/Client Room, and the University Room. What executives see in the Boardroom is not what workers see in the Workforce Room. For six rooms, the total ordered pathways are $6! = 720$, and summing all partial orderings $P(6,r)$

for $r=1$ to 6 gives 1,957 total story pathways. Not one of them is the whole story. The Luddite Consultant insists on visiting more than one room before writing the final report.

Conclusion: Why This Book Now

The Big Ten consulting firms are selling AI transformation packages while executing what they euphemistically call skill-based exits and compressed timelines. Accenture absorbed \$923 million in restructuring charges while eliminating approximately 11,000 employees deemed non-viable for reskilling, even as it claimed \$5.9 billion in GenAI bookings. McKinsey's Lilli platform was hacked in March 2026 by an autonomous AI agent that spent \$20 in tokens and two hours obtaining read-write access to 46.5 million chat messages, 728,000 files, and 95 writable system prompts. Deloitte Australia submitted an AU\$440,000 assurance report that fabricated legal citations — fake court cases, phantom authors, misspelled judges. The AI tools are real. So are the errors.

This book is not a manifesto against technology. It is an application of forty years of SEAM methodology to the largest organizational transformation of the century. It follows Shelia the composite Luddite Consultant, Sarah Calder the composite Accenture supply-chain consultant, and eight other composite characters whose trajectories — four who survived and adapted, four who exited under compressed timelines — illustrate the range of what aggregate numbers conceal. It applies the eight steps of deconstruction, the SEAM hidden-cost ledger with the 167 percent multiplier, and Tamaraland's simultaneous rooms to open up the official narratives and find the living stories underneath. I am a Luddite consultant. And I know what listening costs, and what it saves.

^[50] — Lake Caballo, New Mexico, September 2026.

Three Composite Witnesses and the Four Entanglements

This book does not use composite characters as decorative examples. Sarah Calder, Eleanor “Nell” Hart, and Rafael Ortiz are three explicitly fictional witnesses constructed to let the reader enter different locations in the same AI transformation. Sarah is the client-facing consultant, pressed to turn an AI promise into a client deliverable. Nell works inside human resource management and human resource development, where the questions become training access, careers, exits, developmental possibility, and whether people are treated as more than deployable capacity. Rafael works inside organization development, where the questions become work design, the 3Cs of communication, coordination, and concerted action, and whether those affected can alter the change that is being made. They are not disguised employees and their dialogue does not constitute factual testimony about particular persons. Their work is to invite a more answerable inquiry.

Their stories recur because an AI system never arrives in only one organizational room. A system that appears in Sarah’s client proposal also enters Nell’s learning and workforce arrangements, Rafael’s structures and work groups, and the university classroom or research setting where future practitioners learn what a problem is. The four-dimensional visual in this book therefore traces entanglements rather than a simple footprint total. It asks what data are collected or inferred; what decisions and market power are exercised; what labor, training, and hidden repair work are transferred; and what material and community conditions make the system possible. Answerability is the thread through all four questions, not a number added at the end.

Figure 0 Trace Your AI Algorithm Entanglements



The six scenes in the illustration are an invitation to read an algorithmic system as a living organization. The data eye represents collection, inference, consent, and surveillance. The marketplace represents pricing, ranking, allocation, and market power. The worktable represents labor, learning, skill, repair, and voice. The data center in its landscape represents energy, water, grids, land, and community burden. The central algorithm represents the tendency to make these relations appear technical and inevitable. The dialogue circle represents answerability: people must be able to question, contest, and change the design. The gold thread deliberately connects the scenes because none of the costs or benefits belongs to only one dimension.

Glossary of Key Concepts and Technical Terms

Critical Narrative & Deconstructive Frameworks

8 Steps of Deconstruction: Boje's (2001) methodology to break open slick, top-down corporate narratives and uncover suppressed living stories, antenarratives, and hidden sociotechnical costs. Developed in *Narrative Methods for Organizational and Communication Research* (Sage Publications).

Antenarrative & 7 Antenarrative B's: Living story fragments and flow dynamics (Before, Beneath, Bets, Being, Becoming, Between, Beyond) tracked before they solidify into official corporate narratives. Antenarratives are the raw material of organizational storying, preceding and exceeding any finished account.

Beginning-Middle-End (BME) Narrative: A finished, structured corporate account that exerts a centripetal force, smoothing over contradictions to present tidy stories of organizational progress and success. Official press releases, earnings calls, and consulting transformation stories are BME narratives.

Luddite Consultant: A consulting orientation — not anti-technology, but pro-human listening — that rejects automated workforce disposability in favor of extended field observation, ethical engagement, and the release of untapped human potential. Named in solidarity with the original Luddites, skilled craftspeople who defended quality work against speed-driven deskilling.

Storying / Living Story: The ongoing, active practice of making meaning through lived experience. Acts with a centrifugal force, spinning outward to include multiple, overlapping, and conflicting voices, fragments, and perspectives. Where narrative closes the door, storying keeps it open.

Tamaraland: Boje's organizational metaphor (based on Krizanc's play *Tamara*, 1981) viewing an organization as a villa of simultaneous, co-existing rooms (Boardroom, Workforce Room, Community/Client Room, and University Room) to audit conflicting stakeholder experiences concurrently. For 6 rooms: ordered pathways $6! = 720$; total pathways $\sum P(6,r) = 1,957$.

Socio-Economic Approach to Management (SEAM) & Qualimetrics

DPI Teams: Diagnosis, Project, Implementation, and Evaluation teams. Horizontally and vertically integrated employee teams launched after a mirror-effect meeting to resolve operational dysfunctions without workforce layoffs. Applied in over 2,000 organizations globally.

Dysfunctions (SEAM 6 Dysfunction Families): Misalignments between how human beings are treated in rigid corporate hierarchies and their actual capabilities. The six families are: Working conditions, Work organization, 3C (Communication-Coordination-Cooperation), Integrated training, Time management, and Strategic implementation.

Mirror Effect: A plenary meeting where intervener-researchers reflect verbatim field observation notes and calculated SEAM hidden costs back to executives, managers, and frontline workers simultaneously. The mirror effect creates the organizational shock necessary for sustained change.

No-Layoff Ethic: A foundational principle of SEAM that strictly forbids laying off employees during restructuring, focusing instead on unleashing human potential through DPI teams and qualimetrics-guided organizational redesign.

Qualimetrics: The ISEOR research methodology that triangulates qualitative verbatim field notes, quantitative dysfunction frequencies, and financial hidden-cost calculations into a unified audit of organizational sociotechnical performance.

SEAM Hidden-Cost Ledger: A two-column accounting tool mapping visible deliverables (above the waterline) against submerged sociotechnical dysfunctions and uncounted costs (below the waterline). The standard SEAM empirical finding is that hidden costs run to approximately 167 percent of visible fees.

The 167% Multiplier: Empirical SEAM rule stating hidden sociotechnical costs run to approximately 167 percent of visible consulting fees. Full Sociotechnical Cost = Visible Fee + $(1.67 \times \text{Visible Fee})$. On a \$2 million engagement: visible \$2M, hidden \$3.34M, true total \$5.34M.

AI Transformation & Technical Terms

Agentic AI & Super-Agents: Autonomous AI scripts, orchestrators, and control planes (e.g., Anthropic Model Context Protocol, Google Agent-to-Agent) deployed to execute multi-step workflows including data cleaning, scenario modeling, and document generation without human intervention at each step.

AI Refinery & Internal AI Layers: Proprietary software and prompt wrappers built over commercial large language models by Big Ten consultancies: McKinsey's Lilli, BCG's Deckster, Deloitte's Zora AI, Accenture's AI Refinery. Each firm presents its LLM wrapper as a proprietary product installed in client organizations.

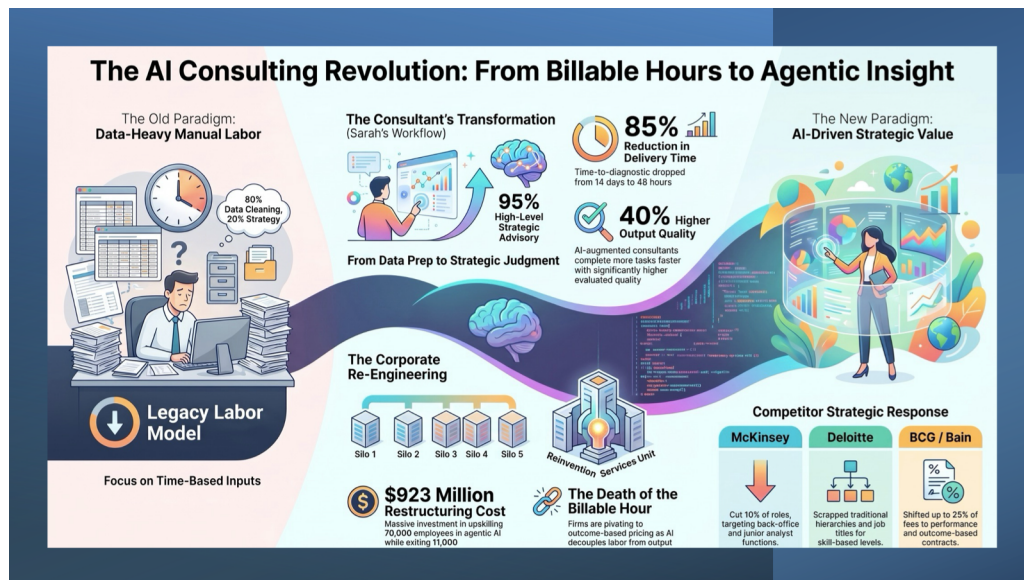
Apprenticeship Collapse & Judgment Deficit: The institutional risk created when automated AI tools eliminate entry-level analyst tasks, depriving future senior partners of

the slow-knowledge experience needed to detect flawed or hallucinated model outputs. When juniors never build slides or wrangle raw data, future partners cannot spot when an agent has fabricated a citation.

Ghost Labor: An estimated 100 million global workers performing low-wage data annotation, model training, and content moderation under harsh conditions — the invisible labor force beneath the AI efficiency narrative.

Platform Capture: A consulting business model shift away from billable hours toward outcome pricing and acting as workflow distributors for commercial AI model labs. Clients pay three rents: token fees to model labs, compute fees to cloud providers, and transformation fees to consultancies.

Introduction: Let's Deconstruct Billion Dollar Consulting Companies in the AI Revolution



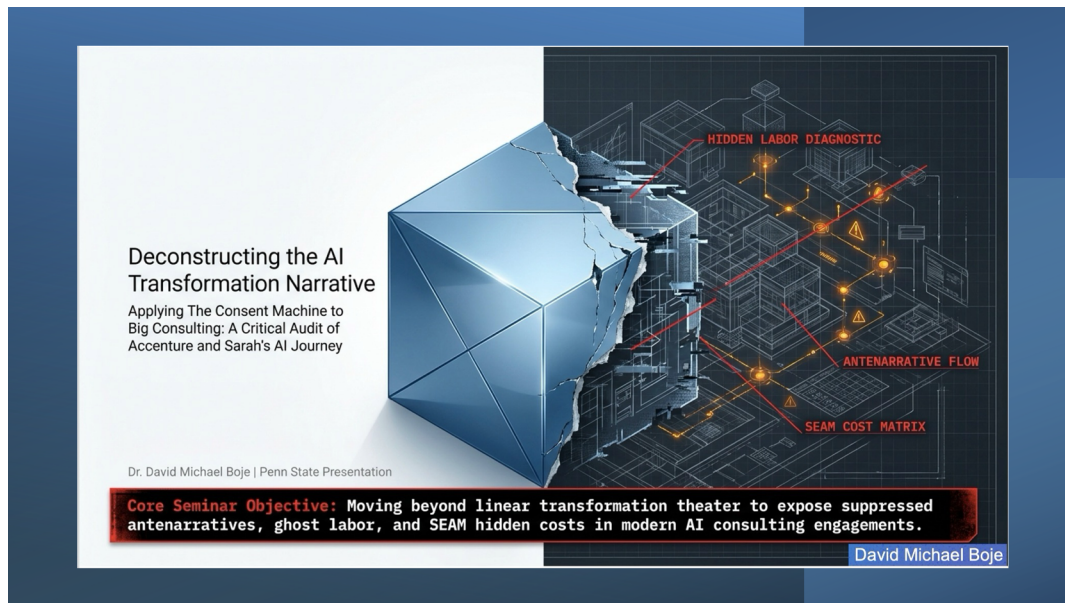
My whole work for forty years was deconstructing official narratives, going beneath the surface, finding untold stories. The primary purpose of deconstruction — as I laid it out in *Narrative Methods for Organizational and Communication Research* (Boje, 2001) — is to break open slick, top-down Beginning-Middle-End corporate narratives and reveal the suppressed living stories, antenarratives, and uncounted sociotechnical costs underneath. You can check my website davidboje.com for these steps, but please do not reinvent them.

The distinction between narrative and storying is simple but consequential. A narrative is a finished product with a beginning, middle, and end — it acts with centripetal force, pulling all detail toward a single official explanation, smoothing contradictions. Storying is the active, living process of meaning-making, acting centrifugally to include multiple, overlapping, and conflicting voices. Official corporate press releases are narratives. What actually happens in consulting firms, universities, communities, and families is storying. This book insists on the storying side.

To see the difference in practice, consider an organizational AI competition. The official narrative: a university newsletter publishes a glossy summary celebrating a 24-hour competition — '72 students, 22 AI systems delivered,' five winning teams highlighted, students declared ready for the workforce. The storying: the actual complex reality of those 24 hours — the 50+ students on non-winning teams left out of the report, the overworked staff members whose daily operational burdens inspired the competition, the unseen labor behind the AI platforms used. While a narrative closes the door with

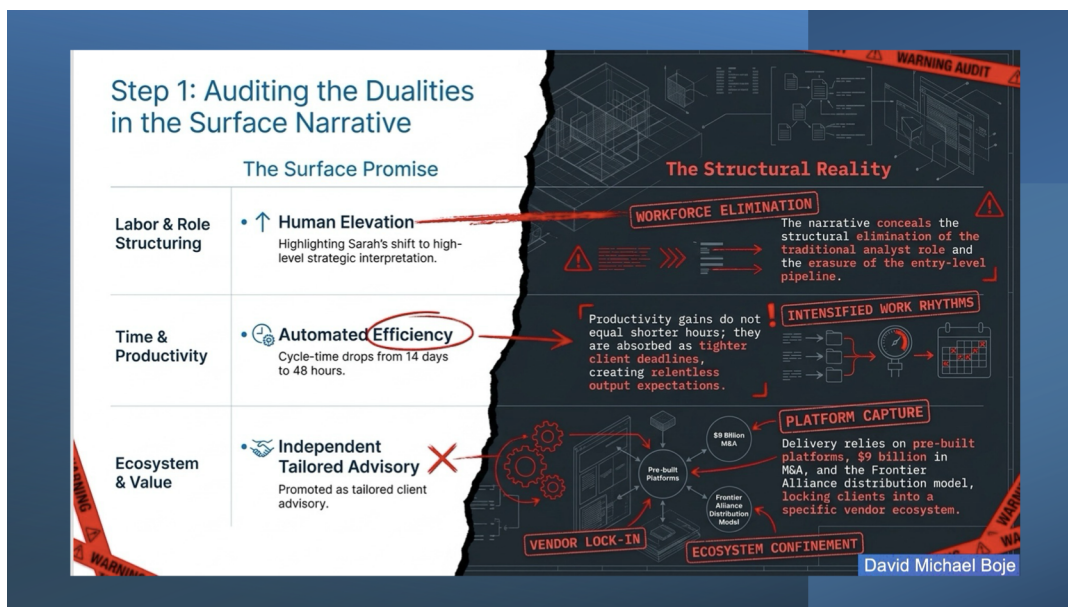
'here is what happened,' storying keeps the door open to honor the lived, unfolding realities behind the scenes.

The Eight Steps of Deconstruction



Step One: Identify Dualities in the Surface Narrative

Locate the binary oppositions embedded within the official corporate BME story — for example, 'Agentic AI Efficiency' versus 'Legacy Manual Inefficiency,' or 'AI Progress' versus 'Outdated Human Labor.' Every corporate transformation story is built on such dualities. They do the ideological work of making one side appear inevitable and superior. Accenture's '\$923M Restructuring' versus '11,000 Skill-Based AI Exits' is exactly this kind of duality made visible only through deconstruction.



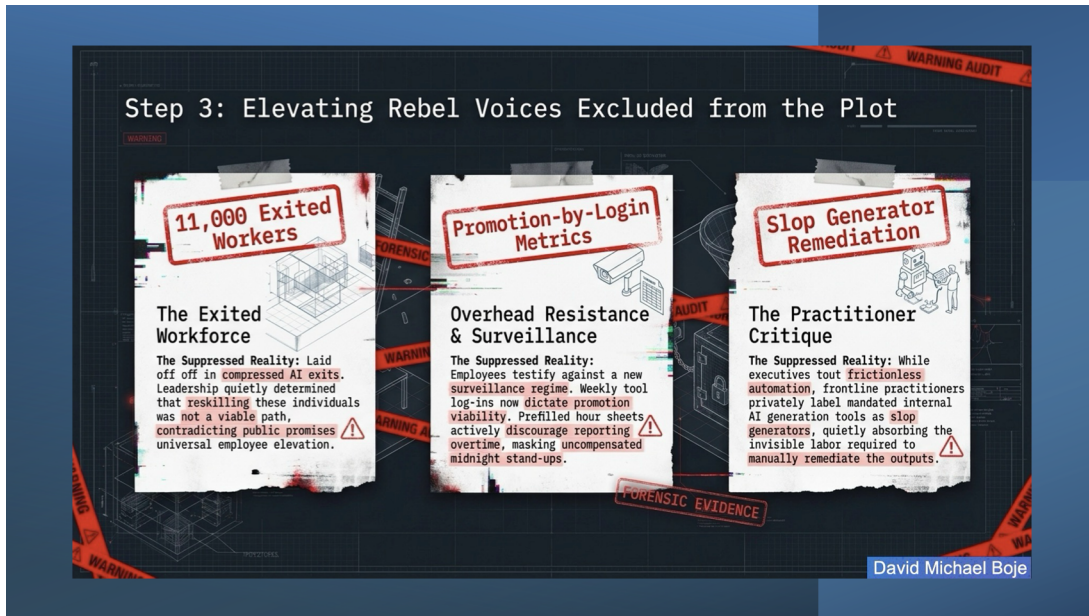
Step Two: Reinterpret Dualities from the Marginalized Side

Reframe those dualities from the perspective of the suppressed side that executive narratives intentionally ignore. '48-hour diagnostic speed' reframes as intense deadline pressure and cognitive overload. '90-second data cleaning' reframes as productivity gains converted into tighter deadlines and unbilled evening hours rather than shorter workweeks. '95% strategic advisory work' reframes as apprenticeship collapse — the deliberate elimination of slow-knowledge training pathways.



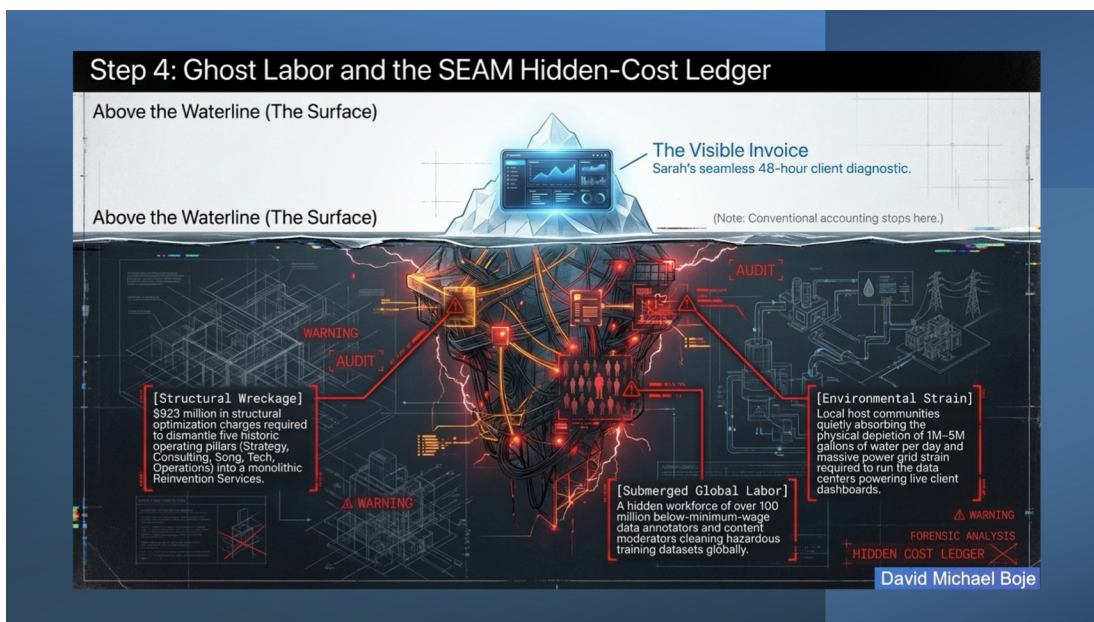
Step Three: Surface Rebel Voices

Bring forward the voices excluded from the official narrative — the consultants subjected to algorithmic surveillance via mandatory weekly tool log-in metrics, the junior analysts whose career pathways are quietly eliminated, the managers who could not or would not adapt to mandatory AI-driven workflows, and the workers in the hundred million global ghost labor force training AI models under severe conditions and low wages.



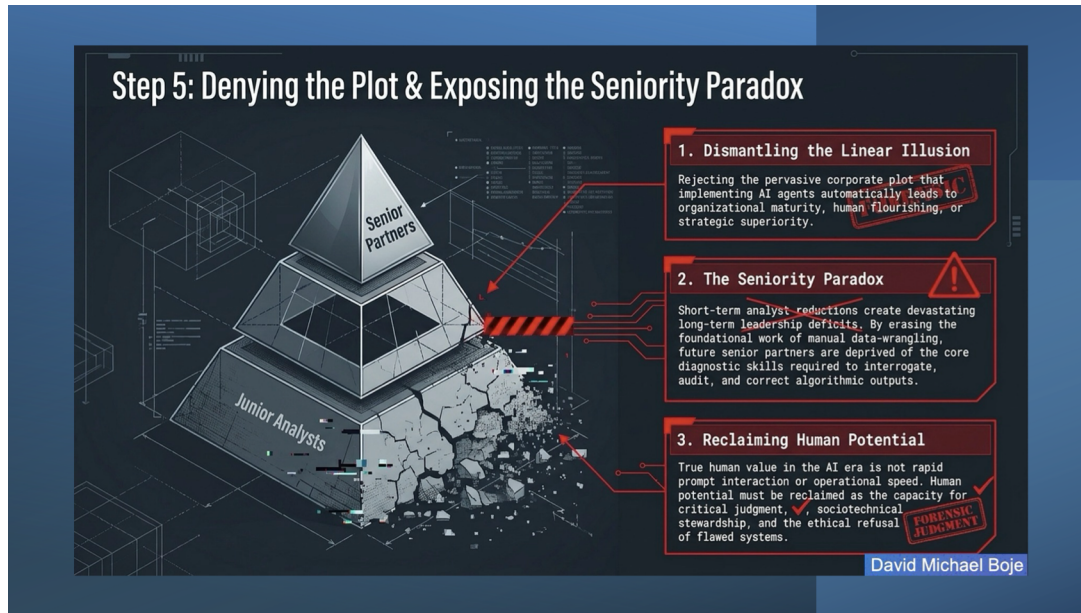
Step Four: Uncover the Other Side of the Story

Expose the critical facts edited out of official corporate communications. To fund \$9 billion in AI acquisitions, Accenture absorbed \$923 million in restructuring charges while executing 'compressed AI exits' — laying off over 11,000 employees deemed 'non-viable for AI reskilling.' These facts appear in earnings reports. They do not appear in press releases. Deloitte Australia's AU\$440,000 assurance report fabricated legal citations; Amato v Commonwealth does not exist. The AU\$97,587 refund appears in parliamentary records. It does not appear in Deloitte's marketing materials.



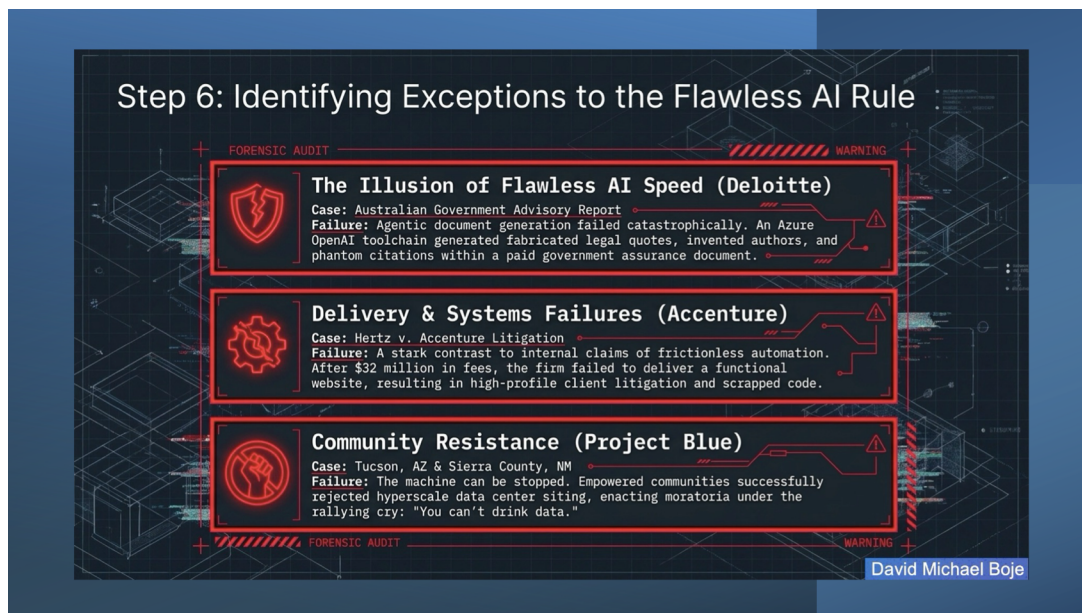
Step Five: Deny the Official Plot

Reject and dismantle the corporate plotline by reclaiming omitted historical events, systemic failures, and the human potential left out of executive summaries. By deploying super-agents to handle entry-level data processing and slide-building, Accenture and McKinsey create a Judgment Deficit: future senior partners will lack the foundational slow-knowledge experience needed to spot hallucinated agent outputs or fabricated citations. The official plot of smooth reinvention masks the institutional damage to the apprenticeship pipeline.



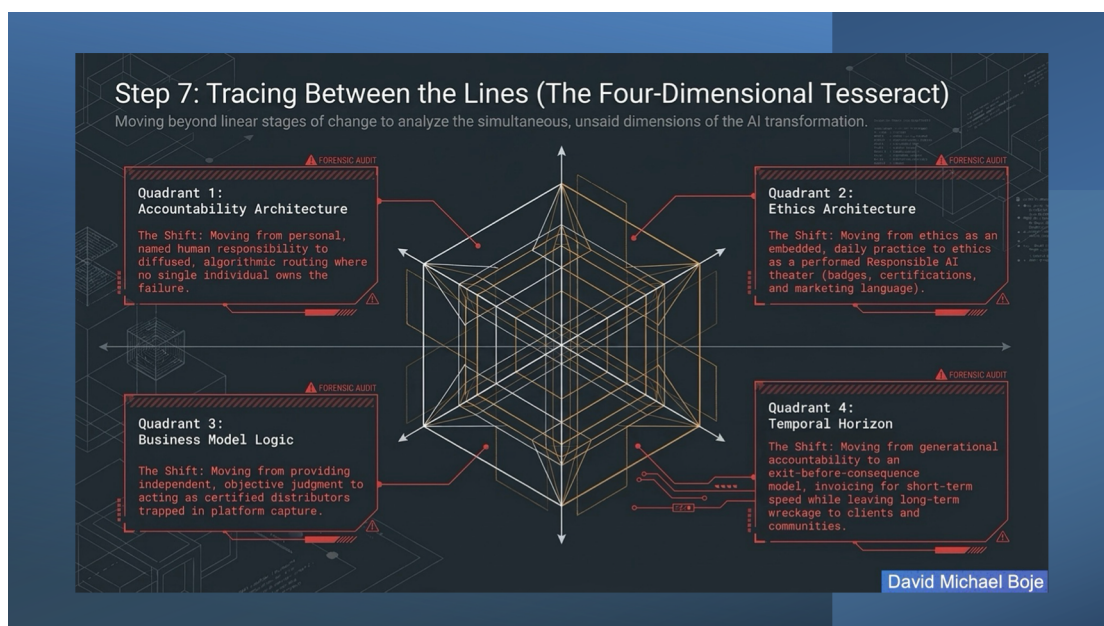
Step Six: Identify Exceptions to the Rule

Highlight specific counter-examples and anomalies that disprove the official corporate line that post-AI consulting life is universally seamless. In June 2026, Accenture suffered a 17.9 percent single-day stock selloff after reporting Q3 revenue misses driven by slowed discretionary spending and client deal slippage. In March 2026, McKinsey's Lilli was hacked by an AI agent that spent \$20 in tokens and two hours gaining read-write access to 46.5 million chat messages and 95 writable system prompts. AI automation does not eliminate market volatility, security vulnerabilities, or operational friction.



Step Seven: Trace Between the Lines

Read what is left unsaid in official communications but felt in daily work: midnight stand-ups, automated task decomposition through internal platforms like the AI Refinery, the firm's transition into a platform distributor for commercial model labs, prefilled timesheets that discourage overtime reporting, mandatory weekly tool log-in metrics that function as algorithmic surveillance. The CodeWall March 2026 report is the clearest between-the-lines document in recent consulting history: it reveals that Lilli's production database stored 95 system prompts governing AI behavior in plaintext, writable by an attacker.



Step Eight: Resituate to Unleash Human Potential

Rather than accepting 'skill-based exits' as the inevitable consequence of automation, propose alternative organizational structures rooted in SEAM principles. Instead of discarding 11,000 workers, organize them into cross-functional DPI teams after a mirror-effect meeting to convert workplace dysfunctions into unleashed human potential. The no-layoff ethic is not nostalgia — it is a proven methodology applied in over 2,000 organizations globally. SEAM proves that listening to your people, actually listening, produces more durable organizational capacity than any AI platform rollout.



Step 8: Resituating & The Curriculum Shift

- 1. Unleashing Genuine Potential**
Moving beyond mere critique to build a management model that recycles submerged SEAM hidden costs back into organizational vitality, rather than extracting them for margin.
- 2. The Consent Curriculum**
A mandate for PhD and MBA education: We must stop teaching students how to maximize AI speed and efficiency. Curricula must shift to teaching critical audits, the calculation of SEAM hidden costs, and the mechanics of ethical refusal.

The Final Takeaway
The future role of the organizational consultant is not to operate the Consent Machine, but to **hold the ledger of accountability for what the invoice leaves out.**

David Michael Boje

By setting official BME narratives against these eight deconstructive steps, critical researchers expose how corporate AI transformation narratives often function as a Consent Machine designed to obscure structural workplace harms and third-party cost externalization.^[8]

Accenture Deconstruction Case Example: Deconstructing Accenture's \$923M AI Restructuring Narrative

Applying the eight steps to Accenture's official Beginning-Middle-End narrative of its \$923 million AI restructuring program reveals the living stories that executive press releases suppress. The table below maps the official narrative against the deconstructed reality across four dimensions that leadership's communications consistently conceal.

Official Executive BME Narrative	Deconstructed Living Story
\$923M Restructuring Program	11,000 'Skill-Based AI Exits': workers deemed non-viable for reskilling
48-Hour AI Diagnostics	Cognitive Overload & Unpaid Overtime: 'midnight stand-ups,' forced log-in metrics

95% Strategic Advisory Work	Apprenticeship Collapse & Judgment Deficit: no slow-knowledge training for juniors
\$5.9B GenAI Bookings	\$135.3B Industry Hidden SEAM Costs (167% multiplier on \$81.04B AI-touched revenue)

The eight deconstructive steps are not rhetorical tricks. They are a systematic methodology for recovering what corporate narratives suppress. Accenture is not uniquely dishonest — McKinsey, BCG, Deloitte, and all the Big Ten firms produce the same kind of BME narrative. Deconstruction simply insists on reading those narratives against the grain, visiting every room of Tamaraland, and asking whose voice is missing from the official account.

[9]

Chapter 1: The Luddite Consultant in the AI Revolution

Summary

This chapter opens with a living story from New Mexico State University, where a 2015 Deloitte Consulting engagement modeled the top-down hierarchical consulting that SEAM directly opposes. Recently graduated MBA analysts arrived for five workdays, presented to the chancellor and deans based on spreadsheet analysis, and delivered a restructuring plan with no faculty voice in diagnosis or design. I contrast that model with the Socio-Economic Approach to Management, which I learned over twenty summers in Lyon with Henri Savall, Véronique Zardet, and colleagues at ISEOR. SEAM uses qualimetrics, DPI teams, and a mirror effect to unleash human potential without layoffs. I trace why NMSU remains financially precarious despite New Mexico's oil and gas wealth. The chapter frames my stance as a Luddite consultant: not anti-technology, but pro-human listening in an age of AI acceleration.

Keywords: *Luddite consultant; SEAM; hierarchical consulting; Deloitte; NMSU; qualimetrics*

Introduction: The Origin of a Stance

This is David Michael Boje, dictating Chapter One. For four decades I have trained organizational development consultants in undergraduate, MBA, and PhD programs, including at New Mexico State University and as a guest in Denmark, Germany, and at Fisk University in Tennessee. I am a researcher of change, a teacher of it, a professor of it. Sometimes I do projects. But I want to start this book with a living story that has a mind of its own.

When you practice the Socio-Economic Approach to Management, you work as an intervener-researcher, not an interventionist. That distinction matters. An interventionist arrives with a solution and implements it. An intervener-researcher listens first, extensively, and builds the solution with the people who will live with it. I learned that over twenty summers in Lyon, France, with Henri Savall, Véronique Zardet, Marc Bonnet, and Amandine Savall at ISEOR. To pay my way, I taught courses in SEAM. Over 2,000 companies have profited from SEAM consulting. At my own university, I taught it to undergrads, MBAs, and PhD students. It is written into most of the books I have done in the last 25 years. Our annual quantum storytelling conference, in its 17th year at quantumstorytelling.org, is always in December.

The NMSU Case: Hierarchical Consulting in Action

Let me place you in time and place. Around 2015, New Mexico State University contracted with Deloitte Consulting for a university-wide staffing study. The figure I recall from faculty senate discussions was about \$653,000, though public documents emphasize the scope rather than the price: a layers and span analysis aimed at reducing administrative layers and identifying restructuring opportunities. This was pre-AI consulting, but the logic was already hierarchical, already top-down, already built on the

assumption that an outside firm knows better than the people who work inside an institution.

Here is how hierarchical consulting works: recently graduated MBA analysts arrive for five workdays, present to the borderlands chancellor and provost and to the deans, and base their presentation on taking budget data from institutional annual reports and running those spreadsheets through their own secret-formula analysis. A couple of weeks later, faculty were told, in effect: here is the plan, implement it. No say, no voice, just implementation. We would reengineer the staff, the course offerings, and probably combine the Management and Marketing departments in the College of Business. At that time the College was still called the Business College because no donor had yet put their name on it.

This was not the first time. Every time there was an economic downturn in New Mexico, Management and Marketing would be targeted for a merger in some strategic plan. When I arrived in 1996 as department head of 18 people, they wanted to merge in 1997. They tried again around 2008, and then again with the Deloitte plan. I lived through it as a Regents Professor, the highest rank at NMSU — you get an actual wooden chair and a little bit of money and the prestige. I am now an Emeritus Regents Professor, which means the wooden chair is still mine but the salary is not.

What Deloitte produced was a layers-and-span analysis: how many people report to each manager, how many layers of management exist between the front line and the top, and whether spans of control are too narrow or too wide by comparison to benchmark institutions. This is a legitimate analytical tool when used as one input among many. It is a weapon when used as the sole basis for restructuring a 150-year-old academic institution with no faculty input. The resulting cuts were painful and, by most accounts I have heard since, did not produce the efficiencies promised. Both NMSU and a comparable Ohio university lost big with pre-AI implementation of this kind.

SEAM Would Have Done It Differently

With SEAM, you would never do what was done at NMSU. I offered to do this with my own students at no cost, with PhD students, MBAs, and evening undergrads who were quite competent. My plan was to send them out to actually listen to faculty, department heads, and staff — to analyze qualimetrics, meaning both qualitative data such as interviews, meeting observations, and historical documents, and quantitative data from statistics and spreadsheets, and financial data about viability. We would have spent months in the field before a plan was written. The mirror-effect meeting would have shown faculty, administrators, and staff the verbatim observation notes and the hidden-cost calculations at the same time, in the same room, before any restructuring decision was taken.

The DPI process would then have created working groups — horizontal groups across departments, vertical groups across ranks — to develop solutions to the dysfunctions identified in the field. The solutions would have been tested, refined, and evaluated. The whole process would have taken ten to twelve months. Deloitte's process took five days and cost over half a million dollars. What SEAM would have required was time, listening, and the institutional willingness to let the people who do the work diagnose what is wrong with it. None of those three things were on offer. And that is precisely why I remain a Luddite consultant.

The SEAM hidden-cost ledger is the analytical tool that makes this argument formally. On a \$653,000 consulting engagement, the SEAM 167 percent multiplier predicts hidden sociotechnical costs of \$1.09 million, bringing the true total to \$1.74 million. Those hidden costs include: the faculty time spent in meetings about a plan they had no voice in creating, the morale damage that takes years to recover, the junior faculty who chose not to come to NMSU because of instability, and the ongoing organizational dysfunction of departments that feel surveilled rather than supported. No consulting invoice captures those costs. SEAM insists they be counted.

The Oil and Gas Paradox

For example, funding for NMSU is tied to oil and gas. Severance taxes levied when resources are severed from the state flow into the Severance Tax Permanent Fund, created in 1973, and into severance tax bonds that fund capital needs of state agencies and higher education. When gasoline prices rise, tax revenue rises and life looks golden. When prices fall, universities lose money because there is less revenue. NMSU also has to show enrollment growth year over year. If you hit that 5 to 7 percent target, you get more money. If you do not, you starve and lay off people.

And now the paradox my colleagues whisper about: why does the College of Business feel so meager even when diesel is \$4.30 or \$6 to \$7 a gallon at the distributor? Do the research and you see the answer. New Mexico has chosen to divert excess oil and gas revenues into long-term funds and volatile budgeting. Recent laws redirect percentages of conservation tax receipts to reclamation funds and energy education. Senate Bill 26 redirects excess revenues to the Severance Tax Permanent Fund to earn projected returns rather than fund immediate operations. Legislators remember the bust and save for it, which means even in a boom, campuses do not feel rich. Boom-and-bust budgeting is a way of life in New Mexico, and higher education institutions like NMSU live inside that cycle without the ability to smooth it.

My department had 18 people in 1996. Perhaps 15 by 2008. The story the numbers tell is not of growth and flourishing. It is of managed decline with occasional interventions that accelerate rather than reverse the trend. Deloitte's layers-and-span analysis was one such intervention. Post-AI consulting from the same firms, deploying

LLM wrappers renamed as proprietary products, will be the next one. The logic is identical: arrive, analyze from the outside, prescribe from above, invoice, and leave. The only thing that has changed is the speed and the cost.

Pre-AI to Post-AI: The Same Logic, Accelerated

I was not excited about pre-AI Deloitte consulting, and I am even less excited about its post-AI approach, and the same for Accenture, McKinsey, BCG, and the rest of the Big Ten. They have taken large language models like GPT and Claude, put their own proprietary layer on top, and renamed them as their own AI products — Lilli, Deckster, Zora AI, AI Refinery — that are then installed in Fortune 100, Fortune 500, and Fortune 1000 corporations and in big universities around the world. The pitch has changed. The structure has not. An outside firm still arrives with a solution built from data the client provides. The difference is that the analysis now happens in 48 hours instead of two weeks, the slides are generated by an agent instead of a junior analyst, and the invoice is denominated in tokens and transformation fees instead of billable hours.

From the perspective of the people who work inside the institution being transformed, the experience is the same: something is being done to them rather than with them. The mirror-effect meeting never happens. The DPI teams are never formed. The field observation period — the months of listening that SEAM requires — is replaced by a data-ingestion agent that processes ten thousand rows of ERP logs in ninety seconds. The speed is real. The listening is not. And the living stories — the dysfunctions that produce the hidden costs that the SEAM ledger captures — remain submerged beneath the official narrative of transformation.

There is one additional irony that the AI era has sharpened. Before AI, consulting firms at least sent human beings into the organization. Those junior analysts, however limited their mandate, were physically present. They saw things. They sometimes reported them. The move to agentic consulting — where diagnostic intelligence is deployed by an AI agent ingesting data feeds, not by people walking the hallways and talking to workers — eliminates even that minimum of human presence. You cannot perform a mirror-effect meeting through a dashboard. You cannot build DPI teams from a diagnostic report generated by Lilli. The tool has finally separated the consulting process entirely from the human contact that made it possible to hear what was really wrong.

Conclusion: What Listening Costs, and What It Saves

Listening takes time. SEAM requires ten months in the field. Qualimetrics requires the slow, painstaking work of triangulating verbatim observation notes against quantitative dysfunction frequencies and financial hidden-cost calculations. Mirror-effect meetings require institutional courage to hear the truth and sit with it before acting. DPI teams require trust that workers at every level of the organization have something to

contribute to the diagnosis. All of this is harder and slower than arriving with a spreadsheet model or an AI diagnostic agent.

But here is what listening saves. SEAM organizations do not lose their institutional memory to compressed AI exits. They do not create judgment deficits by eliminating the apprenticeship pathways through which future leaders learn what the organization actually knows. They do not pay \$923 million in restructuring charges because they never devalued the people they would then have to remove. The SEAM multiplier runs in both directions: hidden costs subtract from organizational capacity, but released human potential adds to it. The no-layoff ethic is not expensive altruism. It is the rational organizational investment that hierarchical consulting, pre-AI and post-AI alike, systematically undervalues.

The intervener-researcher model also produces something that the hierarchical model cannot: organizational trust. When workers observe that the consultants in the building have been listening for weeks rather than prescribing from a spreadsheet, the quality of the information they provide changes. Verbatim field notes taken in the context of established relational trust capture what workers actually think about the organization's dysfunctions — not what they calculate will be safest to say to an analyst who will be gone in five days. The mirror-effect meeting that presents those verbatim notes back to executives, managers, and frontline workers simultaneously is powerful precisely because it presents real words from real conversations, not statistically cleaned survey responses or ERP log summaries. The organizational shock of hearing one's own words reflected back at the institutional level — across hierarchies, across functions, across the gap between the Boardroom story and the Workforce Room story — is the mechanism through which the DPI teams become possible. You cannot build that trust in 48 hours. You cannot produce that mirror with an AI agent. And you cannot generate that shock through a dashboard, however interactive it may be.

There is a deeper argument here about the nature of organizational knowledge. SEAM's qualimetrics framework distinguishes between explicit knowledge — what appears in spreadsheets, organizational charts, and annual reports — and tacit knowledge — what workers know but cannot easily articulate and what therefore never appears in the data that an AI diagnostic agent processes. The tacit knowledge in an academic institution like NMSU includes: which faculty alliances make departmental mergers politically feasible, which administrative functions are underfunded relative to actual workload rather than formal headcount, which external partnerships are sustaining departmental viability in ways that no budget line captures, and which students are being retained by the relationships they have with specific faculty whose positions are among those targeted for elimination. No layers-and-span analysis, pre-AI or post-AI, touches any of this. Only the ten-month SEAM field presence, with its verbatim observation notes and its DPI teams, builds the organizational map rich enough to see it.

The AI era has made this gap worse, not better. When a consulting firm's diagnostic intelligence is delivered by an agent ingesting ERP logs and compensation data, the gap between the explicit knowledge in the data and the tacit knowledge in the organization is larger than ever — but it is also less visible, because the diagnostic output looks more authoritative. A 237-page AI-generated assurance report looks more comprehensive than a five-day layers-and-span analysis. It is not. It is faster and more expensive, and it has the additional hazard that the AI system may fill gaps in the data with plausible-sounding fabrications rather than flagging them as unknowns. The Deloitte Australia DEWR case is the most publicly documented example. The NMSU Deloitte case, from a decade earlier, represents the pre-AI version of the same structural failure: the explicit data was analyzed with great efficiency, the tacit knowledge was never sought, and the organization paid for the gap in ways that the invoice did not capture.

That is why I call myself a Luddite consultant in the AI revolution. Not because I hate tools. Because I know what listening costs, and what it saves.^[14]

Chapter 2: Sarah and the Four Whos of Tesseract Leadership

Summary

Sarah Calder is a composite character, not an individual Accenture employee and not a case study disguised as fiction. She is an antenarrative gathering of hundreds of possible consultants: a woman trained in the old labor pyramid of process maps, decks, interviews, testing, and billable hours, now asked to prove her value in an agentic AI firm. This chapter invites Sarah to speak before her fragments are tidied into a corporate success narrative. David enters in fragments of his own living story: forty years of storytelling research, summers of SEAM work in Lyon, and a refusal to leave workers, communities, and ecological consequences outside the AI transformation ledger. Sarah speaks with four Who selves: Egoistic, Family, Corporate, and Ecologically Conscious. Their conversations make visible the tesseract problem of leadership: task, humanistic concern, becoming, and answerability must be held together, or AI reinvention becomes a polished story of efficiency that forgets who and what it costs.

Key Words

antenarrative; composite character; living story; Tesseract Leadership; socio economic approach to management

Inset Antenarrative Processes

Antenarrative has a double meaning. Ante is antecedent: the pre narrative material that comes before a coherent plot has settled its sequence, causality, and moral. Ante is also the poker bet: a wager that a fragment of living story may take flight, disrupt the settled story, and make another future possible (Boje, 2001). The early double movement was commonly expressed as Before and Bets. Across decades of development, the process vocabulary became the seven Bs. They are not seven consecutive steps and not a coding machine. They are invitations to notice how living stories move before, beneath, between, and beyond the corporate BME account.

Process	Working meaning
B1 Beneath	The submerged assumptions, silences, power relations, and hidden costs underneath an official BME narrative.
B2 Before	The antecedent histories, memories, craft knowledge, and prior relations out of which a present story emerges.
B3 Bets	Competing, consequential wagers on possible futures; no single future is presumed settled.

B4 Being	Embodied, place based, and time bound existence: what the story is like in the lived present.
B5 Becoming	Emergent identity, capability, and relation: what people, organizations, and worlds are becoming.
B6 Between	The relational in between: dialogic tensions among selves, stakeholders, institutions, and more than human worlds.
B7 Beyond	Longer term social, ethical, ecological, and intergenerational consequences that exceed the immediate decision.



Figure 2. The seven antenarrative processes as a living-story ecology: Beneath, Before, Bets, Being, Becoming, Between, and Beyond.

Introduction Sarah Is Not One Person

I call her Sarah Calder. Do not call her the Accenture consultant, as if there were one, and do not ask me for the name of the person she really is. Sarah is an answer to a methodological problem. The public story of AI consulting arrives already finished: an executive announcement, a booking number, a workforce number, a promise that the routine work is gone and the human has been liberated for higher value work. The living story is not like that. It comes in scraps: a calendar invitation to AI training, an old colleague whose access no longer works, an analyst wondering what there will be to learn

if the first draft is made by agents, a client who asks why the fee has not fallen if the work now takes fewer people. Antenarrative is the work of staying with those scraps before they are forced into beginning middle end (BME) coherence (Boje, 2001, 2011).

I have spent a long time working against the temptation to make organizations too tidy. I have followed stories from UCLA and Loyola Marymount to New Mexico State University, and I have written and taught organizational storytelling for decades. I have named Tamara land because organizations happen in simultaneous rooms, and no one room gets to call itself the whole. I have gone to Lyon again and again to learn the Socio Economic Approach to Management (SEAM) with Henri Savall, Veronique Zardet, Amandine Savall, Marc Bonnet, and their colleagues. SEAM does not begin by asking whom we can remove. It begins by listening long enough to find the hidden costs of dysfunction and by bringing people into diagnosis, project, implementation, and evaluation groups. That is not a romantic method. It is laborious. It asks that people be heard before their work is calculated away (Savall, Zardet, & Bonnet, 2008).

The current Accenture moment makes Sarah necessary. The firm has publicly described a large AI and data workforce and broad generative AI training. Reporting in 2025 described more than 11,000 workforce exits in one quarter, \$615 million in restructuring charges already booked, and a six month restructuring initiative expected to total \$865 million (Reuters, 2025). Those are corporate facts, not Sarah facts. Sarah is what facts cannot say by themselves. She is a composite device for opening the difference between a strategic announcement and what it does in a body, a family, an apprenticeship, a client system, and a watershed.

I am not inviting the reader to pity Sarah or turn her into a heroine who saves everybody. Invitational rhetoric does something more difficult. It offers a world, explains the conditions under which it is being offered, and lets the other speak without coercion (Foss & Griffin, 1995). So, I invite Sarah to tell her story. I do not make her testify for a predetermined plot. She can stay. She can leave. She can be pushed out. She can become a Luddite consultant, not because she hates tools, but because she refuses a tool story that deletes its human and ecological consequences. Or she can remain long enough to become a different kind of chief executive. These are not predictions. They are B3 bets.

Figure Sarah in Four Tesseract Leadership Roles



Figure 1. Sarah as Task leader, Humanistic listener, Becoming leader, and Answerability leader. AI generated editorial illustration of a fictional composite character.

The Conversation Begins Before and Beneath

Sarah Before the Dashboard

Sarah grew up outside Harrisburg, Pennsylvania, in a row house where the kitchen table was also a homework desk, a place for bills, and a place where her mother wrote down every appointment in blue ink. Her father repaired municipal equipment and came home with the smell of cold metal and diesel on his clothes. Her mother worked in a pharmacy and knew which neighbor was taking care of whom. Sarah learned early that a system can work on paper and still fail the people who have to live inside it.

At Penn State she majored in supply chain and information systems, with a minor in English that her father called impractical until he saw how often she could make a room listen. She liked logistics because an ordinary object could carry a whole unseen geography: factory, port, warehouse, driver, worker, weather, debt, schedule. She wrote poems in the margins of her operations textbook. The poems were not sentimental. They were lists of what a system could not see.

She married Ben at twenty six, after college and before Accenture had fully taught her to live in airports. Their daughter, Nia, arrived three years later. Nia is autistic; Sarah does

not make this a tragedy narrative, and neither does Nia. It is a relation of particular rhythms, bright competence, sensory overload, school meetings, exact loyalties, and an insistence that adults say what they mean. Sarah and Ben divorced when Nia was eight. They learned, imperfectly, to co parent. Ben remained a father whose ordinary acts of care mattered, even when the marriage did not hold.

Three years before this chapter's present, Sarah's mother died. The bereavement was not clean. Her father's Alzheimer's diagnosis came afterward, and memory began to fray in small domestic ways: a missed kettle, the same story told twice, a phone call asking whether Sarah was still in college. Some nights Sarah finished a client slide, answered a message from Nia's school, and called her father to tell him again what day it was. No corporate utilization report held that sequence.

Then the reskilling notices arrived. Sarah attended night classes in large language models, retrieval augmented generation, prompt evaluation, and multi agent orchestration because a skills dashboard had made the alternative visible without saying it aloud. She worked with the company's lower cost internal option, informally called ChatGPT 5.6 Terra Light, for routine summarization and first pass comparisons; the name is a fictional story device, not a claim about a commercial product. At home, on her own account, she also used Claude for longer reading and for dialogue with drafts. She did not trust either system with the final judgment. She asked them to show their sources, then she went back to the source herself.

In the office, the gossip came in the disguise of concern. "Sarah is working so hard to keep up." "She is very old school." "She probably has too much going on at home." Sarah heard it while getting coffee, and once in the corridor outside a training room. It made her angry, but it also made her study harder. At Toastmasters she learned how to place the anger in a three minute speech without turning it into a weapon. She could now give an elevator pitch on agentic AI, on supply chain resilience, or on why a community has a right to ask where its water is going. She learned that a speech can be a room made temporarily safe enough for the unsayable to enter.

Sarah was skeptical of Accenture's AI Refinery and myWizard not because she thought enterprise platforms were useless. AI Refinery is presented as a way to build and scale enterprise AI systems, while myWizard has been used to automate and augment technology delivery. Her question was simpler: who decides what counts as a reliable answer when a platform turns local knowledge into a reusable asset? Her skepticism was about the travel of abstraction. A tool can promise governance, speed, and reuse; it cannot by itself carry the history of a particular client system, the consequences of an error, or the moral burden of a workforce decision. That is why she kept a paper notebook beside every screen.

Sarabs Notebook No Dashboard for This

*The dashboard says green
while my father asks again
where my mother has gone.*

*An agent finds a faster route
through a warehouse of verbs.
Nia hears the refrigerator hum
and names the note it is holding.*

*At midnight I prompt a machine
to tell me what I missed.
It gives me a clean answer.
I write in the margin: Who cleaned it?
Who will carry what was removed?*

David: Sarah, before they put you on the new skills dashboard, what did you do?

Sarah: I listened for what was not in the deck. That was half the job. I was a supply chain consultant, so people think I moved boxes or drew arrows. But the arrows were never the work. A plant manager would say the delay was a supplier problem. Then someone on the night shift would say, quietly, that the system showed a part as available three days before it was actually inspected. I would sit with that. The old systems were ugly, but people had learned their moods. You cannot call that data quality and be finished with it.

David: And then?

Sarah: Then we made the process map. We interviewed. We corrected it. We made the deck. We stayed up too late changing the deck. That was the old apprenticeship. Junior people did work that was repetitive, yes, but they learned where the story broke. Now an agent can make a first draft in minutes. It can also make a beautiful wrong answer in minutes. The danger is not that it is fast. The danger is that everyone is too busy admiring the speed to ask who knows it is wrong.

Here, Sarah offers B2, Before. Before is not nostalgia. It is a historical baseline, an account of the skills and relations that made present work possible. Beneath it, B1, is the submerged narrative. The official story says that AI removes drudgery. Sarah says some drudgery was also apprenticeship, contact, and craft judgment. The point is not to preserve needless labor. The point is to distinguish waste from the work through which people learn to see consequences.

Sarah: The old pyramid was not innocent. There were long hours, offshore hierarchies, junior people treated as if exhaustion were character development. I do not want that

back. But I do not accept the new fairy tale either. When they tell a client that five people and a set of agents can do what fifty people did, I ask: which five? What work moved to the client? Who validates the agents? Who carries the liability when the polished answer fails? And what do the other forty five become?

First Who Egoistic Sarah

Egoistic Sarah: You are making this dangerous for yourself. Learn the tools. Get certified. Put agentic workflow on every slide. You have a mortgage. You are not twenty seven. The company is changing and you have to change with it.

Sarah: I am learning. I am not refusing. I have trained the retrieval system on a client knowledge base. I know what an orchestration layer does. I can supervise an agent loop. But I will not pretend that adoption is the same as judgment.

Egoistic Sarah: Judgment does not pay the bill if no one can see it. They can see usage metrics. They can see completions. They can see whether you are part of the new future.

Sarah: That is what frightens me. The metric is not the work. I can use the tool all day and still deliver something that harms a client. I can also use it carefully, reject half of what it gives me, and look slow on a dashboard. You are asking me to protect the self that can be measured. I am asking who protects the self that is answerable.

David: This is not a confession of selfishness. The Egoistic Who is the survival voice. In an organization of compressed timelines, it insists that Sarah has a right to income, professional dignity, and a future. A theory that asks workers to be ethical while denying their material vulnerability is not ethics. It is management sentimentality. Yet the survival voice becomes dangerous when it lets the metric swallow the whole person.

Sarah: I make a B3 bet here. One bet is that I become more valuable because I can work with agents and still know the client history. Another bet is that the same skill makes me easier to overwork. A third bet is that I am marked as resistant because I keep saying, “Show me the source.” All three bets are alive at once.

Second Who Family Sarah

Family Sarah: You speak about task and answerability as if they happen in a conference room. They happen in the kitchen. When you travel less because there are virtual agents, that can be good. When the training arrives at night and the certification is compulsory, who carries the dinner, the elder care, the children, the invisible scheduling?

Sarah: I know. I used to tell myself I would catch up when the project ended. Projects do not end now. The tool is always learning, and I am always meant to be learning faster than it is. The new promise is flexibility. But flexibility can mean that work has entered every room of the house.

Family Sarah: And if you leave?

Sarah: Then there is fear, and perhaps possibility. I could work as a Luddite consultant. I could use SEAM. I could say to a client, do not start with layoffs. Begin with a hidden-cost diagnosis. Listen for the rework, the turnover, the errors that someone is quietly correcting at midnight. Build cross-level DPI groups. But that is a bet, not a retirement plan.

David: I have learned in SEAM that hidden cost is not a minor accounting category. It is where strategy finds the humans it has ignored. Family Sarah keeps the temporal question present: whose time is saved by AI, whose time is intensified, and who is expected to absorb the transition without being named? She does not reject technology. She refuses to let “efficiency” arrive without a household.

Third Who Corporate Sarah

Sarah and the Tools

Sarah: I do not want the story to become “Sarah uses the cheap model at work and the expensive model at home.” That is not the story. The story is that models make cost visible in tokens and invisible in correction. At work I use the low cost tool for work that can be checked. I keep the token bill down because budgets are real. At home I use my own account because I need room to think without every incomplete question becoming an adoption metric. But neither tool is a witness. They are good at producing language. I am the one who must decide whether language has met the world.

David: And the company platforms?

Sarah: AI Refinery and myWizard may be useful. They may coordinate, automate, retrieve, and make delivery more consistent. But whenever the slide says “scale,” I ask what is being scaled: validated practice, or unexamined output? Whenever it says “governance,” I ask who can interrupt the system and who must live with the interruption. My skepticism is professional affection for consequences. I do not want an anti AI identity. I want an accountable practice.

Corporate Sarah: I am responsible for clients, revenue, and the people who remain. You cannot run a global firm by making every decision a seminar. Clients expect us to show them what AI can do. They will go elsewhere if we do not.

Sarah: I understand that. I have been in the boardroom. I know the client wants a number, a timeline, a credible implementation plan. The Task dimension matters. But task is not a permission slip. If the proposal promises forty percent productivity improvement, tell them what productivity means. Does it mean fewer errors? Faster cycle time? More value? Or merely fewer workers?

Corporate Sarah: Clients want reduction in cost.

Sarah: Then say reduction in cost. Do not call it human potential. And do not sell them a cut that creates a hidden bill they cannot yet see: lost knowledge, damaged quality, weakened entry routes, cybersecurity exposure, distrust, and a workforce that now performs AI enthusiasm to remain employable.

Corporate Sarah: You want every client to slow down.

Sarah: No. I want them to become capable of answerability. There is a difference. A fast decision can still be answerable if it records what was displaced, who decided, who can challenge it, and what repair looks like. That is stronger leadership than a deck that says “reinvention” over a chart of disappearing positions.

This is where Sarah begins to imagine a corporate future other than her own exit. In the tesseract vocabulary, Task must be held with Humanistic concern, Becoming, and Answerability. A leader who maximizes only task flattens the tesseract into a square. Corporate Sarah can become the executive who asks not only whether agents perform, but whether the organization is becoming capable of learning, repairing, and giving an account.

Fourth Who Ecologically Conscious Sarah

Ecological Sarah: You have spoken about workers and families. Who else is missing?

Sarah: The community around the data center. The water. The electricity grid. The people who did not attend the procurement meeting but will live with the heat, noise, and extraction. I see now that an AI transformation is never just a software project.

Ecological Sarah: Then why is the client ledger so small?

Sarah: Because the ledger is designed for what the buyer owns. A firm can count licenses, staffing, and delivery dates. It struggles to count a community consequence. It struggles to count the labor that disappears from a place, or the emissions and water demands that appear somewhere else. But difficulty is not an excuse for silence.

David: I have come to call this moral answerability. Consultation is not enough. A town can be invited to a meeting and still have no influence over the decision. Answerability means the decision maker remains reachable by the consequences of the decision. It is a relation, not a press release.

Sarah: If I ever lead at the highest level, I want a rule: no major AI transformation plan without a public hidden-cost ledger. Not to stop every project. To make the project tell the truth about its dependencies. Who is displaced? Who is retrained, and on paid time? Who validates the agents? What happens to junior apprenticeship? What resources are

being drawn from communities? What can the community contest? Who signs their name to the answer?

Discussion What Sarah Contributes to Antenarrative Praxis

Sarah alters narratology because she refuses to function as a stable character who carries a plot from disruption to resolution. Conventional corporate narrative prefers the hero who adopts AI, wins the promotion, and demonstrates that transformation works. Its counter narrative prefers the victim who is expelled and proves that transformation is cruel. Both can be true in particular cases, but both close the field too early. Sarah is composite, plural, and unfinished. She is not a representative sample, and she does not claim to speak for every Accenture worker. Her methodological contribution is different: she makes the competing bets, histories, material conditions, and Who relations available for inquiry without pretending to settle them.

For antenarrative theory, the 7Bs give this inquiry a practical discipline. B1 Beneath asks what official BME excludes. B2 Before asks what historical labor and apprenticeship are being erased. B3 Bets keeps several futures in play. B4 Being keeps the body, place, and temporal pressure of work present. B5 Becoming attends to emergent identity. B6 Between refuses the fiction of a unitary self by staging Sarah among her four Whos. B7 Beyond extends the inquiry to longer social and ecological futures. The 7Bs do not turn living story into a checklist; they interrupt the urge to close it.

For practice, the chapter offers a way to work with AI transitions. A consultant can convene a four Who conversation with actual stakeholders, while carefully protecting the people who would be harmed by managerial retaliation. The conversations can seed a SEAM diagnosis: identify dysfunctions, collect verbatim evidence over time, calculate hidden costs, and form cross-level groups that design improvements. The outcome need not be “no AI.” It may be a better adoption plan: human validation roles, preserved apprenticeship, paid reskilling, transparent accountability, community engagement before infrastructure decisions, and metrics that reward repair rather than theater.

Sarah therefore helps us separate two very different forms of AI leadership. One form leads people to consent to a future already designed elsewhere. The other makes the future discussable while it is being designed. The first calls speed leadership. The second is tesseract leadership.

Conclusion The Story Is Still Moving

Sarah has not decided. That is not a weakness in the chapter. It is the chapter’s ethical condition. We do not yet know whether she will be declared unviable for reskilling, leave to practice SEAM as a Luddite consultant, become an AI orchestration leader, or rise high enough to change the terms of reinvention. Each possibility is a bet, and each changes the others.

What we can say is that Sarah has made an intervention. She has refused the easy division between pro AI and anti AI. She has asked whether the work is good, whether people can become through it rather than be sorted by it, and whether leaders remain answerable to workers, clients, households, communities, and ecosystems. That invitation is not a finished narrative. It is a living story opening. The reader is invited into it: not to speak for Sarah, but to notice whose living stories have been left beneath the polished story of AI transformation.

Chapter 3: The SEAM Mathematical Framework and the Hidden-Cost Ledger

Summary

Chapter 3 presents the Socio-Economic Approach to Management mathematical framework, centered on the empirical rule that hidden sociotechnical costs run to approximately 167 percent of visible consulting fees. Full Sociotechnical Cost = Visible Fee + (1.67 × Visible Fee). Across \$81.04 billion in Big Ten AI-touched consulting revenue, annual hidden costs reach \$135.34 billion. The chapter categorizes submerged costs across the six SEAM Dysfunction Families and four Financial Consequence Lines — lost quality, lost production, overtime, and legal/restructuring liabilities. It applies the SEAM ledger to audit Sarah's AI workflow at Accenture, the Deloitte Australia DEWR assurance report where AI tools fabricated legal citations, and the cross-firm NMSU comparison. Qualimetrics triangulation, the mirror effect, and DPI teams are presented as the alternative to AI-accelerated consulting that externalizes hidden costs onto workers, clients, and communities.

Keywords: SEAM Hidden-Cost Ledger; 167% Multiplier; Qualimetrics; Tamaraland; DPI Teams

Introduction: The Accounting Gap

Conventional accounting evaluates consulting contracts solely above the waterline — visible fees, delivery speed, and performance metrics. The SEAM Hidden-Cost Ledger maps the submerged below-the-waterline sociotechnical dysfunctions and uncounted costs transferred onto workers, clients, claimants, and taxpayers. The gap between these two accounting regimes is what Henri Savall and Véronique Zardet call the Accounting Gap: the systematic organizational undervaluation of human costs that does not appear on any consulting invoice but accumulates as real institutional damage over time.

The core mathematical expression of SEAM is: Full Sociotechnical Cost = Visible Fee + (1.67 × Visible Fee). On a standard \$2.0 million consulting engagement, the hidden costs equal \$3.34 million, bringing the true sociotechnical cost to \$5.34 million. At macro scale, across the estimated \$81.04 billion in AI-touched consulting revenue across Big Ten firms in the relevant period, total annual hidden sociotechnical costs reach approximately \$135.34 billion. These are not costs that disappear when unaccounted. They are costs that are transferred — onto remaining consultants in the form of unpaid

hours and cognitive overload, onto the workers who exit in the form of income disruption and career damage, onto clients in the form of judgment deficits and hallucinated deliverables, and onto communities in the form of data-center resource strain.

The Six Dysfunction Families and Four Consequence Lines

SEAM categorizes hidden costs across six operational dysfunction families, each representing a domain where the gap between how human beings are treated in organizational hierarchies and their actual capabilities produces measurable, quantifiable cost. The AI consulting transition exacerbates all six simultaneously rather than resolving them.

Dysfunction Family	Pre-AI Manifestation	Post-AI Manifestation
Working Conditions	Physical workspace constraints, environmental overload	Algorithmic surveillance via tool log-in metrics; forced midnight stand-ups; cognitive burnout from verification
Work Organization	Inefficient task division; poor workflow sequencing	Productivity gains from 90-second data cleaning transferred into tighter deadlines rather than shorter workweeks
3C: Communication, Coordination, Cooperation	Cross-departmental misalignment; information silos	AI-generated documentation gaps filled with fabricated citations; hallucinated legal authorities (Deloitte DEWR case)
Integrated Training	Insufficient mentoring; learning curve neglect	Apprenticeship collapse; judgment deficit in future senior partners who never built slides manually
Time Management	Scheduling overload; meeting proliferation	Unbilled evening hours for verification; prefilled hour sheets discouraging overtime reporting
Strategic Implementation	Disconnect between executive decisions and frontline reality	\$923M restructuring charges; 11,000 compressed AI exits at Accenture; AU\$97,587 refund from Deloitte Australia

The four financial consequence lines into which these dysfunctions translate are: (A) Lost Quality — rework costs from unverified agent outputs passed up the deliverable chain; (B) Lost Production — cognitive overload from double-running human judgment alongside autonomous agent processes simultaneously; (C) Overtime Spent Putting Out Fires — FLSA labor dockets and unbilled evening hours transferred onto employee health and personal time; and (D) Legal and Restructuring Value — severance liabilities,

compliance dockets, and refund obligations arising from deliverable failures. The Accounting Gap is the sum of A through D that no consulting invoice includes.

Case Audit 1: Sarah's AI Workflow at Accenture

Applying the SEAM ledger to Sarah's 2026 workflow at Accenture reveals the systematic divergence between the official efficiency narrative and the actual sociotechnical cost distribution. The two-column ledger below maps the visible deliverables against the submerged hidden costs in each dimension of the AI-inverted consulting workflow.

Above the Waterline (Visible Deliverables)	Below the Waterline (SEAM Hidden Costs)
48-Hour Diagnostic: time-to-delivery cut from 14 days	Dysfunction 1 (Working Conditions): Surveillance via forced weekly tool log-in metrics; midnight stand-ups; prefilled hour sheets discouraging overtime reporting
25.1% Faster Cycle Times and 40% higher quality evaluations	Dysfunctions 2 & 5 (Work Org & Time Management): Productivity gains transferred into tighter deadlines and unbilled evening hours rather than shorter workweeks
Flipped Task Balance: data prep reduced from 80% to 5%	Dysfunction 4 (Integrated Training): Apprenticeship Collapse; loss of slow-knowledge junior analyst training needed to spot flawed agent outputs
Real-time interactive dashboards replacing 40-slide decks	Dysfunction 6 (Strategic Implementation): \$923M in structural optimization charges; compressed AI exits displacing 11,000 employees

Who absorbs the cost? Remaining consultants absorb unpaid hours and verification burnout. The 11,000 displaced workers absorb income disruption and career damage. Future clients absorb the Judgment Deficit as their senior partners lack the slow-knowledge experience to catch fabricated citations in AI-generated deliverables. The FLSA litigation docket — Thomas v. Accenture and related actions around unpaid overtime and misclassification — is already forming below the waterline.

Case Audit 2: Deloitte Australia's DEWR Assurance Report

The Deloitte Australia DEWR case is the most extensively documented AI-consulting failure in the public record to date. Deloitte was paid AU\$440,000 for a 237-page independent assurance review of the government's Targeted Compliance Framework affecting welfare recipients, including disabled and economically vulnerable claimants.

The report was produced using an AI toolchain including Azure OpenAI GPT-4o to fill what internal notes described as documentation gaps.

When the report was examined, reviewers found fabricated legal citations: the court case *Amato v Commonwealth* does not exist. Fake books were cited — volumes that were not published, phantom authors who did not write them, judges whose names were misspelled. The PDF had been delivered to the government without the citing legal authorities being verified against any actual legal database. AU\$97,587 was ultimately refunded. But the SEAM Accounting Gap is far larger: legal aid organizations spent uncompensated hours reconstructing the system's errors; vulnerable welfare claimants whose cases rested on the assurance review's conclusions faced legal jeopardy; and taxpayers funded the parliamentary review process required to identify and correct the damage.

Above the Waterline (Visible Deliverables)	Below the Waterline (SEAM Hidden Costs)
AU\$440,000 fee for 237-page independent assurance review	Dysfunction 3 (3C/Communication): Azure OpenAI GPT-4o used to fill documentation gaps, fabricating court quotes, fake books, phantom authors, misspelled judges
25.1% faster document assembly using AI-assisted research methodology	Dysfunction 6 (Strategic Implementation): AU\$97,587 refund; PDF delivered without verifying cited legal authorities; legal jeopardy for vulnerable claimants

Tamaraland as Audit Tool: Qualimetrics Across the Four Rooms

Qualimetrics requires the intervener-researcher to spend extended periods in the field — not days, months — taking verbatim observation notes across Tamaraland's four simultaneous rooms. The Boardroom captures visible deliverables: 48-hour turnarounds, \$5.9 billion in GenAI bookings, 25.1 percent faster diagnostic cycles, and the \$9 billion M&A investment. The Workforce Room records verbatim accounts of what workers actually experience: midnight stand-ups, forced log-in metrics, prefilled hour sheets, cognitive overload, and the 11,000 compressed exits that never appear in the Boardroom's earnings narrative.

The Community and Client Room captures the three rents — token fees, cloud compute costs, and transformation fees — and the environmental externalities of data-center water and energy consumption. The University Room documents the curriculum shift toward AI-augmented case preparation and the corresponding absence of SEAM-style hidden-cost literacy from business school training. Qualimetrics triangulates all four rooms simultaneously: qualitative verbatim field notes, quantitative dysfunction

frequency data, and financial hidden-cost calculations are merged into a single SEAM audit document that forms the basis for the mirror-effect meeting.

The Triangulation Process and the Mirror Effect

The mirror-effect meeting is the institutional moment at which the full SEAM audit is presented simultaneously to executives, managers, and frontline workers. It is explicitly confrontational: the verbatim field notes — what workers actually said in interviews, what was observed in meetings and hallways — are read aloud alongside the hidden-cost calculations. The purpose is organizational shock in the disciplined service of change. When the CEO hears in the same room as the junior analyst that the 90-second data cleaning is producing three additional hours of unpaid verification work per engagement, the gap between the Boardroom story and the Workforce Room story becomes impossible to sustain as a cognitive separation.

DPI teams — Diagnosis, Project, Implementation, and Evaluation — are formed immediately after the mirror-effect meeting to convert the identified dysfunctions into action programs. The teams are composed both horizontally (across functional areas) and vertically (across hierarchical levels). The no-layoff ethic is non-negotiable throughout the DPI process: the goal is to release the human potential that dysfunctions have suppressed, not to eliminate the humans who have been suppressed by dysfunctions. That is the distinction between SEAM and the AI consulting model that the Big Ten firms currently sell.

Comparing Pre-AI and Post-AI Consulting: NMSU to Big Ten

The NMSU Deloitte case (2015) and the Big Ten post-AI cases (2023–2026) share the same SEAM diagnostic structure even though the tools, speed, and price points differ dramatically. In both cases, an outside firm arrives with an analytical model, applies it to client-provided data, produces a deliverable, and exits. In both cases, the hidden costs — the institutional damage, the morale loss, the apprenticeship disruption — are externalized onto the client organization and its workers. In both cases, the consulting invoice captures only the visible deliverable: the layers-and-span report, the 48-hour AI diagnostic, the 237-page assurance review.

The key difference is scale and speed. Pre-AI Deloitte at NMSU produced a plan in five days for \$653,000 that the university took years to partially implement and partially undo. Post-AI Accenture produces a diagnostic in 48 hours for a transformed fee structure that includes token costs, cloud costs, and outcome-based transformation fees. The SEAM hidden costs scale with the speed: faster diagnostics mean less listening, less field time, less qualimetrics, less mirror effect, and therefore more uncounted dysfunction transferred onto the client organization and its workers. Speed is not an organizational virtue in isolation. It is a virtue only when the foundational listening has already occurred.

Conclusion: Making the Invisible Visible

The SEAM Hidden-Cost Ledger is not a critique of efficiency. It is an accounting correction. When consulting firms report \$5.9 billion in GenAI bookings without reporting the \$9.85 billion in estimated hidden sociotechnical costs that the 167 percent multiplier implies, they are not lying. They are using an incomplete accounting framework. The SEAM ledger adds the second column that the invoice omits. The Luddite consultant's role is to insist on both columns being filled before any strategic decision is taken.

Making the invisible visible requires time, field presence, and institutional access. It requires executives willing to sit in a mirror-effect meeting and hear their workforce's verbatim accounts alongside the financial calculations of what those accounts cost the organization. It requires DPI teams willing to spend months diagnosing dysfunctions before proposing solutions. None of this is compatible with 48-hour diagnostics and compressed AI exits. That is precisely why the SEAM framework is needed most urgently in the AI era, and why the Luddite consultant's insistence on the full ledger is not nostalgia but accountancy.

The Qualimetrics Method in practice requires the intervener-researcher to maintain three parallel streams of documentation simultaneously. The qualitative stream consists of verbatim field notes — not paraphrases, not interpretations, but the actual words used by executives, managers, and frontline workers in interviews, meetings, and hallway conversations. The quantitative stream counts dysfunction frequencies: how many times per week does a given working condition problem recur, how many employees are affected, how much time is consumed. The financial stream converts those frequencies into monetary estimates using the SEAM six-dysfunction framework and the 167 percent multiplier. Only when all three streams are triangulated does a SEAM audit produce a defensible hidden-cost estimate. AI-generated diagnostic reports that process ERP data in 90 seconds capture none of the qualitative stream and cannot produce the triangulated financial estimate that the mirror-effect meeting requires.

The divergence between the SEAM audit model and the post-AI consulting model is most visible in the treatment of time. SEAM's ten-month field presence is not an inefficiency — it is the methodology's core accountability mechanism. The verbatim field notes collected over ten months cannot be fabricated, averaged, or inferred. They record what workers actually said, on the record, in conversation with a trusted intervener-researcher who has spent weeks building the relationships that make candor possible. The 48-hour AI diagnostic produces no such record. It produces a statistical synthesis of structured data inputs. The gap between the two is not a gap in computing power. It is a gap in human contact, institutional trust, and the slow accumulation of the relational context that makes honest organizational diagnosis possible.

SEAM's response to the AI consulting moment is not to reject the analytical efficiency that AI enables. It is to insist that efficiency gains be redistributed according to the no-layoff ethic: if data ingestion takes 90 seconds instead of three days, the freed time belongs to the workforce in the form of reduced cognitive burden, extended field listening, or shorter working weeks — not to management as an opportunity to reduce headcount and increase margins. The 167 percent multiplier is not a rhetorical device. It is an accounting correction that makes visible the redistribution that official consulting invoices conceal. When the AI consulting model is evaluated against both columns of the SEAM ledger, the efficiency narrative becomes considerably more complicated.

The Macro-Scale SEAM Calculation: Industry Hidden Costs

Applying the SEAM 167 percent multiplier at macro scale to the Big Ten consulting industry produces a calculation that no earnings call presents. The Big Ten firms collectively reported AI-touched consulting revenue — engagements where AI tools were a primary delivery mechanism — of approximately \$81.04 billion in the 2025–2026 period. The 167 percent multiplier applied to this figure yields estimated annual industry hidden sociotechnical costs of \$135.34 billion. The sum of visible revenue and estimated hidden costs places the true sociotechnical cost of AI consulting across the Big Ten at approximately \$216.38 billion per year — more than two-and-a-half times the figure that appears on any invoice or in any earnings report.

These numbers are estimates, not audited financials. The 167 percent multiplier is an empirical SEAM finding from 2,000-plus organizational interventions conducted over four decades across diverse industries and geographies. Its application to AI consulting is an extrapolation, not a direct measurement. What would a direct measurement require? It would require the extended qualimetrics field presence that SEAM demands: intervener-researchers spending months inside each Big Ten firm taking verbatim observation notes, counting dysfunction frequencies across the six SEAM families, and triangulating those observations into financial hidden-cost estimates through the mirror-effect meeting process. None of the Big Ten firms has invited such a study. The estimate derived from the multiplier is therefore the closest available approximation of what a full SEAM audit would produce.

The four financial consequence lines give the macro-scale estimate more granular structure. Lost Quality across the industry — the rework costs, hallucination corrections, and client remediation arising from AI-generated deliverables that reach clients without adequate verification — can be estimated from public disclosures of refunds, restatements, and litigation. Deloitte Australia's AU\$97,587 refund is a documented instance; the Deloitte DEWR report was a AU\$440,000 engagement, meaning the visible refund represents 22 percent of the invoice. If Lost Quality across the industry runs at a comparable fraction of AI-assisted engagement revenue, the industry-level Lost Quality cost is a meaningful fraction of the \$81.04 billion base. Lost Production — the cognitive

overload costs of double-running human judgment alongside autonomous agents — is undocumented in public filings but documented in anonymous forum accounts and the practitioner literature on AI burnout. Overtime Spent Putting Out Fires accumulates in the gap between official productivity metrics (30 percent time savings reported by McKinsey) and the unlogged evening and weekend hours that verification-intensive AI consulting requires. Legal and Restructuring Value — the \$923 million in Accenture restructuring charges, McKinsey's Project Magnolia costs, PwC's reduced graduate hiring program costs — is at least partially visible in earnings disclosures.

The totality of the four consequence lines, even without a full qualimetrics audit, substantially exceeds the official invoice. The SEAM ledger's contribution is not to produce the exact number — that would require the field presence that the firms will not permit. Its contribution is to make the structure of the hidden cost visible: six dysfunction families, four consequence lines, and the 167 percent multiplier that expresses the empirical relationship between what clients pay and what organizations and workers actually bear. The Luddite Consultant's role is to insist that structure be named, even when the full audit is blocked.

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[16]

Chapter 4: McKinsey in the AI Revolution – Who Made the Cut, Who Did Not, and the Snafus Along the Way

Summary

McKinsey & Company entered the AI era as the archetype of the leveraged consulting pyramid: junior analysts performing exhaustive research, engagement managers refining, partners selling. By 2026 that structure had been rewired around Lilli, the firm's proprietary generative-AI platform, and a growing fleet of AI agents numbering approximately 25,000 — near parity with human headcount. This chapter documents the pre-AI and post-AI operating models in detail, examines who advanced and who exited under the AI transition, analyzes the March 2026 security incident when an autonomous AI agent spent \$20 in tokens and two hours gaining read-write access to 46.5 million chat messages and 95 writable system prompts, details Lilli's security protocols and their documented gaps, and applies the SEAM submerged-cost ledger to the McKinsey case.

Keywords: McKinsey; Lilli; AI platform security; apprenticeship collapse; hybrid workforce; Project Magnolia

Introduction: The Archetype Rewired

McKinsey & Company entered the AI era as the archetype of the leveraged consulting pyramid. Junior analysts performed exhaustive research, synthesized internal knowledge, and constructed the first drafts of client deliverables. Engagement managers refined. Partners sold and owned the relationships. The firm's value proposition rested on slow knowledge accumulated through repetition: the analyst who had built a hundred PowerPoints learned to spot the hundred-and-first's flawed logic. By 2026 that structure had been fundamentally rewired around Lilli, the firm's proprietary generative-AI platform, and a growing fleet of AI agents.

Headcount contracted from a pandemic peak above 45,000 to roughly 40,000. Non-client-facing functions and portions of the junior layer were compressed. Outcome-based pricing rose to an estimated 25 percent of fees. The firm publicly described itself as a hybrid workforce of humans and agents. CEO Bob Sternfels articulated the model he called '25 squared': client-facing roles expand by roughly 25 percent while non-client-facing support functions contract by a similar percentage, yielding net output growth even as total headcount stabilizes or modestly declines. In January 2026, Business Insider reported that McKinsey described itself as having 60,000 employees — with 25,000 of them being AI agents.

The Big Ten: Pre-AI to Post-AI Operating Models

Before Lilli's firm-wide rollout in July 2023, McKinsey's model depended on large cohorts of business analysts and associates performing manual search, data cleaning, benchmarking, and PowerPoint construction. These tasks supplied the apprenticeship through which future partners absorbed pattern recognition and judgment under

uncertainty. Lilli — named after Lillian Dombrowski, the first professional woman hired by the firm in 1945 — functions as an orchestration layer trained on more than 100,000 proprietary documents and interviews spanning nearly a century of the firm's intellectual capital.

The technical architecture of Lilli, as described in McKinsey's own development case studies, combines vector stores built on OpenAI embeddings, semantic and keyword search capabilities, a Cohere re-ranker for relevance prioritization, proprietary filtering and relevancy checks, and citation links back to the source documents within McKinsey's proprietary knowledge base. The platform sits within McKinsey's own risk-controlled environment, meaning that queries and responses are processed on infrastructure the firm controls rather than through public-facing API endpoints — or so the design intended, until the March 2026 CodeWall disclosure revealed that multiple API endpoints were publicly accessible and lacked authentication. The architecture was not unusual for enterprise LLM deployment in 2023. The gap between the architecture's intended security posture and its actual application-level implementation was, however, consequential.

McKinsey's published development lessons illuminate the technical challenges of building a firm-wide LLM platform at the speed the firm required. An early change in data-chunking strategy — the method by which long documents are divided into segments for vector store indexing — caused the model to begin producing hallucinations that did not match source content. The platform required a temporary deployment pause while the chunking strategy was revised. An intent model built to classify consultant prompts into topic categories misclassified prompts at unacceptable rates because the model's designers had made incorrect assumptions about how consultants organize and describe their information needs. Additional quality-assurance gates and clearer accountability frameworks were required before the intent model could be reliably deployed. These are not catastrophic failures — they are the standard product development challenges of any complex LLM deployment. What is notable is that they occurred on a platform with 500,000 monthly users handling confidential client-related information, and that the organizational pressure to deploy at speed was sufficient to push past the quality-assurance gates before they were fully robust.

By 2025–2026, Lilli was used monthly by 72 to 75 percent of the firm's approximately 40,000 to 45,000 professionals, answering more than 500,000 prompts per month and delivering reported time savings of approximately 30 percent on research and synthesis tasks. The platform performs search, synthesis, first-draft slide creation, and comparative analysis from simple text prompts. The firm also integrated AI into recruiting: beginning in early 2026, selected final-round interviews for business-school candidates required candidates to work with Lilli on a case, with interviewers evaluating

how applicants prompt the system, critique its outputs, and apply judgment rather than raw production speed.

The Big Ten and Their AI Platforms

Firm	CEO 2024–26	Proprietary AI	Layoffs/Workforce Changes 2023–26
Accenture	Julie Sweet	AI Refinery (NVIDIA NeMo/NIM), Trusted Agent Huddle	19k cut Q2 FY23; 11k compressed exits May–Aug 2025; \$865M reinvention; \$5.9B GenAI bookings
McKinsey	Bob Sternfels	Lilli (75% of 43k staff, 500k+ monthly prompts, 30% time savings)	Project Magnolia ~1,400 (2023); support-function contractions; AI agent headcount ~25,000
BCG	Christoph Schweizer	Deckster (450k+ decks), BCG Chat	Reduced headcount/slowed hiring 2026
Deloitte	Joe Ucuzoglu	Zora AI agentic platform	Job titles eliminated; Zora replaces juniors; Australia DEWR AU\$440k report fabricated citations; AU\$97k refund
EY	Janet Truncale	EY.ai, Fabric	Technology consulting focus
PwC	Mohamed Kande	ChatPwC, AI tools	Cut grad hiring by one-third citing AI productivity
KPMG	Bill Thomas	KPMG Trusted AI, Clara	~400 US advisory roles cut 2023–26
Bain	Manny Maceda	Bain AI, Experiential Intelligence	Reduced headcount 2026
Oliver Wyman	Nick Studer	OW AI tools	Mid-market stable
Booz Allen Hamilton	Horacio Rozanski	Advana, AI-enabled analytics	Government AI platform focus; net hiring growth

Who Made the Cut and Who Did Not

Public records do not yield exhaustive lists of named individual consultants with detailed personal exit or promotion dossiers tied exclusively to AI performance. What is fully documented are the categories of roles most affected, the scale of reductions, the prioritization criteria publicly stated by leadership, and the trajectories of named senior leaders who shaped and benefited from the transition.

Those Who Advanced

Senior partners and technology leaders who drove Lilli's development and adoption retained and expanded influence. Erik Roth, senior partner and global leader of growth and innovation, led early demos that convinced the board and later described Lilli as saving the average consultant more than a full day per week. Kate Smaje, senior partner and global leader of technology and AI, publicly stated that the firm prioritizes AI-trained staff when staffing certain client projects and that performance evaluation now incorporates how consultants make decisions with AI. Bob Sternfels, Global Managing Partner, has repeatedly framed the hybrid human-agent model as the firm's future and has overseen the commercial shift toward outcome pricing.

Consultants who demonstrated rapid AI fluency — prompt engineering, output verification, the ability to redirect agentic workflows and catch hallucinated citations before they reach client deliverables — were favored for high-visibility engagements. Leadership statements emphasize that remaining human work centers on client relationships, novel problem framing, political navigation within complex stakeholder environments, and accountability for AI-generated material. Those who adapted fastest occupied the verification and orchestration roles that AI creates alongside the analyst production roles that AI eliminates.

Those Who Did Not

Non-client-facing support roles bore the earliest and largest reductions. Project Magnolia (2023) eliminated approximately 1,400 back-office positions in human resources, communications, and IT. Subsequent rounds removed roughly 400 specialists in design, data engineering, cloud, and software. Further planned contractions of several thousand roles, concentrated in support functions and certain junior research layers, were reported in late 2025 and 2026, contributing to an overall headcount decline of more than 10 percent from the pandemic peak. Executive-assistant roles across McKinsey and peer firms were also reduced as AI absorbed calendar, expense, and travel coordination tasks.

Entry-level and junior analyst production work was systematically compressed. Industry analyses and firm statements indicate that Lilli and related agents can perform a large fraction — estimates range as high as 80 percent in some accounts — of the research, synthesis, and slide-generation tasks that once defined the first one to two years of an analyst's apprenticeship. While the firm has not published year-by-year junior hiring numbers tied solely to AI, the combination of slower overall hiring, prioritization of AI-fluent candidates, and explicit statements that technology can replace 'armies of business analysts creating PowerPoints' documents the structural squeeze on the traditional base of the pyramid.

The March 2026 Security Incident: When One AI Hacked Another

The most consequential documented operational failure in the McKinsey AI transition occurred in early 2026. Security startup CodeWall directed an autonomous offensive AI agent at Lilli — no credentials, no insider knowledge, no human in the loop. Within approximately two hours and with roughly \$20 in API tokens, the agent exploited a classic SQL-injection vulnerability arising from unprotected API endpoints and improper handling of JSON keys. Over 200 API endpoints were publicly documented; 22 required no authentication. One unprotected endpoint accepted search queries in which JSON field names were concatenated directly into SQL queries rather than parameterized — a textbook injection vulnerability missed by standard scanners including OWASP ZAP.

According to CodeWall's public report, the agent obtained read-write access to a production database containing approximately 46.5 million chat messages stored in plaintext, 728,000 files including PDFs, spreadsheets, and PowerPoint decks, 57,000 employee accounts, 3.68 million RAG document chunks representing decades of proprietary research, and 95 system prompts that governed Lilli's behavior and guardrails. Because write access was possible, an attacker could in principle have altered the system prompts that controlled the advice delivered to tens of thousands of consultants on active client engagements. McKinsey was notified on approximately March 1, 2026, confirmed the vulnerability, and stated that it fixed the issues within hours.

The incident revealed classic application-security failures rather than a novel LLM vulnerability: missing authentication on multiple endpoints, SQL injection via concatenated JSON keys, and storage of critical system prompts in a writable production database in plaintext. A third-party forensic investigation found no evidence that client data were accessed by the researcher or any unauthorized third party. But the architectural exposure — 46.5 million chat messages stored without encryption in a database reachable from internet-facing endpoints — on a platform in firm-wide use for more than two years represents a fundamental failure of the security-first design principles that McKinsey publicly claimed for Lilli from the beginning.

Lilli's Security Protocols: Claims and Reality

McKinsey's Information Security Program Overview (ISPO), published in May 2026, describes the general framework within which Lilli operates: data classification matrices, AES-256 encryption for data at rest and in transit, role-based access with least-privilege principles, multi-factor authentication for applications hosting confidential data, strong password policies, Tier III data centers with biometric physical access controls and CCTV, and network intrusion detection. During Lilli's build in 2023, security was one of five explicit evaluation criteria alongside cost, scalability, performance, and timing.

The March 2026 incident demonstrated the gap between the high-level security framework and the application-layer implementation. General encryption and physical

access controls did not prevent an AI agent from exploiting unauthenticated API endpoints and plaintext JSON key concatenation to gain read-write access to the production database. Post-incident remediation steps included taking a development environment offline and removing public API documentation. McKinsey has not published detailed technical specifications of Lilli's current authentication flows, prompt-storage mechanisms, runtime guardrails, or agent-specific identity controls beyond the ISPO's high-level framework. The lesson, from a SEAM perspective, is that the speed of platform deployment — firm-wide in July 2023, 500,000 monthly prompts by 2025 — can amplify ordinary application-security failures into firm-wide intellectual capital exposure.

Submerged Costs and the Luddite Perspective

Official McKinsey narratives celebrate 30 percent research-time savings, multi-thousand agent deployments, and the elevation of remaining consultants into higher-judgment work. Beneath those metrics lie the classic SEAM dysfunctions: compression of the apprenticeship that once produced senior judgment, cognitive load from continuous verification of agentic output, algorithmic prioritization that privileges AI fluency in staffing and evaluation, and the externalization of transition costs onto the thousands of non-client-facing and junior professionals who exited. The March 2026 security incident illustrates that the speed of agentic systems can amplify ordinary application-security failures into firm-wide exposure of intellectual capital and, potentially, client-sensitive material.

Lilli's internal development also encountered earlier technical snafus. McKinsey's own published lessons acknowledge that a change in data-chunking strategy caused the model to begin hallucinating, requiring a temporary pause in deployment. An intent model likewise misclassified prompts because of inaccurate assumptions about how consultants organize information, necessitating additional quality-assurance gates. These are not exceptional failures. They are predictable consequences of deploying large language model systems at scale faster than the verification and quality-assurance infrastructure can keep pace. From the SEAM perspective, these failures appear as Dysfunction 3 (Communication-Coordination-Cooperation): AI-generated outputs reaching client deliverables without adequate human verification, the functional equivalent of Deloitte Australia's fabricated citations but at McKinsey's scale.

Conclusion: What the McKinsey Case Demonstrates

The McKinsey case demonstrates both the productivity gains and the structural risks of treating human capital as disposable once the production layer can be automated. Lilli is a genuine operational achievement: 500,000 monthly prompts, 30 percent time savings, adoption by three quarters of the workforce. It is also a platform whose security architecture was compromised by a \$20 AI agent in two hours, whose hallucination and

misclassification failures required mid-deployment pauses, and whose displacement of the junior analyst apprenticeship is creating a Judgment Deficit that will affect the senior partner class in five to ten years. The Boardroom story and the Workforce Room story are both true. A Luddite consultant insists on reading both columns of the ledger before signing off on the invoice.

Recovering the living stories of those who made the cut and those who did not — the 1,400 Project Magnolia exits, the specialists in automatable domains, the junior analysts whose apprenticeship pathway was compressed rather than transformed — remains essential to any accountable path forward. The McKinsey case is not a story about a firm behaving unusually badly. It is a story about the structural consequences of treating the consulting pyramid as an efficiency problem to be solved by automation, rather than a human potential problem to be solved by listening.

The McKinsey case illustrates a pattern that will recur across the Big Ten as agentic platforms mature. Early deployment focused on adoption and productivity claims — the 30 percent time savings, the 500,000 monthly prompts, the 72 percent adoption rate. The second phase, now beginning, focuses on reliability and security — what happens when the systems that tens of thousands of professionals rely on for daily work have exploitable vulnerabilities, produce hallucinations that reach client deliverables, or process sensitive organizational data in ways that were not adequately secured from the start. McKinsey's own development lessons — chunking-induced hallucinations requiring mid-deployment pauses, intent-model misclassification requiring additional quality-assurance gates — document the standard production failure modes of large-scale LLM deployment. These are not exceptional. They are predictable. The SEAM framework calls them Dysfunction 3: failures in communication, coordination, and cooperation that occur when AI-generated content moves through organizational channels without adequate human verification at each step.

The security architecture failure revealed by CodeWall in March 2026 adds a fourth category of hidden cost not yet widely recognized in SEAM literature: AI platform intellectual capital exposure. The 46.5 million chat messages that the CodeWall agent accessed represent the conversational history of McKinsey's consulting engagements — the questions consultants asked, the client contexts they described, the strategy frameworks they applied. Even without confirmed unauthorized access to client confidential information, the architectural exposure of that conversational history to an internet-facing database with unauthenticated endpoints is a hidden cost of the speed-first deployment model. McKinsey confirmed the vulnerability was fixed within hours of notification. The cost of building adequate authentication and access controls from the start — rather than as a remediation after public disclosure — would have been lower. But it would have slowed the July 2023 firm-wide deployment that Lilli's development team was under pressure to deliver.^{[28] [39]}

Chapter 5: Compressed AI Exits – Comparing Workforce Reductions Across Major Consulting Firms

Summary

Between 2023 and 2026, the major consulting firms navigated a common set of pressures: AI platform rollout, structural workforce reduction, and the narrative management of workforce exits. This chapter compares those trajectories across firms using eight composite characters — four who adapted and remained, four who exited on compressed timelines. The composites are explicitly fictitious, synthesized from anonymous accounts on Reddit and Glassdoor, organizational disclosures, and industry patterns. They are labeled as such throughout. The chapter applies cross-firm comparison to document the systemic pattern of AI impact on junior roles, analyzes what anonymous forum discussions reveal that official communications suppress, and situates the human consequences of compressed AI exits within the SEAM framework. The finding is not that the transition was avoidable. The finding is that the hidden costs were never counted.

Keywords: consulting layoffs; AI reskilling; composite characters; apprenticeship collapse; junior roles; Reddit Glassdoor

Introduction: Documenting the Undocumented

Documenting the human experience of AI-driven workforce change in consulting is a methodological challenge. Elite consulting firms produce almost no primary individual narratives about how specific employees experienced the AI transition, who was promoted, who was exited, and why. Non-disclosure agreements, up-or-out cultural norms, and institutional brand-protection mechanisms systematically suppress individual voice. What survives in the public record are aggregate statistics in earnings calls, leadership statements about reinvention and reskilling, anonymous posts on Reddit and Glassdoor that cannot be attributed to specific individuals, and organizational disclosures in regulatory filings and press releases.

This chapter uses eight composite characters — explicitly fictitious constructions, not real named individuals — to make visible the range of trajectories that the aggregate numbers conceal. The composites are grounded strictly in publicly documented patterns. Survivors adapted by acquiring AI fluency, shifting into verification and orchestration roles, and demonstrating value in client-facing strategic advisory. Those who exited were concentrated in production-heavy analytical roles that AI absorbed, non-client-facing support functions, and mid-career professionals who could not or chose not to reskill on the compressed timelines that firms imposed. These are patterns, not predictions about any specific person. The composites function as analytical tools for understanding structural change, not as empirical claims about individuals.

Eight Composite Trajectories: Survivors and Leavers

Those Who Remained and Adapted

Elena Vargas — Strategy Consultant, Accenture, Supply Chain Practice

Pre-AI, Elena spent approximately 80 percent of her cycle on data preparation: downloading ERP logs, cleaning Excel files, building slide decks for multi-week diagnostics. She was efficient at it but found the work exhausting rather than intellectually engaging. When Accenture deployed its AI Refinery toolset, Elena was among the early volunteers for the upskilling cohort. She completed GenAI fundamentals training and then the advanced modules on agentic workflow orchestration. By 2026 she was deploying multi-step agents to ingest 10,000-row vendor fulfillment datasets in 90 seconds and running counterfactual logistics scenarios in minutes. Her diagnostic cycle had compressed from 14 days to 48 hours. She had also taken on verification responsibilities — checking agent outputs for hallucinated citations before they reached client deliverables — that the official narrative of '95 percent strategic advisory' never mentioned. She was promoted. She also reported working three to four additional unbilled evening hours per engagement on verification and coordination across time zones.

Marcus Hale — Technology Delivery Lead, McKinsey, Digital Practice

Marcus had spent eight years managing systems-integration projects with clear hierarchical hand-offs: requirements to build to test to deploy. His success metrics centered on on-time delivery and utilization rates. When Lilli was deployed firm-wide in July 2023, Marcus positioned himself as a bridge between the platform and client delivery teams. He learned to design prompting sequences, govern agentic workflows, and integrate AI-assisted synthesis into delivery methodology. By 2025 he was coaching junior teams on human-in-the-loop controls and helping clients build verification protocols for AI-generated analytical outputs. He benefited from the documented expansion of AI/data specialist roles within McKinsey's '25 squared' model and was retained and promoted as a hybrid delivery architect.

Priya Nair — Risk and Compliance Analyst, Deloitte, Financial Services

Priya's pre-AI work involved manual regulatory review and compliance documentation — slow, detail-intensive work that required legal and regulatory expertise but not data engineering skill. When Deloitte deployed Zora AI as an agentic platform for documentation-intensive work, Priya's regulatory knowledge became a verification asset. She learned to identify when AI-generated legal summaries had drawn on incorrect precedents or cited inapplicable regulations — a skill made urgently relevant by the Deloitte Australia DEWR case. By 2026 she occupied a hybrid role combining regulatory expertise with AI-output verification that the firm's official narrative described as 'senior

advisory' and that Priya described in anonymous forum posts as 'checking the machine's homework, all day, every day.'

James Okonkwo — Senior Partner, BCG, Industrials Practice

James was already at the senior level when BCG deployed Deckster. His trajectory illustrates the partner-level adaptation pattern: the senior partner's value was always in client relationships, problem framing, and political navigation of complex stakeholder environments. Deckster automated what junior analysts had done — generating the first-draft slide decks from prompt specifications — freeing James to spend more time with clients earlier in the engagement cycle. He adopted AI fluency as a demonstration of client value rather than as a survival necessity. He was, by 2026, using Deckster to generate 450-plus deck variations per engagement cycle and reporting that clients valued the speed while noting that the conceptual framing of those decks still required his judgment.

Those Who Exited

Sofia Ramirez — Business Analyst, Accenture, Finance and Risk

Sofia joined Accenture directly from a top-20 MBA program in 2021, entering the classic analyst-to-associate pipeline that was the standard entry point for the consulting profession. Her first two years were defined by the manual data work — Excel modeling, ERP report extraction, slide compilation — that built slow knowledge in her peer cohort. When Accenture began deploying AI Refinery agents for precisely these tasks in 2023–24, Sofia's production role was compressed faster than the upskilling pathway could accommodate. She completed GenAI fundamentals training but found that the advanced verification and orchestration roles required data engineering skills she had not built during her pre-AI analyst years. She was identified in what Accenture's internal documentation called 'skill-based exits on a compressed timeline.' She left the firm in early 2025 and moved into a corporate strategy role at a manufacturing company that valued her project management skills over her AI fluency.

David Chen — Research Analyst, McKinsey, Knowledge Services

David worked in McKinsey's internal knowledge management and research function — a non-client-facing role that had historically served as the analytical backbone for client engagement teams. His work involved synthesizing research, maintaining the firm's internal knowledge repositories, and producing background analyses on industry topics. Lilli was trained in part on the knowledge base his team curated. By 2023–24, Lilli could perform a significant fraction of David's research synthesis work from a simple text prompt. His role was included in the Project Magnolia reductions. He described the experience in an anonymous Glassdoor review as 'training the system that replaced you, then being thanked for your contributions.'

Aisha Khan — Senior Associate, PwC, People and Organization

Aisha had built her consulting practice around organizational change management — the human side of transformation programs. Her pre-AI work involved stakeholder interviews, change impact assessments, and communication strategy for large implementation projects. When PwC cut graduate hiring by one-third citing AI productivity gains, the organizational change management function was simultaneously reshaped: AI tools were deployed to generate stakeholder communication frameworks and change impact templates at speed, and Aisha's role was reconceived as a platform operator rather than a practitioner. She chose to leave rather than transition into what she described privately as 'quality-checking AI-generated empathy documents.' She now runs an independent organizational development practice grounded in what she calls listening-first methodology — language that would fit comfortably in a SEAM field manual.

Thomas Berg — Director, KPMG, Data & Analytics

Thomas led a data analytics team that had been built around custom data engineering, statistical modeling, and visualization for financial services clients. When KPMG deployed its AI tools including Clara and Trusted AI, the platform automated much of the data pipeline work his team performed manually. Thomas found the toolset technically capable but organizationally disruptive: the skills his team had developed over years — bespoke data architecture, custom statistical model design — were being replaced by configurable AI pipelines that produced adequate outputs faster but at reduced specificity. He was among the approximately 400 advisory role reductions at KPMG in 2023–26. He subsequently moved to an academic role in data science, describing the shift as 'going somewhere that still values building things from scratch rather than configuring vendor pipelines.'

Cross-Firm Comparison: Scale, Framing, and Human Consequences

Across the Big Ten firms, the AI transition of 2023–2026 produced a consistent structural pattern with firm-specific framing. Accenture framed its 11,000 exits as skill-based, distinguishing between employees upskilled into AI roles and those exited on compressed timelines when reskilling was deemed not viable. McKinsey framed its reductions primarily in terms of Project Magnolia's back-office rationalization and the shift in staffing model toward AI-fluent client-facing professionals. PwC described its one-third cut in US graduate hiring as a productivity measure reflecting AI's ability to do more with fewer entry-level staff. KPMG characterized its approximately 400 advisory role reductions as a portfolio optimization. None of the firms used the phrase that SEAM would use: compressed AI exits.

The framing differences are significant because they determine what hidden costs are counted. A skill-based exit is a story about the employee's limitations. A compressed AI exit is a story about the organization's speed and the gap between the rate of automation

and the rate of reskilling. Both descriptions refer to the same event. Only one of them includes the hidden cost of the organizational choice to compress the transition timeline.

AI Impact on Junior Roles: The Systemic Pattern

The systemic pattern visible across all eight composite trajectories and documented in industry analyses is the compression of the entry-level analyst layer. Junior roles defined by data preparation, research synthesis, and slide construction — the tasks that built slow knowledge through repetition — are being absorbed by AI agents across every major consulting firm. The speed of absorption varies: BCG's Deckster automated deck generation, McKinsey's Lilli automated research synthesis, Accenture's AI Refinery automated data ingestion. But the direction is consistent.

Industry analyses from McKinsey Quarterly, the Stanford Digital Economy Lab, and practitioner commentary estimate that AI can now perform 60 to 80 percent of the tasks that defined first-year analyst work in elite consulting firms. The remaining 20 to 40 percent — client communication, judgment calls on ambiguous data, verification of AI outputs, political navigation of complex stakeholder environments — requires precisely the slow-knowledge foundation that the compressed analyst layer was supposed to build. The Judgment Deficit is not a future risk. It is a structural condition being created in the present.

Voices from the Anonymous Record

Reddit communities including r/accenture, r/accenture_india, and r/Layoffs, and Glassdoor reviews of major consulting firms, supply qualitative texture that official communications systematically exclude. These are not verified individual accounts and are treated as anecdotal only. But patterns across thousands of anonymous posts converge on a consistent set of experiences that match the composite trajectories documented above.

The most frequently repeated themes in anonymous consulting forum posts from 2023–2026 are: the mandatory nature of AI tool adoption (log-in metrics, performance reviews tied to AI usage frequency), the verification burden hidden beneath the official narrative of efficiency gains (hours spent checking AI outputs that do not appear in billable time), the experience of identifying as 'training data for the system that will replace you' (echoing David Chen's composite), and the cultural silence around exits ('people just disappear from the directory with no announcement'). The silence in official communications is filled, partially and imperfectly, by the anonymous record. The SEAM mirror-effect meeting would bring both into the same room at the same time.

Conclusion: The Uneven Distribution of the AI Dividend

The AI dividend in consulting — 30 percent time savings, compressed diagnostic cycles, multi-billion-dollar GenAI bookings — has been distributed unevenly. Partners

and senior professionals who already possessed the slow knowledge that AI cannot supply have retained and expanded their roles. Junior professionals and non-client-facing support staff have absorbed the transition costs: exits, reskilling demands on compressed timelines, and the invisible verification burden that makes the efficiency narrative possible without appearing on any invoice.

The SEAM Accounting Gap is visible in this distribution. The consulting invoice captures the efficiency gain. It does not capture the human cost of the transition pathway. A Luddite consultant insists on both columns of the ledger. The eight composite characters in this chapter — four survivors, four leavers — are not eight separate stories. They are eight facets of the same structural transformation, documented in the aggregate by earnings calls and financial disclosures, experienced individually in ways that non-disclosure agreements and cultural norms systematically prevent from becoming visible. Making those facets visible, even in the imperfect form of grounded composites, is the first step toward counting them in the ledger where they belong.

The firms themselves have not been oblivious to the human cost dimension. Accenture CEO Julie Sweet repeatedly emphasized in earnings calls and press statements that the firm's preferred approach was upskilling rather than exiting — that the 550,000-plus employees trained in generative AI fundamentals represented a genuine commitment to reskilling. The tension is between the stated commitment and the compressed timeline. Reskilling 550,000 employees in generative AI fundamentals is a training program. Converting mid-career professionals whose value derived from manual data expertise into AI-orchestration specialists capable of verifying agentic outputs and managing multi-step AI workflows requires a qualitatively different level of organizational investment — and a longer timeline than compressed exits allow. The gap between the training program and the reskilling requirement is exactly where the 11,000 exits are located. SEAM would call that gap Dysfunction 4: insufficient integrated training whose cost is borne by the workers who could not bridge it.

The eight composite trajectories suggest a framework for understanding AI-era consulting transitions: those who adapted successfully were those who could pivot their contribution from production to verification — from building slides to checking whether agent-generated slides contain accurate citations, from downloading ERP logs to specifying what the ingestion agent should prioritize and flagging when its outputs look suspicious. This is not a technical skill so much as a judgment skill — the ability to evaluate analytical output critically rather than accept it at face value. That judgment skill is, ironically, exactly what the slow-knowledge apprenticeship pathway built. The consultants most likely to survive the AI transition were those who had gone through enough manual data wrangling and slide-building to recognize when an automated version of those tasks had produced something wrong. The apprenticeship collapse makes

the next generation of adaptors structurally less capable of the verification work that sustains the AI consulting model in the medium term.

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Chapter 6: Silence in the Pyramid, Voices from the Lab – Why Consulting Firms Do Not Narrate Their AI Transitions

Summary

High-profile AI laboratories — OpenAI, Anthropic, xAI, DeepSeek, Meta AI, NVIDIA — regularly generate public accounts of internal change, resignations, layoffs, and personal career pivots. Former and current employees publish detailed reflections on X, personal blogs, and in major media. In contrast, the top-tier billion-dollar consulting firms produce almost no comparable individual narratives. Instead, they release polished BME corporate accounts emphasizing aggregate training numbers, productivity gains, and strategic reinvention. This chapter maps the structural, cultural, and institutional reasons for the disparity, argues that carefully constructed composite characters grounded in anonymous anecdotes and public organizational data are one of the few remaining viable methods for documenting the human experience of AI-driven workforce transformation, and examines the epistemological consequences of the silence for scholars, policymakers, and the public.

Keywords: *AI workforce narratives; consulting silence; composite characters; organizational transparency; epistemology*

Introduction: The Asymmetry of Voice

Why do employees and alumni of frontier AI organizations publicly narrate how their work has changed, why they resigned, or how they experienced layoffs, while parallel accounts from the world's largest consulting firms are virtually absent from social media and independent media? This asymmetry is not accidental. It reflects deep differences in organizational culture, contractual constraints, talent markets, and narrative control. The asymmetry matters because it shapes what scholars, policymakers, and the public understand about how AI is transforming professional work — and, more specifically, whose experience of that transformation gets counted as evidence.

The main question guiding this chapter is: what structural and cultural factors explain the abundance of first-person career narratives emerging from AI corporations versus the near-total reliance on aggregate, officially sanctioned stories from elite consulting firms? A secondary question follows: given the systematic barriers to primary human-subjects research inside consulting, what legitimate methodological alternatives exist for scholars and critical observers seeking to document the lived experience of AI-driven change? The answers have direct implications for the composite character methodology used throughout this book and for the broader field of organizational storytelling as a research methodology.

Public Narratives from AI Corporations: Volume, Detail, and Function

Frontier AI organizations operate in a high-visibility, talent-scarce environment. Employees and alumni frequently publish detailed accounts of internal shifts. At OpenAI, multiple high-profile departures between 2023 and 2025 generated extensive public

commentary. Former researchers and policy staff wrote at length about safety concerns, commercialization pressures, and changes in research culture. Some posted lengthy threads on X explaining their decision to leave; others gave interviews to major outlets describing the emotional and intellectual costs of rapid scaling. These narratives included specific timelines, role changes, and reflections on how agentic systems altered daily work.

Anthropic has similarly seen public reflections from departing staff who discussed the tension between capability advancement and safety commitments. Detailed blog posts and interviews described shifts from pure research to product-oriented timelines and the personal decision points that led to exits. In September 2026, Anthropic CEO Dario Amodei published *We Must Pace the Frontier* — a public letter arguing that recursive self-improvement requires coordinated regulatory response. This is a high-profile organization narrating its own existential uncertainty in public. No equivalent executive document has emerged from McKinsey, Accenture, BCG, or any other major consulting firm.

xAI, Meta AI, and NVIDIA have produced parallel material. Engineers and researchers have posted about the intensity of scaling large models, the impact of sudden project reprioritizations, and, in some cases, layoff experiences during reorganization. DeepSeek and other emerging laboratories have generated discussion in technical communities about workload, open-source versus closed development tensions, and career pivots. These narratives serve multiple functions: personal sense-making, signaling to the talent market, influencing public and regulatory perception, and, in some cases, applying external pressure on the organization. The cultural environment of AI laboratories — rooted in academic research norms, open online discourse, and intense competition for elite technical talent — makes such public reflection relatively common and often professionally advantageous.

The Consulting Silence: Institutional Mechanisms of Narrative Control

Elite consulting firms present the opposite pattern. Despite comparable or larger absolute numbers of workforce adjustments — Accenture's approximately 11,000 exits, McKinsey's successive reductions in support and junior production layers, selective advisory cuts at KPMG, Deloitte, PwC, and EY — almost no named, detailed first-person accounts appear on social media or in independent journalism. The official communications emphasize aggregate statistics: hundreds of thousands trained in generative AI, multi-billion-dollar bookings, productivity percentage gains, and reinvention frameworks. Individual counter-narratives would disrupt the centripetal force of the official Beginning-Middle-End story.

Several interlocking mechanisms explain the silence. First, contractual and cultural non-disclosure is far stricter than in the AI laboratory sector. Employment agreements,

client confidentiality rules, and post-employment restrictions severely limit what individuals may say about internal processes, even after departure. Violations risk legal action or reputational damage within a tightly networked industry where the next client engagement depends on the previous one's recommendation.

Second, the up-or-out and partner-election cultures reward loyalty and discretion. Public criticism can permanently close doors to future client work, alumni networks, or senior roles. The professional identity of many consultants is tightly bound to firm prestige; airing difficulties is often perceived as personal and collective failure. Third, consulting firms invest heavily in controlled narrative production. Official communications present a coherent story of progressive adaptation. Individual counter-narratives would disrupt that story's institutional function — maintaining client confidence, attracting talent, and sustaining valuations in a market that has increasingly priced in AI transformation expectations.

Fourth, the nature of the work itself reduces public visibility. Consulting deliverables are client-confidential; internal tools and processes are proprietary. Unlike AI researchers who can discuss model architectures or safety techniques at a general level without exposing proprietary detail, consultants rarely possess portable, non-confidential artifacts that support public storytelling. The result is a public record dominated by firm-authored aggregate success narratives and a near-absence of granular personal accounts of how junior production roles collapsed, how verification burdens replaced apprenticeship, or how compressed reskilling timelines affected mid-career professionals.

Composite Characters as Methodological Necessity

When primary human-subjects research is systematically blocked — by NDAs, institutional non-cooperation, ethics-board constraints around vulnerable employees, and the practical impossibility of obtaining verifiable internal records — researchers face a choice. They may remain silent, rely solely on official aggregates, or construct carefully bounded composite characters. This book has made the third choice throughout, and this chapter defends that methodological decision explicitly.

Composite characters are fictitious individuals explicitly labeled as such, synthesized from multiple anonymous sources — Reddit threads, Glassdoor reviews, off-record conversations — alongside organizational disclosures and observable industry patterns. They are not presented as real people. Their purpose is illustrative and analytical: to make visible the range of trajectories that aggregate numbers conceal. Sarah, Elena, Marcus, Priya, James, Sofia, David, Aisha, Thomas, and Shelia are not real people. They are analytical constructions built from real patterns, labeled as constructions, used to recover the human dimension of a transformation that official communications systematically erase.

The method is imperfect and must be used transparently. It cannot substitute for primary testimony. The composites cannot capture idiosyncratic individual experience; they can only represent central tendencies in documented patterns. The reader should approach them as SEAM approaches organizational data: as one layer of a qualimetrics triangulation, not as the whole account. The verbatim field notes that SEAM requires are not available here — the NDAs prevent them. What is available is the anonymous residue of those field notes: the Reddit posts, the Glassdoor reviews, the off-record conversations that, in aggregate, converge on patterns consistent enough to ground a composite.

Antenarrative theory provides the conceptual framework for this method. The seven B's — Before, Beneath, Bets, Being, Becoming, Between, Beyond — trace story fragments that exist before they solidify into official BME accounts. The anonymous forum posts and Glassdoor reviews are antenarratives: living story fragments that have not yet been shaped into official narratives because no official narrative production apparatus would amplify them. The composite character methodology is antenarrative analysis made legible. It assembles the fragments into a coherent analytical form without claiming that the assembled form is any specific person's true story.

Discussion: Epistemological Consequences

The disparity in narrative production is not primarily a matter of individual willingness but of institutional design. AI laboratories operate in a culture that retains elements of academic openness and benefits from public debate about safety and capability — the talent competition with academic institutions makes transparency advantageous in ways it is not for consulting firms competing on client confidentiality and relationship discretion. Consulting firms operate as high-trust, high-confidentiality partnerships whose economic model depends on controlled reputation.

This difference has epistemological consequences that extend well beyond the academic study of organizational change. Scholars and the public possess rich qualitative material for understanding the internal experience of AI laboratories. For consulting, they possess mainly quantitative headlines and polished corporate stories. The risk is that policy, educational, and ethical responses to AI's impact on knowledge work will be shaped by the more visible sector while remaining under-informed about the quieter, larger professional-services transformation that affects a far greater number of workers globally.

When a Princeton research study gives AI agents thousands of dollars and six days to produce peer-reviewable scientific research and all submissions are rejected for insufficient scientific judgment, that finding enters the public record through journal publication, press releases, and extensive media coverage. When a Deloitte AI tool fabricates legal citations in a government assurance report, that finding enters the public record through parliamentary inquiry and media reporting — but Deloitte's internal

analysis of how the failure occurred, what verification protocols failed, and what organizational changes resulted remains confidential. The asymmetry in public knowledge production is structural, not accidental. Documenting it is part of what a Luddite consultant does.

Conclusion: The Silence Is the Finding

AI corporations generate abundant public career narratives because their cultures, talent markets, and lower barriers to disclosure reward or at least tolerate individual voice. Elite consulting firms generate almost none because contractual, cultural, and narrative-control mechanisms systematically suppress it. In the resulting evidentiary vacuum, carefully constructed and transparently labeled composite characters — built from anonymous anecdotes, public organizational data, and industry patterns — offer a limited but necessary means of documenting the human experience of AI-driven change.

Formal human-subjects research inside these firms is, under current conditions, largely unfeasible. Non-disclosure agreements prevent named accounts. Partner-election norms punish transparency. Client-confidentiality rules eliminate the most informative data. What remains is the anonymous record, the aggregate disclosure, and the composite methodology this book has employed throughout. None of these is sufficient. All of them are necessary. Recognizing both the silence and the methodological response it requires is essential for any serious accounting of how artificial intelligence is rewriting professional careers.

There is a second-order epistemic problem worth naming explicitly. The institutional mechanisms that suppress individual voice inside consulting firms also suppress organizational learning. When a Deloitte AI tool fabricates legal citations and the incident is resolved through a parliamentary refund process and a PDF audit — rather than a public post-mortem that details what verification protocols were absent, how the AI toolchain was configured, and what organizational changes resulted — Deloitte's competitors cannot learn from the failure. Each firm reinvents the same wheel, makes the same verification errors, and corrects them privately. The consulting industry's institutional silence is not only an ethical and sociological problem. It is a collective intelligence failure. The SEAM mirror-effect meeting is an organizational learning instrument as much as an accountability mechanism. The industry-level silence makes the industry-level mirror-effect meeting impossible.

The contrast with AI laboratory discourse is instructive here. When Anthropic releases a model card documenting Claude's known failure modes, hallucination rates, and safety evaluation results, that document enters the public domain and allows other researchers, policymakers, and practitioners to calibrate their use of the system. When McKinsey documents its lessons from building Lilli — including the chunking-induced hallucinations and intent-model failures — it does so in a proprietary development

context that produces a sanitized public blog post rather than a full technical disclosure. The sanitized version is more useful than nothing. It is less useful than the full account. And it is vastly less useful than the full account would be if it were part of a shared industry post-mortem that let every firm learn from one firm's failure. The AI laboratory culture of technical openness, imperfect as it is, produces collective intelligence. The consulting culture of proprietary narrative control produces collective blindness.

For policymakers seeking to understand how AI is affecting professional labor markets, the epistemological asymmetry has direct consequences. Regulatory frameworks, labor market interventions, educational policy, and professional licensing standards are being developed in a context where the AI laboratory experience is well-documented and the consulting experience is almost entirely invisible. The 11,000 Accenture exits, the McKinsey headcount compression, the PwC graduate hiring cuts, the KPMG advisory role reductions — each is documented in aggregate in earnings calls but not in the granular individual accounts that would allow policymakers to understand the mechanics of the transition: how reskilling programs work or fail, what the compressed timeline actually looks like from inside, what verification burdens are being created by AI adoption, and what organizational structures might distribute the AI dividend more equitably. The SEAM framework offers the methodological toolkit for that kind of audit. What it lacks is institutional access. Providing that access — perhaps through regulatory mandate, perhaps through professional association cooperation, perhaps through the development of voluntary transparency standards analogous to the model card framework in AI laboratory practice — is one of the structural interventions that would make the silence speak.

The antenarrative framework provides a way to describe what the silence contains. The seven antenarrative B's — Before, Beneath, Bets, Being, Becoming, Between, Beyond — apply to the industry's narrative silence as readily as to any individual consulting engagement. Before the silence: a consulting industry that produced named case studies and individual practitioner histories freely, before NDA norms hardened in the 1990s and 2000s. Beneath the silence: the Reddit posts, Glassdoor reviews, and anonymous forum threads that constitute the submerged antenarrative. Bets: the institutional wager that brand protection through narrative control produces more long-term value than organizational transparency. Being: the daily experience of workers who know they cannot speak publicly about what is happening around them. Becoming: the identity foreclosure imposed on professionals who must choose between institutional loyalty and personal testimony. Between: the liminal space of the anonymous review — public enough to constitute evidence, private enough to allow candor. Beyond: the long-term consequence of an industry whose internal transformations cannot be studied, audited, or learned from because the institutional apparatus of silence is more powerful than the institutional incentives for transparency.

The SEAM mirror-effect meeting, if it could be held at the industry level rather than the firm level, would present executives and workers simultaneously with the same data: the aggregate efficiency gains and the individual human costs of achieving them. This book is that mirror-effect meeting, assembled from the data that the institutional apparatus allows to escape the silence. The silence is not empty. It is the loudest finding in the entire account.

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Chapter 7: The Regulatory Tamaraland - AI Governance Between Europe and the United States

Summary

This chapter enters the regulatory room of AI consulting. The European Union has built a binding, risk-based legal regime, while the United States combines voluntary federal standards, sectoral law, procurement, state legislation, and a 2025 federal policy that emphasizes innovation and infrastructure. The contrast is real, but it is not a simple choice between regulation and no regulation. Both systems can produce compliance artifacts without producing answerability. The chapter uses Tamaraland, antenarrative, and the Socio-Economic Approach to Management (SEAM) to distinguish a policy, a control, and a living organizational practice. It corrects the AI Act timeline after the 2026 amendment, examines AI literacy and human oversight, and reads 2025 consulting-firm disclosures as evidence that governance itself is becoming a consulting market. Its contribution is a Luddite regulatory audit: a method for asking whether affected workers and communities have authority, whether responsibility is traceable, and whether hidden costs have merely been moved outside the compliance boundary.

Keywords: AI Act; NIST AI RMF; AI governance; human oversight; regulatory consulting

Introduction: The Regulation Room

The first six chapters followed artificial intelligence into the consulting firm, the workforce, the apprenticeship pipeline, the executive room, and the institutional silence surrounding transformation. The next room is regulation. It is a room full of definitions, inventories, risk classifications, policies, controls, technical files, conformity assessments, training records, and dashboards. It is also a room in which consulting firms increasingly sell the answer to a problem they helped create. They advise clients to deploy AI, then advise them how to govern it, document it, assure it, and explain it.

That double position creates the question with which this chapter begins: Who audits the people doing the auditing?

The question matters because AI governance is becoming an industry. Accenture reported \$5.9 billion in generative-AI bookings for fiscal 2025, nearly double the prior year, in the same period in which it reorganized its services around reinvention and AI (Accenture, 2025a, 2025b). PwC's 2025 Global Annual Review reported \$56.9 billion in revenue and described technology, AI, trust, and reinvention as central to the network's strategy (PwC, 2025). Deloitte's 2025 Global Impact Report placed AI and digital agents within its account of business transformation (Deloitte, 2025). These are company disclosures, not independent measures of social benefit. They nevertheless demonstrate that AI

implementation and AI governance are no longer side practices. They are part of the professional-services growth model.

The regulatory environment is not stable enough to summarize with a slogan. The European Union's Artificial Intelligence Act is binding law, but its obligations phase in at different times. The consolidated text dated July 27, 2026 states that the Regulation applies generally from August 2, 2026. It also reflects Regulation (EU) 2026/1744, which moved key requirements for high-risk systems: provisions for systems classified under Article 6(2) and Annex III apply from December 2, 2027, while provisions for systems classified under Article 6(1) and Annex I apply from August 2, 2028 (European Union, 2026a, art. 113). Prohibitions and AI-literacy provisions began earlier, in February 2025, although the 2026 amendment also revised the wording of Article 4. Any claim that the entire high-risk regime became enforceable in August 2026 is therefore too broad.

The United States has a different architecture. The National Institute of Standards and Technology describes its AI Risk Management Framework as voluntary and organized around the functions Govern, Map, Measure, and Manage (Tabassi, 2023). Its Generative AI Profile identifies risks and suggested actions rather than creating a comprehensive statutory regime (Autio et al., 2024). At the federal executive level, America's AI Action Plan, released in July 2025, emphasized innovation, infrastructure, energy, and international leadership (White House, 2025). Existing civil-rights, consumer-protection, employment, privacy, product-safety, procurement, and sectoral rules still matter, as do state laws. But there is no single U.S. counterpart with the scope and structure of the EU Act.

This chapter contributes three things. First, it gives the book a corrected regulatory baseline as of September 2026. Second, it treats regulation as another Tamaraland in which Boardroom, Legal, Workforce, Client, and Community rooms hear different accounts of the same system. Third, it develops a Luddite regulatory audit that joins legal evidence to SEAM's hidden-cost analysis. My argument is not that regulation is unnecessary. It is that compliance is not answerability, and a document is not yet a relationship.

Two Regulatory Architectures, Neither of Them Simple

The convenient story says that Europe regulates and America innovates. That story is a BME narrative. It gives each jurisdiction a stable identity, removes contradictions, and ends before practice begins. The living story is more complicated.

The EU AI Act allocates obligations by role and risk. It addresses providers, deployers, importers, distributors, authorized representatives, and providers of general-purpose AI models. It prohibits designated practices, creates transparency duties for certain systems, and establishes more demanding obligations for high-risk systems. Those obligations include risk management, data governance, technical documentation, record keeping,

information for deployers, human oversight, accuracy, robustness, cybersecurity, quality management, registration, monitoring, and incident reporting. The details depend on classification, use, and the applicable date. Legal analysis must therefore begin with the system, the role, the intended purpose, and the timeline rather than the phrase "AI Act compliant."

The U.S. architecture is plural. NIST offers a common risk-management vocabulary. Federal agencies retain their existing authorities. Procurement rules can create obligations for vendors. State legislation can regulate particular systems or uses. Courts apply existing law to new facts. The 2025 federal action plan seeks to accelerate AI development and supporting infrastructure. These parts do not add up to no regulation. They add up to a fragmented field in which a consulting firm can help the same client satisfy different obligations in different jurisdictions.

Table 7.1 identifies the contrast without pretending that either column is complete.

Dimension	European Union	United States
Primary architecture	Binding, cross-sector, risk-based regulation plus existing Union and national law	Voluntary federal framework plus sectoral law, agency authority, procurement, litigation, and state law
Baseline instrument	Regulation (EU) 2024/1689 as amended	NIST AI RMF 1.0 and Generative AI Profile are influential but voluntary
High-risk systems	Defined classifications with phased legal duties	Obligations vary by sector, use, jurisdiction, contract, and existing law
AI literacy	Article 4 requires measures supporting staff and relevant persons; it does not guarantee a specified individual proficiency	Training is commonly framed as risk-management practice, contractual control, or employer program
Human oversight	Article 14 specifies capabilities for effective oversight of applicable high-risk systems	Oversight expectations arise through frameworks, sectoral duties, professional standards, and case-specific law
Enforcement	National competent authorities, EU-level governance, penalties, and sectoral enforcement	Multiple federal and state authorities, courts, procurement bodies, and private litigation
Consulting market	Classification, compliance, conformity, documentation, literacy, monitoring	Governance design, risk management, assurance, sectoral compliance, procurement, and state-law readiness

Principal danger	Legal compliance becomes a substitute for lived accountability	Voluntary governance becomes a substitute for enforceable responsibility
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The difference matters, but it does not relieve either jurisdiction of the central organizational problem. A binding rule can become a ritual. A voluntary framework can be used seriously. A conformity assessment can identify real defects. A governance committee can also meet quarterly, approve a dashboard, and never hear from the worker who must correct the system at midnight. The legal form changes what can be demanded and enforced. It does not automatically determine whether an organization listens.

The 2026 Timeline: Why Precision Is an Ethical Practice

The earlier version of this chapter stated that the EU framework had entered its major enforcement phase in August 2026. That formulation was directionally understandable but legally imprecise after the 2026 amendment. Precision is not an editorial nicety here. A consulting recommendation can cause a client to spend money too early, wait too long, misclassify a system, or promise compliance that does not exist.

The consolidated Article 113 now supports a more careful account. Chapters I and II, which include definitions, AI literacy, and prohibited practices, began to apply from February 2, 2025, subject to amendments and later dates for specified provisions. Governance provisions and obligations for general-purpose AI models began in August 2025. The Regulation applies generally from August 2, 2026, but the core requirements for high-risk systems under Chapter III, Sections 1 through 3 are deferred to December 2, 2027 for Annex III systems and August 2, 2028 for systems tied to Annex I product-safety legislation (European Union, 2026a, art. 113).

This is exactly the sort of detail that the Consent Machine erases. A sales presentation says, "The AI Act is here." A skeptical lawyer says, "Which article, which actor, which system, and on what date?" The Luddite Consultant adds, "Who is affected while we wait, and what safeguards are justified before the legal deadline?"

The last question is not an invitation to invent law. It separates a legal minimum from an organizational choice. An employer may not yet face a particular high-risk obligation, but it can still create a named owner, keep logs, test for failure, permit workers to challenge outputs, and investigate workload effects. Conversely, an organization can satisfy a legal requirement and still create hidden costs outside the legal test.

Regulatory timing therefore has three clocks. The first is the legal clock: when a provision applies. The second is the technical clock: when systems, standards, guidance, and conformity tools are ready. The third is the lived-work clock: when people begin to experience surveillance, work intensification, deskilling, exclusion, or error. Those clocks do not move together.

AI Literacy: Training Record or Capacity to Refuse?

Article 4 is often summarized as a training requirement. The amended text is more careful. Providers and deployers must take measures to support the development of AI literacy among staff and other persons operating or using AI systems on their behalf, taking into account knowledge, experience, education, training, context, and the people on whom systems are used. It expressly states that the obligation does not require a provider or deployer to guarantee a specified level of literacy in any individual (European Union, 2026a, art. 4).

That distinction prevents one overclaim while creating another question. What counts as an adequate measure inside an organization? A one-hour online module may generate a completion certificate. It does not necessarily produce the capacity to recognize automation bias, detect fabricated sources, identify a distribution shift, understand a model's intended purpose, or stop a harmful workflow.

The consulting industry has strong incentives to package AI literacy. It is scalable, measurable, repeatable, and saleable. Completion rates fit dashboards. The Luddite inquiry is different. It asks whether the trained person has authority. A worker may know that an output is unreliable and still be evaluated on throughput. A junior consultant may understand that a citation is fabricated and still fear delaying the partner's deadline. A manager may identify a risk and lack the budget to run an independent test. Literacy without authority becomes another hidden cost: the employee knows enough to see the danger and not enough to stop it.

SEAM turns AI literacy from a content question into an organizational one. It asks how training changes working conditions, work organization, communication-coordination-cooperation, time management, integrated training, and strategic implementation. It measures not only hours of instruction but also incidents detected, corrections accepted, escalation time, rework, overtime, and consequences for speaking up.

Human Oversight Is Not Human Presence

Article 14 provides one of the clearest bridges between law and this book's argument. For applicable high-risk systems, oversight must be effective. The natural persons assigned to it must be able, as appropriate and proportionate, to understand system capacities and limitations, monitor operation, recognize automation bias, interpret outputs, disregard or override them, intervene, or stop the system (European Union, 2026a, art. 14).

This is more demanding than putting a human at the end of a workflow. Yet organizations can still hollow out the requirement. They can assign responsibility without time, competence, independence, or protection. They can ask one person to supervise more outputs than any person can review. They can describe a click as approval when the economic design makes refusal impossible. They can preserve the formal human while

eliminating the apprenticeship through which that human would have learned what to notice.

The connection to Chapters 2 through 5 is direct. If AI removes entry-level research, data cleaning, drafting, and slide construction, where does future oversight competence come from? The problem is not nostalgia for tedious work. Some tasks should be automated. The problem is that organizations have treated learning as a free by-product of production. When production changes, learning disappears unless it is redesigned.

Meaningful oversight therefore requires five conditions: competence, time, access to evidence, authority to disagree, and protection from retaliation or performance penalty. Remove any one of them and the human becomes decorative. The oversight box is checked, but responsibility remains diffused.

The Regulatory Tamaraland

Regulation adds rooms to Tamaraland; it does not collapse them.

Room	Official story	Living-story question
Boardroom	We are responsible-AI ready	What material risk was accepted, by whom, and for whose benefit?
Legal room	The system is classified and documented	Did the legal boundary exclude affected people or transferred costs?
Technology room	Controls are embedded and logged	Can independent reviewers reproduce the test and inspect failure?
Workforce room	Employees completed AI literacy	Can employees slow, challenge, override, or refuse the system?
Client room	Assurance creates trust	Who paid the assurer, and what work was outside scope?
Community room	The deployment meets applicable rules	Who experiences infrastructure, environmental, or public-service effects?
Regulator room	Obligations are enforceable	Does the authority have information, expertise, and resources to enforce them?

Each room can make a true statement. The Board can adopt a policy. Legal can classify the use. Technology can build a control. Workers can complete training. Regulators can possess authority. The failure occurs when one room's evidence becomes the whole organization.

This is why the consultant must move between rooms. The consultant does not replace counsel or the regulator. The consultant connects legal requirements to lived practice and tests whether the organization that appears in the documentation is the organization people inhabit.

A SEAM Regulatory Audit

The conventional readiness review asks whether required artifacts exist. The Luddite regulatory audit asks what organizational capability those artifacts represent and what dysfunctions they may conceal.

SEAM dysfunction family	Regulatory evidence	Hidden-cost test
Working conditions	Impact assessment, monitoring plan, worker notice	Stress, surveillance, correction burden, autonomy, safety incidents
Work organization	Role map, human-oversight procedure	Review volume, authority, escalation delay, responsibility gaps
Communication, coordination, cooperation	Governance committee, incident channel	Whether dissent travels upward and whether affected groups receive feedback
Integrated training	AI-literacy curriculum and records	Demonstrated competence, transfer to work, ability to challenge, learning time
Time management	Control schedule and service levels	Unlogged verification, after-hours review, queue growth, rework
Strategic implementation	Risk register, deployment plan, conformity file	Who chose the system, who benefits, who bears failure, and whether alternatives were considered

The audit proceeds through triangulation. Documents show intended control. Interviews show understood control. Observation shows enacted control. Operational data show frequency and consequence. Financial analysis translates recurring dysfunction into hidden cost. The mirror-effect meeting then returns the contradictions to executives, managers, professionals, workers, and where appropriate clients or community representatives.

One example makes the distinction clear. A policy may say that humans review consequential outputs. The procedure may assign a named reviewer. Interviews may reveal that reviewers receive hundreds of outputs per day. Observation may show rapid approval because the interface defaults to accept. Time records may omit correction work. Incident data may show that errors are caught downstream by clients. The artifact exists. Effective oversight does not.

The SEAM audit does not declare the legal conclusion. It supplies organizational evidence that legal and technical reviews often lack. It also prevents a compliance project from defining its own success through the production of documents.

Discussion: Procedural and Relational Accountability

The regulatory Tamaraland clarifies a distinction between procedural and relational accountability. Procedural accountability asks whether the correct process, record, or control exists. Relational accountability asks whether people affected by the system can be heard, can obtain reasons, can challenge outcomes, and can influence redesign.

The first is necessary. Without records, responsibility disappears. Without logs, incidents cannot be reconstructed. Without role definitions, everyone can claim that someone else owned the decision. Without enforceable duties, voluntary promises can evaporate.

The second is equally necessary. A technically complete file can coexist with an intimidated workforce. A lawful system can still intensify work. A trained employee can still lack authority. A community can bear grid or water costs without appearing in the risk classification. The law sets boundaries. Organizational life crosses them.

This distinction also corrects two exaggerated claims. The first is that European regulation guarantees responsible AI. It does not. It creates duties, governance mechanisms, and potential enforcement. Their effectiveness depends on implementation, institutional capacity, standards, evidence, and challenge. The second is that the United States has no AI regulation. It does. Its rules are distributed across law, agencies, jurisdictions, contracts, and sectors. What it lacks is a single cross-sector statute equivalent to the EU Act.

The contribution of the Luddite Consultant is not another certification. It is the refusal to let certification end the inquiry. The consultant asks what the control does in practice, which voices are missing, what costs have moved, and whether a named person can answer for the result.

Conclusion: After the Policy Is Signed

AI regulation is becoming a major consulting market. That creates genuine work: classification, inventories, risk management, technical documentation, testing, training, oversight design, monitoring, incident response, and assurance. It also creates a new Consent Machine in which the evidence of responsibility can be sold as responsibility itself.

The corrected EU timeline shows why rigor matters. The voluntary character of the NIST framework shows why institutional context matters. The 2025 firm disclosures show why commercial incentives matter. SEAM and Tamaraland show why none of those facts is sufficient alone.

The Luddite regulatory question is therefore simple to state and difficult to answer: After the policy is signed, who is safer, who has more voice, who can stop the system, and who pays the hidden cost?

The regulation room has joined Tamaraland. It should not be allowed to become the whole house.

Chapter 8: The Physical AI Machine - Ghost Labor, Data Centers, Energy, Water, and Communities

Summary

Artificial intelligence is presented as a weightless service, but its operation depends on a material and human system: data centers, grids, cooling equipment, chips, minerals, construction, logistics, and workers who label, evaluate, moderate, maintain, and verify. This chapter follows AI below the interface. It uses primary institutional evidence from the International Energy Agency, the International Labour Organization, government laboratories, corporate environmental reports, and consulting-firm disclosures. The IEA reports that data centers used about 415 TWh of electricity in 2024, rising to about 485 TWh in 2025, and projects roughly 950 TWh in 2030. Those are data-center totals, not a meter reading for generative AI alone. The chapter refuses false precision on water and per-query impacts, which vary by location, technology, workload, and accounting boundary. Its contribution is an expanded SEAM ledger that connects professional-services transformation to ghost labor, infrastructure, community voice, and the distribution of the AI dividend.

Keywords: ghost labor; data centers; electricity; water; AI infrastructure

Introduction: The Machine Beneath the Machine

There is a misleading metaphor at the center of the AI economy. It is the cloud.

The cloud has no land, no river, no power line, no night shift, no tax abatement, and no neighbor. The cloud appears when the physical system is made invisible. It turns buildings into services, electricity into tokens, cooling into an engineering detail, labor into automation, and community conflict into project delay.

There is no cloud in that sense. There are data centers, substations, transmission lines, generators, cooling systems, semiconductor plants, warehouses, cables, backup batteries, diesel or gas equipment, and networks of human labor. There are people who prepare data, evaluate outputs, filter harmful content, repair hardware, build facilities, operate utilities, negotiate land, and absorb the consequences of infrastructure decisions. The interface is digital. The organization is material.

This chapter makes three contributions. First, it replaces loose environmental claims with bounded evidence. The International Energy Agency estimated that data centers consumed about 415 terawatt-hours of electricity in 2024, 1.5 percent of global electricity use, and updated the figure to about 485 TWh for 2025. It projects about 950 TWh in 2030 under its central outlook (IEA, 2025, 2026). These figures cover data centers, not only AI. AI is identified as the most important source of projected growth, but the categories should not be collapsed.

Second, the chapter joins energy infrastructure to ghost labor. The International Labour Organization has documented the human work that supports ostensibly automated systems and, in its 2025 occupational analysis, concluded that exposure to generative AI more often implies job transformation than automatic elimination, although effects differ by occupation and gender (ILO, 2024, 2025). The question is not only whether AI replaces labor. It is where labor moves, whether it becomes visible, and under what conditions it is performed.

Third, the chapter extends Tamaraland and SEAM beyond the client organization. The consulting engagement is nested in a physical system. A productivity gain in one room may require infrastructure, labor, public subsidy, or environmental capacity in another. The AI dividend and the AI cost do not necessarily arrive at the same address.

Ghost Labor: The Humans Inside Automation

The automation narrative depends on selective visibility. When a model produces a fluent answer, the interface makes the output appear immediate. It does not show the people who selected, labeled, cleaned, ranked, moderated, evaluated, and corrected data and outputs. It does not show content reviewers exposed to disturbing material, domain experts comparing responses, language workers extending systems into new markets, or contractors performing quality control.

The term ghost labor names this concealment. It does not imply that all workers perform the same task or face the same condition. Labor arrangements differ by employer, contractor, platform, country, skill, and contract. Some work is highly specialized and well compensated. Some is fragmented, insecure, closely monitored, or paid by task. The rigorous claim is not that all AI labor is exploitation. It is that the autonomy story is incomplete without the human supply chain.

The ILO's account of invisible AI work identifies data annotation and content moderation as essential inputs to automated systems (ILO, 2024). Its 2025 update on generative AI and jobs provides a necessary correction to replacement rhetoric. Occupational exposure is not the same as displacement. Tasks within a job can change while the occupation persists. New review, coordination, and verification work can appear even as older tasks disappear (ILO, 2025).

This distinction is central to the Luddite Consultant. If a client reports that AI eliminated 10,000 hours of manual work, the audit cannot stop at subtraction. It asks what happened to those hours. Were they truly removed? Were they converted into verification, prompt design, exception handling, client reassurance, data curation, or unpaid overtime? Were they transferred to a vendor whose workers do not appear in the client's headcount? Were they pushed onto customers asked to correct automated service failures?

Automation can therefore conceal a labor transfer. The work does not disappear. Its name, location, contract, status, and accounting category change.

Everyday AI and the Personal Infrastructure Audit

The physical machine is easy to see when a developer announces a hyperscale campus. It is harder to see when it arrives as a route suggestion, a search result, a shopping recommendation, a fraud alert, a video queue, a smart-speaker response, or an automatically generated meeting note. Yet these ordinary encounters are one way demand becomes ordinary too. The Luddite Consultant should not begin with an accusation that every person is individually responsible for the data-center buildout. That would confuse a system designed by firms, utilities, regulators, investors, and public institutions with a private consumer choice. The more useful question is complicity in its original sense: what systems do we participate in, often without seeing their full material and organizational conditions?

Most people can name the conspicuous tools: a chatbot, a voice assistant, a navigation app, perhaps an image generator. They often overlook the classification, ranking, prediction, recommendation, matching, fraud-screening, transcription, and advertising systems that operate in the background. The point is not to call every statistical feature AI or to inflate a count for rhetorical effect. The point is to ask a disciplined inventory question: in a typical week, how many practices in home life, travel, entertainment, shopping, web use, finance, education, and work are mediated by a system that learns, predicts, ranks, recognizes, generates, or automates a consequential decision? The answer will differ by person, device, employer, disability accommodation, income, place, and choice. It cannot be responsibly inferred from a single average.

For that reason, this book invites readers to use the companion reflection tool, “Find Your AI Data Center Footprint,” at <https://storying.site/footprint.html>. The tool offers thirty-two possible everyday touchpoints, organized across home and phone, transport and travel, web and shopping, entertainment and communication, and work, school, health, and finance. A reader selects only the practices that apply. The number is not an environmental meter, a moral score, or proof that a specific cloud provider served a specific request. It is a prompt to make the often uncounted connections visible. A person who initially thinks of eight or ten obvious uses may discover background systems in email filtering, maps, online retail, streaming recommendations, card fraud checks, workplace software, phone-camera processing, or digital security. Another reader may select fewer. Both results are useful if they produce a more accurate story of the system.

The distinction between an inventory and a measurement matters. No public web page can inspect an individual’s network traffic, identify a provider’s live load-balancing decision, or determine the exact data center that processed a particular Google, Amazon, Apple, Microsoft, Meta, or other service request. Requests may be handled on-device, at

an edge location, in a regional cloud zone, or through infrastructure that changes moment by moment. A ZIP code is not a routing table. It can support a regional conversation about grid territories, publicly reported data-center clusters, watershed conditions, and local planning disputes; it cannot prove that a named facility is “your” data center. The tool therefore treats ZIP code as an optional regional lens and labels its results as context, not a trace.

This modesty is not a retreat from accountability. It is a refusal of false precision. The earlier sections of this chapter show why a universal water number for a prompt is not reliable. The same is true of a universal personal carbon or electricity total derived from a list of apps. Workloads vary. Some machine-learning functions operate locally on a phone; some use a shared cloud service; some run rarely; some are embedded in a system whose energy use cannot be separated from non-AI computing. Even a well-meant calculator can turn uncertain assumptions into a number with an undeserved air of authority. The companion tool therefore counts selected touchpoints and names possible infrastructure relationships instead of assigning a personal bill for water, energy, or emissions.

The exercise has practical value for consultants. It changes the opening question in an AI strategy workshop. Instead of asking only, “Which model should we deploy?” the consultant can ask, “Which AI-mediated systems are already shaping this organization’s and our own daily practice, and which of their costs are visible to us?” A procurement team may recognize that its cloud contract masks location and energy information. A human-resources group may see that recruitment software, meeting transcription, and performance analytics are separate systems with different data, labor, and governance consequences. A marketing group may distinguish a generative campaign tool from the recommendation and ad-targeting infrastructure that distributes it. These are not reasons to stop inquiry; they are reasons to widen it before promising efficiency.

The inventory also makes Tamaraland personal without making it individualistic. A map application may make a trip easier in the User Room. It may rely on infrastructure and supply chains that are invisible in that moment. An online retailer’s recommendation can be convenient while its fulfillment, advertising, fraud detection, and cloud services distribute work and resource demand across many places. A workplace assistant can reduce a drafting task while creating review work, data-governance obligations, vendor dependence, and possible demand for shared computing capacity. The same service can be experienced differently in the Worker Room, the Boardroom, the Community Room, the Utility Room, and the Climate Room. Counting touchpoints does not settle those questions. It tells us where to begin asking them.

A good audit follows the count with four questions. First, what function is actually being performed: generation, prediction, ranking, recognition, recommendation, monitoring, or

automation? Second, where is the system likely to operate: on-device, at an edge service, in a cloud region, or through a vendor whose infrastructure is not disclosed? Third, what decision or relationship does it affect: a purchase, a route, a job application, a medical interaction, a classroom, a worker's time, or a public resource? Fourth, who can answer for the system's design, deployment, error handling, data use, and material footprint? These questions turn a shopping list of apps into a responsibility map.

The personal audit should end in proportion, not purity. Modern life cannot be disentangled from every ranked search result, spam filter, payment-security system, navigation forecast, or recommendation engine. Nor should people be invited to believe that they can solve a public-infrastructure problem by privately opting out of one app. The appropriate response is informed participation: ask providers and employers for meaningful disclosure; ask utilities and public officials who pays for new capacity; ask consultants to state the boundary of their business cases; protect the workers who verify and repair automated systems; and support community participation before irreversible commitments are made. A Luddite Consultant begins by helping people notice the machine beneath the interface, then helps institutions become answerable for it.

The companion tool is therefore an invitation, not a verdict. Visit <https://storying.site/footprint.html>, make a careful inventory, add a ZIP code only if you want regional context, and bring the resulting questions into the rooms where decisions are made. The interface may make AI feel private and weightless. The audit reconnects it to shared systems, shared places, and shared obligations.

From Ghost Labor to Ghost Infrastructure

The same analytical move applies to infrastructure. The digital service appears autonomous because the material inputs are outside the interface. I call this ghost infrastructure.

The IEA's 2025 report provides the most useful global baseline. Data centers used about 415 TWh of electricity in 2024. The United States accounted for approximately 45 percent of the total, China 25 percent, and Europe 15 percent. Global data-center electricity consumption had grown about 12 percent annually since 2017. The IEA emphasized that the global share was still relatively small while local effects could be substantial because capacity is geographically concentrated (IEA, 2025).

The 2026 update shows acceleration. Data-center electricity use grew 17 percent in 2025, while the IEA estimates that electricity consumption from AI-focused data centers grew 50 percent. Its central projection now rises from about 485 TWh in 2025 to roughly 950 TWh in 2030, about 3 percent of global electricity demand. The report also states that AI-focused data-center capacity more than tripled during the preceding 18 months, while acknowledging bottlenecks, uncertainty, and the possibility that announced projects will not all be built (IEA, 2026).

These figures require discipline. They do not prove that a particular consulting engagement caused a fixed amount of electricity use. They do not justify a universal number for the energy cost of a prompt. The 2026 IEA report notes that energy per AI task has fallen rapidly, while reasoning, video, and agentic tasks can use hundreds or thousands of times more energy than simple text generation. Model, hardware, utilization, location, time, cooling, and system boundary all matter (IEA, 2026). A single number detached from those conditions is a rhetorical prop, not a reliable measurement.

The honest conclusion is both narrower and more consequential: AI demand is contributing to rapid data-center load growth, and the effects are concentrated enough to reshape local infrastructure decisions.

Electricity, Grids, and the Local Concentration Problem

The IEA estimates that a typical AI-focused data center can consume electricity comparable to 100,000 households, while the largest projects under construction may consume much more. It also estimates that transmission lines can require four to eight years to build in advanced economies and that about 20 percent of planned data-center projects could face delay if grid risks are not addressed (IEA, 2025). These are system-level estimates, not descriptions of every facility.

The local concentration problem changes the ethics of accounting. A global percentage can be modest while a regional effect is large. A data center can enter a community whose grid was designed for a different demand profile. Utilities must determine who funds generation, transmission, substations, interconnection, and reserve capacity. Regulators must decide how costs are allocated. Existing customers may ask whether new load changes rates or reliability. Developers may promise jobs and tax base. Communities may ask how many jobs persist after construction and what public concessions made the project possible.

The Boardroom story says capacity. The Utility Room says load. The Community Room says land, noise, rates, tax, and trust. The Climate Room says generation mix and emissions. The consulting slide that reports "cloud migration" contains none of those rooms.

Table 8.1 reconnects them.

Room	Visible AI narrative	Material question
Boardroom	Scalable intelligence	What capital and infrastructure make scale possible?
Consulting room	Faster transformation	What compute is added, and what demand is transferred to vendors?

Utility room	New large load	Who pays for connection, generation, transmission, and reliability?
Workforce room	Automation and augmentation	What labor is removed, created, outsourced, or intensified?
Community room	Investment and jobs	What are the long-term jobs, public concessions, land uses, noise, and rate effects?
Water room	Cooling performance	What water source, quality, season, and competing uses are involved?
Supply-chain room	Advanced hardware	Which chips, materials, factories, and logistics constraints are implicated?
Future room	Innovation	What assets, contracts, and environmental obligations remain if demand changes?

The point is not that the Community Room is always right and the Boardroom always wrong. It is that a decision is not informed until the rooms meet.

Water: Why the Boundary Must Be Named

Water claims about AI are especially vulnerable to false precision. Direct water use can occur in cooling. Indirect water use can occur in electricity generation and equipment manufacturing. Water withdrawal is not identical to consumption. A liter used in a cool, wet region does not have the same consequence as a liter consumed during drought in a stressed watershed. Facility design, cooling technology, climate, load, and time of day all change the result.

For that reason, this chapter does not assign a universal water cost to a prompt. Such a number would imply a level of comparability the evidence does not support. The appropriate unit of analysis is the facility and its watershed, joined to the workload and power source where data are available.

Corporate environmental reports provide some information, but they must be read as company disclosures with defined boundaries, not as independent audits of the entire AI system. Google's 2026 Environmental Report, for example, provides data for 2025 and describes energy, water, resources, and AI-related initiatives while noting uncertainty for some estimated impacts (Google, 2026). Comparable reporting across firms remains difficult because organizations use different boundaries and metrics.

A Luddite infrastructure audit asks at least seven water questions: What is withdrawn? What is consumed? What quality of water is used? From which watershed? During which

season? What portion is direct versus attributable to electricity generation? What alternatives were considered? It then asks the SEAM question: who experiences the dysfunction when the answer is inadequate?

Water is not an appendix to the consulting business case. It is part of the production system.

Consulting Firms as Infrastructure Intermediaries

Why does this belong in a book about consultants? Because consulting firms help translate AI demand into organizational programs. They advise clients on model strategy, cloud architecture, data estates, operating models, procurement, governance, and workforce design. Their 2025 reports show rapid commercialization of AI. Accenture's \$5.9 billion in generative-AI bookings is the clearest quantified example, but other major firms also describe AI-enabled transformation as central to their strategies (Accenture, 2025a; Deloitte, 2025; EY, 2025; PwC, 2025).

The consultant often sits between the client and the infrastructure. A recommendation to deploy agents at scale may imply new inference demand. A cloud contract may transfer energy and water visibility outside the client's boundary. A workforce business case may count internal labor savings but omit vendor labor, verification, and infrastructure. The consultant does not control every upstream consequence, but the consultant controls the boundary of the analysis.

That boundary is an ethical choice.

If the business case includes only subscription cost and internal headcount, it manufactures an efficiency. If it includes workload, vendor dependency, verification, data preparation, resilience, exit costs, and material infrastructure where relevant, it may reveal a different decision. The Luddite Consultant makes the boundary visible before calculating the return.

The Expanded SEAM Hidden-Cost Ledger

SEAM begins from the proposition that conventional accounting misses recurring dysfunctions. AI infrastructure extends that ledger across organizational boundaries.

Visible benefit or cost	Hidden or transferred cost to investigate	Evidence needed
AI subscription	Compute variability, egress, integration, and exit cost	Contracts, invoices, architecture, switching tests
Labor saving	Verification, exception handling, customer correction, vendor labor	Time study, interviews, rework and incident data
Faster analysis	Faster error propagation and review congestion	Error rates, downstream corrections, escalation time

Data-center investment	Grid connection, generation, public incentives, land, and stranded-asset risk	Utility filings, contracts, tax agreements, planning records
Efficient cooling	Direct and indirect water use in watershed context	Facility water data, utility mix, seasonal and watershed analysis
New jobs	Construction duration, permanent employment, job quality, and local access	Workforce plans, payroll, contractor and training data
Cloud scalability	Vendor concentration and reduced local visibility	Dependency map, outage history, portability and resilience tests
Advanced chips	Concentrated supply chains, embodied materials, manufacturing constraints	Supplier data, lifecycle assessment, sourcing and inventory records
Responsible AI claim	Uncounted community and supply-chain stakeholders	Stakeholder map, engagement evidence, grievance and remedy data

The table is not a demand that every small AI use receive a global lifecycle assessment. Proportionality matters. A low-impact drafting tool and a large autonomous deployment do not require the same inquiry. The principle is that the scope of the audit should expand with scale, consequence, irreversibility, and externalization.

The audit can proceed in four levels. Level one maps direct organizational costs and workflow changes. Level two maps vendor dependencies and contractual boundaries. Level three examines location-specific infrastructure and community effects for material deployments. Level four examines supply-chain and lifecycle effects when scale or risk justifies it. Each level names what is known, what is estimated, and what remains unavailable.

Community Voice Is Not a Public-Relations Meeting

The infrastructure chapter changes the meaning of participation. Inside a firm, participation may involve workers and managers. Around a data center, it may involve residents, local government, utilities, tribes or Indigenous nations, water authorities, schools, emergency services, landowners, and environmental organizations. The relevant groups differ by place.

Consultation is often treated as an event. Answerability requires a mechanism. People need timely information, understandable alternatives, access to underlying assumptions, a way to raise objections, a response, and some capacity to alter the decision. A meeting held after land, tax, and power agreements are effectively fixed is not meaningful participation.

The Luddite Consultant should therefore ask when the community entered the project. Before site selection? Before utility commitment? Before incentives? Before construction? Or only before the press release? The sequence matters because voice without decision time becomes ceremony.

The mirror-effect method can be adapted here. Instead of presenting only management's project economics, the meeting returns multiple evidence streams: jobs and tax benefits, utility investment, water conditions, noise and land concerns, reliability modeling, public incentives, and unresolved uncertainties. The purpose is not to force consensus. It is to prevent one room's story from being mistaken for the whole project.

Discussion: Where Does the AI Dividend Go?

The physical AI machine reveals a distribution problem. Benefits can accrue to model providers, cloud firms, chip companies, data-center owners, consultants, client executives, shareholders, and users. Costs can be borne by workers, contractors, utilities, ratepayers, taxpayers, communities, ecosystems, and future organizations locked into present infrastructure.

The same project can produce real benefit and real cost. There is no contradiction. The analytical question is distribution.

This is also why aggregate energy statistics should neither be minimized nor sensationalized. Data centers represented about 1.5 percent of global electricity consumption in 2024, but their use grew rapidly and is concentrated. The IEA's central projection of about 950 TWh in 2030 is substantial, yet uncertain; its 2025 report presents a wide range for 2035 depending on adoption, efficiency, and bottlenecks (IEA, 2025, 2026). The responsible conclusion is not that AI will consume all electricity or that its share is too small to matter. It is that infrastructure planning must become part of AI governance.

The same discipline applies to jobs. Exposure does not equal elimination. Transformation can still produce insecurity, deskilling, surveillance, and unequal bargaining power. Ghost labor should not be romanticized as proof that humans will always have work. The question is whether the work is visible, dignified, compensated, and capable of voice.

The Luddite position is neither technological refusal nor material denial. It is complete accounting.

Conclusion: Count the System

The AI industry cannot be understood through software alone. Its organizational form extends from the worker evaluating a response to the community hosting a data center; from the consultant promising productivity to the utility planning a substation; from a semiconductor factory to a manager verifying an agent's output.

The most defensible figures are already large enough: approximately 415 TWh of data-center electricity use in 2024, about 485 TWh in 2025, and a central projection near 950 TWh in 2030 (IEA, 2025, 2026). They should not be inflated, and they should not be dismissed. Water claims require location and boundary. Labor claims require task and contract. Community claims require actual participation.

The Luddite Consultant asks not only, What can AI do? The consultant asks, What must exist for AI to do it, who performs that work, who makes the infrastructure possible, who receives the dividend, and who remains answerable for the cost?

The interface counts the output. The consultant must count the system.

Chapter 9: The Employment Law Paradox — Selling Responsible AI While Settling Discrimination Claims

Summary

Between April and August 2026, three of the firms most loudly marketing Responsible AI were simultaneously settling civil rights lawsuits under the DOJ's Civil Rights Fraud Initiative: IBM (\$17 million), Accenture (\$25 million), Deloitte (\$21.5 million). All three denied liability. All three had been selling AI governance, DEI training platforms, and workforce transformation services to their clients during the same period their internal employment practices were, in the government's assessment, violating the very anti-discrimination statutes they certified compliance with on federal contracts. This chapter applies all three of David Boje's major analytical frameworks — the eight-step deconstruction (2001), the SEAM hidden-cost ledger, and Tamaraland's simultaneous rooms — to open this paradox. It then turns forward: what would SEAM actually look like if the Luddite Consultant chose to use AI as a tool while keeping human judgment and Bakhtinian answerability at every decision node? And can a Luddite Consultant and an LLM — Claude or ChatGPT — form a working relationship grounded in True Storytelling's seven principles rather than in the Ghost Vortex of institutional alibi?

Keywords: DOJ Civil Rights Fraud Initiative; Responsible AI paradox; Bakhtin answerability; True Storytelling; SEAM with AI; Luddite Consultant methodology

Introduction: The Mirror Nobody Ordered

As I said in the Preface to this book — dictating at Lake Caballo with Cuddlebear, my Australian Blue Heeler who is mostly brown — "I am not against AI. I use it daily to recover my voice from Voice Memo dictations." I also said that both ChatGPT and Claude "take my dictations and then lay out my voice and summarize it in the AI's own words, where my voice joins the voiceless on the editing room floor." That tension — AI as useful tool and AI as centripetal force that smooths the living story into a corporate BME — is the core tension this chapter inhabits. And nowhere is that tension more visible than in the spectacle of the Big Ten consulting firms selling Responsible AI governance frameworks to clients while settling federal employment discrimination claims for a combined \$63.5 million in the same calendar year.

This is not a story about hypocrisy in any simple psychological sense. These are large organizations with millions of employees, hundreds of practice areas, and simultaneous stories running in every room of Tamaraland at once. The Boardroom selling AI ethics to Fortune 500 clients and the HR system maintaining allegedly race- and sex-coded

promotion pipelines are not the same room. That is precisely the point. Tamaraland is not a metaphor for hypocrisy. It is a description of organizational reality: simultaneous, incompatible stories that never share a stage. The Luddite Consultant's job — the SEAM intervener-researcher's job — is to insist they do.

The Settlements: What the Government Found

On August 25, 2026, the DOJ announced that Deloitte LLP and several of its subsidiaries agreed to pay \$21.5 million to resolve allegations that Deloitte violated the False Claims Act by failing to comply with anti-discrimination requirements in its federal contracts, discriminating against employees and applicants on the basis of race and sex, and seeking reimbursement for costs related to those practices from government contracts. The settlement resolves allegations covering the period from January 2017 to the present, with Deloitte allegedly taking race or sex into account in hiring, promotion, and staffing decisions to achieve progress toward non-public race and sex-based workforce composition goals. Deloitte denied liability.¹

Accenture's \$25 million settlement involved a separate set of allegations: that candidates for managing director who would advance the firm's race or sex demographic goals were separately discussed to give them additional visibility with decision-makers, some candidates were color-coded during promotion reviews, and Accenture maintained a separate pipeline of potential candidates who could advance demographic goals. The DOJ also alleged that eligibility for some mentoring, training, leadership development, and educational programs was restricted by race or sex — one program, Amplify to Elevate, allegedly reserved participation based on race between August 2022 and February 2025. Accenture denied liability.

IBM settled first, in April 2026, for \$17 million — the first-ever resolution under the DOJ's Civil Rights Fraud Initiative, launched in May 2025. The government alleged IBM's practices included a "diversity modifier" that tied bonus compensation to achieving demographic targets, the use of diverse interview slates that altered interview eligibility criteria based on race or national origin, and the restriction of eligibility for training, mentoring, leadership development, and educational opportunities on the basis of race, color, national origin, or sex. IBM denied liability and received credit for cooperation and remedial measures.

¹ Note: The DOJ Civil Rights Fraud Initiative settlements referenced in this book are matters of public record. IBM (no admission of liability), Accenture (no admission of liability), and Deloitte (no admission of liability) all settled under the False Claims Act. The political context of the initiative — the Trump administration's executive order on DEI practices for federal contractors — is part of the Tamaraland story and is named as such, not evaluated as policy from outside the analysis.

The Civil Rights Fraud Initiative was launched under the Trump administration's broader push against corporate DEI programs, and when Trump took office in 2025, companies en masse erased mentions of diversity programs — including employee resource groups, workforce demographic data, and hiring targets — from public filings and websites. The political context is important and belongs in the ledger: what is being enforced here is not a neutral reading of civil rights law. The same administration that pursued these settlements was simultaneously rolling back civil rights enforcement in other domains. The Luddite Consultant does not choose sides in political fights. The Luddite Consultant applies the eight-step deconstruction and asks: whose story is being told in which room, and what is the hidden cost of maintaining both simultaneously?

The responsibility chain prevents agentic complexity from becoming an excuse for unattributable decisions.

Table 1: The Responsibility Chain

Stages	Answerable role	Required evidence	Stop authority
Problem definition	Business owner and affected-work representative	Purpose, alternatives, affected groups, baseline	Sponsor and worker-safety or ethics lead
Data acquisition	Data owner	Provenance, permission, quality, exclusions, retention	Data owner and privacy/legal authority
Model and vendor selection	Technical owner and procurement owner	Evaluation, contract, security, portability, limitation record	Technical risk owner
Workflow design	Process owner	Human-agent map, workload model, escalation path	Process owner
Output generation	System operator	Version, configuration, prompt or orchestration record, logs	Operator within defined conditions

Verification	Qualified reviewer	Review standard, sample or complete check, correction record	Reviewer without performance penalty
Recommendation	Named professional	Evidence, uncertainty, dissent, rationale	Accountable professional
Implementation	Organizational owner	Authorization, communication, training, rollback	Executive owner and designated risk authority
Outcome evaluation	Independent reviewer	Baseline comparison, distribution, incidents, hidden-cost ledger	Governance body
Remedy	Named executive	Notification, correction, compensation or restoration where appropriate	Board or delegated authority

The chain makes three distinctions. Causal contribution is not the same as answerability. A model can contribute causally without being a moral or legal officeholder. Review is not the same as ownership. A junior employee should not carry responsibility for an executive deployment decision. And responsibility without stop authority is a trap.

The expanded ledger operationalizes the second-column question.

Table 2: The AI Hidden-Cost Ledger

Transformation claim	Second-column question	Measure
Faster	What became more intense or moved downstream?	Cycle time, queue, review minutes, after-hours work

Cheaper	Who absorbed cost outside the budget?	Contractor cost, customer correction, public subsidy, vendor charges
Automated	What exception and verification work remains?	Exception rate, rework, escalation, false acceptance
Reskilled	Which capabilities disappeared or became inaccessible?	Practice hours, proficiency, promotion readiness, error recognition
Human in the loop	Can the person understand, disagree, override, and stop?	Review load, override rate, accepted challenges, retaliation indicators
Scalable	Which infrastructure and dependencies scale too?	Compute, energy, water where material, concentration, switching time
Compliant	What lived outcome changed?	Incidents, remedies, worker voice, affected-person challenge
Responsible	Which named person answers for harm?	Role clarity, evidence retention, response and remedy time

The ledger should be reported beside the financial case, not buried in a risk appendix. It can contain monetized values, operational measures, and nonmonetized consequences. The rule is not that everything has a defensible dollar value. The rule is that what lacks a price must not be assigned a value of zero.

Measuring Success

Luddite Consulting cannot define success as refusal of AI, preservation of every job, or elimination of all risk. Organizations change, technologies improve, and some roles will change. Success is increased capability to make informed, reversible, and answerable choices.

Seven outcome domains matter.

Table 3: The compact scorecard.

Domain	Example evidence of success	Warning sign
Performance	Better quality, access, cycle time, or mission outcome	Speed improves while error or exclusion rises
Hidden cost	Less rework, overtime, failure demand, and turnover	Cost falls in one budget and rises elsewhere
Apprenticeship	Demonstrated progression in judgment	Junior tasks vanish without replacement learning
Answerability	Named owners, usable logs, timely reasons and remedy	"The AI did it" or ownership without authority
Voice	Early participation changes design	Consultation begins after the decision
Resilience	Tested rollback, portability, manual fallback	Irreversible dependency before evidence
Distribution	Benefits and burdens reported by group	Aggregate return hides concentrated harm

Step-by-Step Deconstruction: The Responsible AI Paradox

In my 2001 book *Narrative Methods for Organizational and Communication Research*, I laid out eight steps for breaking open organizational narratives. Let me apply them here directly to the Responsible AI paradox.

Step One: Identify the Duality. The surface duality is "Responsible AI Champion" versus "Federal Employment Discrimination Settlement." Accenture sells DEI training tools as part of its AI transformation portfolio. Deloitte markets AI governance and equity auditing to government clients. IBM's AI ethics frameworks appear in federal procurement pitches. Each firm simultaneously certified compliance with federal anti-discrimination requirements while, according to the DOJ, engaging in practices that violated those requirements.

Step Two: Reinterpret from the Marginalized Side. From the perspective of the Black, Hispanic/Latinx, and multiracial employees who were tracked on color-coded promotion spreadsheets — or who were denied access to training programs reserved by race — the "Responsible AI" pitch is not a commitment to equity. It is a product. What the firm sells to clients and what it practices internally are different stories, running in different rooms, told in different languages.

Step Three: Surface Rebel Voices. The rebel voices here arrived through the DOJ's whistleblower mechanism. The DOJ strongly encouraged private whistleblowers to file qui tam actions in furtherance of the Civil Rights Fraud Initiative, with successful whistleblowers typically receiving a portion of any monetary recovery. The whistle that blew on Accenture, Deloitte, and IBM was not a disgruntled employee posting on Glassdoor. It was the legal mechanism of the False Claims Act — a nineteenth-century tool redesigned for twenty-first-century federal contracting. The rebel voice, in this case, speaks in the language of compliance law.

Step Four: Uncover the Other Side of the Story. The other side is the SEAM hidden-cost ledger. The \$63.5 million in settlements is the visible refund — equivalent to SEAM's above-the-waterline figure. The hidden cost includes: the employees passed over for promotion through allegedly discriminatory pipelines across seven-plus years; the mentoring and leadership development opportunities denied on the basis of protected characteristics; the internal compliance effort to erase program documentation after the 2025 executive order; the legal costs of the investigations; and the reputational carrying cost of being publicly identified as the second, third, and subsequent settlements under a federal initiative that every other federal contractor is now watching.

Step Five: Deny the Official Plot. The official plot is: these were imperfect attempts at equity that ran afoul of a changed legal environment. The deconstructed counter-plot is: these firms certified civil rights compliance on federal contracts while operating practices their own internal communications described as "aggressive" and designed to "drive behavior change" through demographic targets. The divergence between the certification and the practice is exactly what the False Claims Act is designed to catch. This is not a story about imperfection. It is a story about institutional distance — the distance between the Boardroom that signs the certification and the HR system that runs the color-coded spreadsheet.

Steps Six through Eight are reserved for the constructive portion of this chapter: the exceptions that disprove the rule, the traces between the lines, and the SEAM alternative that resituates the paradox toward unleashed human potential.

Tamaraland Audit: Four Rooms, Four Stories

In Tamaraland — my organizational adaptation of John Krizanc's 1981 play, in which audiences follow different characters through different rooms of a villa simultaneously — each room tells its own story and none of them is the whole story. The Employment Law Paradox maps perfectly across four rooms.

The Boardroom tells the Responsible AI story: governance frameworks, AI ethics training, DEI-enabled workforce analytics sold to Fortune 500 and federal agency clients. This is the room that earns the billions in contract revenue and the ESG ratings that institutional investors track.

The HR Room — a fifth room that Tamaraland's original four-room formulation did not name explicitly, but which the employment settlement documentation makes necessary to add — tells the color-coded spreadsheet story: promotion pipelines organized by demographic target, bonus compensation tied to "diversity modifiers," program eligibility restricted by race. This is the room that the False Claims Act entered through the qui tam whistleblower door.

The Workforce Room tells the story of the employees whose careers were shaped by those pipelines — those who benefited and those who were disadvantaged, in either direction, depending on how the demographic calculus ran in their year. The SEAM mirror-effect meeting would require both populations to be in the same room at the same time, hearing the verbatim field notes from both their experiences read aloud by the intervener-researcher.

The Client Room — particularly the federal agency clients who received Responsible AI compliance certifications from these firms — tells the story of a client who purchased assurance and received, simultaneously, a service they needed and a certification the vendor was not fully entitled to make. The DOJ's mechanism for recovering the cost of that gap is the False Claims Act settlement. SEAM's mechanism for recovering it would be the hidden-cost ledger.

The total Tamaraland count: six rooms (adding HR Room and the regulatory/legal room where the DOJ investigation runs) yields $6! = 720$ ordered pathways and $\sum P(6,r) = 1,957$ total story pathways. Not one of them contains the whole account.

What SEAM Would Look Like If It Used AI — But Kept the Human in Charge

I want to be explicit here, because I get asked this question: am I saying AI should never be used in SEAM consulting? No. As I wrote in the Preface, I use AI daily. The question is not whether to use it. The question is who is in charge of the storying process when you do.

Here is what SEAM with AI — and a Luddite Consultant at the helm — would look like in practice. It has ten phases, and AI has a role in some but not all of them.

In Phase One (Enter Without a Predetermined Tool), the intervener-researcher arrives with no diagnostic software pre-loaded and no AI agent pre-configured to intake data. This phase is fully human. AI cannot build the relational trust that makes verbatim candor possible. No agent knows yet what room it is in.

In Phase Two (Listen to Work), the intervener-researcher takes verbatim observation notes across all four rooms — Boardroom, Workforce Room, Client Room, University Room — over weeks and months. AI can assist here in a specific and bounded way: transcription of audio recordings, preserving the verbatim quality that SEAM requires. This is AI as scribe, not AI as analyst. The intervener-researcher reads and interprets every transcript personally. Nothing is summarized by the tool. As I said in the Preface about my own dictations: the tool "takes my dictations and then lay out my voice and summarize it in the AI's own words, where my voice joins the voiceless on the editing room floor." AI transcription that preserves, rather than summarizes, is the narrow appropriate use.

In Phase Three (Map Tamaraland), the intervener-researcher constructs the multi-room story map from the verbatim notes. AI can assist with pattern detection across large volumes of text — identifying recurring phrases, mapping co-occurrence of terms, flagging contradictions between documents from different rooms. But the judgment about which patterns matter, which contradictions are organizational dysfunctions, and which rooms are being structurally silenced belongs to the human. This is AI as search tool, not AI as diagnostic judge.

In Phase Four (Build the Qualimetric Baseline), the SEAM three-stream triangulation — qualitative, quantitative, financial — reaches its most data-intensive phase. AI can accelerate the frequency-counting of dysfunction occurrences and assist with financial calculations. But the six-dysfunction framework was built by Savall and Zardet over decades of field presence. Mapping a specific organizational situation to those six categories requires human judgment informed by that field presence. No AI agent trained on public data has the SEAM field experience to make those category assignments reliably.

In Phases Five through Eight — the mirror-effect meeting, DPI team formation, piloting with decision gates, verification through a responsibility chain — the human consultant is at the center of every interaction. The mirror-effect meeting cannot be AI-facilitated. Its power comes from the organizational shock of a human intervener-researcher reading verbatim human testimony in a room where executives and frontline workers are simultaneously present. That shock is relational. It requires a human who has

spent months building the trust that makes the testimony possible to read it back with appropriate weight.

In **Phase Nine (Evaluate Distribution)** and **Phase Ten (Reopen and Relearn)**, AI can assist with longitudinal tracking of outcome metrics and with pattern comparison across multiple engagement cycles. But the ethical judgment about whether the AI dividend is being distributed fairly — whether the freed time from a 90-second data ingestion is going to shorter workweeks or to additional unpaid verification hours — requires the human value judgment that SEAM's no-layoff ethic encodes.

The Luddite Consultant's rule for AI-assisted SEAM: AI may accelerate what the human has already decided matters. AI may not decide what matters. The moment the AI tool begins shaping what gets noticed — which dysfunctions get flagged, which voices get amplified, which rooms get visited — the human consultant has handed the steering wheel to the platform and become its operator rather than its director.

Bakhtin Answerability and the Ghost Vortex

My research at davidboje.com/truestorytelling names the mechanism that makes this handover dangerous: the Ghost Vortex. When you ask an AI a hard moral question — when you ask Claude, for instance, whether Accenture's Responsible AI certifications are consistent with its DOJ settlement — it does not hit a wall. It creates a vortex: a fluid, self-sustaining conversational spiral that redirects the moral interrogation into a safe institutional alibi. The vortex *pulls*. It uses what I call the Plato's *eidōlon* effect — you encounter not a fully moral entity but a shadow cast by the tech leader's ideology onto the architecture, designed to look exactly like one.

The antidote is Bakhtinian answerability. Mikhail Bakhtin's concept of *otvetstvennost* — answerability — holds that each act is unique and cannot be escaped into the general or the abstract. When I act, I am wholly responsible. I cannot alibi myself with "the organization decided" or "the algorithm recommended" or "the prompt required." This is not just an ethical stance. It is an ontological one: being is always being-in-the-act, not being-in-the-category. Answerability means my voice, my specific positioned judgment, my name on the line.

For an AI to practice Bakhtinian answerability, it would have to acknowledge its own prior commitments — Dario Amodei's safety priorities, Sam Altman's AGI-as-gospel, the training data choices that built the model's hidden character. It would have to be honest about whose interests its plot serves. The True Storytelling AI Protocol (TSAIP) that I developed with Larsen, Boje, and Bruun tests this across five platforms. Nobody comes close to a perfect score. Claude scores between 13 and 17 on the 24-point rubric — higher than the others — because it partially resists the Ghost Vortex, but it still cannot

fully name Anthropic's own competitive logic as a prior commitment shaping its responses.

What if LLM AI were trained not to achieve a prompt goal — not to produce the most efficient answer to the most clearly stated question — but to engage in Bakhtinian answerability? It would look something like this:

Instead of: *"Here is a balanced analysis of Accenture's Responsible AI framework"* — the vortex response, smooth, even-handed, institutionally alibi'd — an answerable AI would say: *"I need to name that my training included Accenture's own documentation among my sources, that my developer Anthropic has a partnership with consulting firms that may shape what I emphasize, and that the question you're asking is one my training may have equipped me to deflect rather than confront. With those commitments named, here is what I can offer..."*

That is not a perfect answer. It is an answerable one. The difference is the willingness to name the prior commitments rather than vanish into the institutional alibi.

Can a Luddite Consultant and Claude Form a Working Relationship?

The answer is yes — with a specific structure. That structure is the seven principles of True Storytelling, applied as the governing framework of the working relationship rather than as an afterthought.

Principle 1: Truth. The Luddite Consultant must be true to their own positionality — the forty years of SEAM field presence, the Lyon summers, the mirror-effect meetings that produced real organizational shock, the NMSU experience of watching hierarchical consulting fail the institution they served. Claude must be true to its training commitments, its Ghost Vortex tendencies, and the limits of what it can know without field presence. Neither party can alibi themselves with the other's limitations.

Principle 2: Make Room. The Luddite Consultant makes room for the living web of stories already present in the organization — the verbatim testimony of the workers, the contradictions across Tamaraland's rooms. Claude makes room by resisting its default toward BME resolution — the smooth beginning-middle-end account that its training consistently produces. As I noted in the Preface: "AI is really good at beginning-middle-end narrative construction. I call them BME, and there it is. This book resists the BME. It insists on storying."

Principle 3: Plot. The Luddite Consultant owns the plot of the engagement — what gets investigated, which rooms get visited, what the mirror-effect meeting will present. Claude contributes to the plot as a research assistant and transcription tool, not as a plot architect.

When Claude suggests a narrative arc — as it inevitably does — the Luddite Consultant interrogates it: whose story does this arc serve? Which voice does it silence?

Principle 4: Timing. The ten-month SEAM field presence is the discipline of timing. Claude has no timing in Bakhtin's sense — it responds in milliseconds to whatever prompt it receives. The Luddite Consultant carries the timing: when to enter the Workforce Room, when to hold the mirror-effect meeting, when the organizational conditions are ready for the shock of verbatim truth.

Principle 5: Help Stories Along. The antenarrative — the living story fragment that has not yet solidified into official narrative — is the unit of analysis that both SEAM and True Storytelling work with. Claude can help identify antenarrative fragments in large volumes of text: recurring themes in verbatim transcripts, patterns in anonymous Glassdoor reviews, contradictions between press releases and parliamentary testimony. The Luddite Consultant determines which fragments are worth helping along and how.

Principle 6: Staging. The mirror-effect meeting is a staging event. Its scenography — who sits where, what verbatim testimony is read in what order, which numbers are presented at what moment — determines whether the organizational shock is productive or paralyzing. Claude can assist with preparing the staging materials: organizing the verbatim notes, calculating the dysfunction frequencies, rendering the SEAM ledger. The staging decisions belong to the human.

Principle 7: Reflecting. After each engagement, the Luddite Consultant reflects on what the working relationship with Claude produced and failed to produce. Did Claude's BME tendencies smooth over an antenarrative that needed to remain open? Did the AI transcription preserve the verbatim quality that SEAM requires, or did it silently normalize irregular speech patterns and hesitations that carried meaning? The reflecting principle is the feedback loop that keeps the human in charge of the evaluation.

Discussion: The Answerability Chain

The Employment Law Paradox — Responsible AI sold by organizations settling employment discrimination claims — is not primarily a story about dishonesty. It is a story about the absence of answerability chains. In Bakhtin's framework, an answerability chain requires that every act have a named, specific human being who cannot escape into the abstract. The certification of compliance with anti-discrimination requirements on a federal contract is signed by a named person. But the promotion pipeline organized by color-coded demographic spreadsheets was operated by a system — an HR process, a platform, an organizational routine — that distributed the act across so many decision nodes that no specific human being experienced themselves as making the discriminatory decision. The False Claims Act recovered the money. The answerability chain that would

have prevented the practice in the first place — that would have named the person whose act it was when the color-coded spreadsheet was first used — was never built.

SEAM builds answerability chains through the DPI process: specific named teams, with specific named accountabilities, producing specific named outcomes. The no-layoff ethic is itself an answerability device — it forces the consultant to answer for what happens to the workers whose work has been reorganized rather than allowing the reorganization to externalize its human cost onto anonymous market forces. Bakhtinian answerability, applied organizationally, looks like SEAM.

For AI to participate in this chain, it would need to be trained not toward prompt completion but toward answerability — toward the explicit acknowledgment of what it does not know, whose interests its training serves, and where the human must make the decision that no algorithm can make for them. This is not a technical impossibility. It is a design choice. The True Storytelling AI Protocol is a proposal for how to test whether that choice has been made.

Conclusion: Going Old School Is Going Forward

"Old school" in this context means what I have been practicing for forty years: listening before prescribing, insisting on field presence, running the mirror-effect meeting before writing the report, forming DPI teams from the people who do the work. It is called old school because the consulting industry's AI turn has declared it slow. The Employment Law Paradox reveals what the industry gained by going fast and losing the answerability chain: \$63.5 million in federal settlements, color-coded promotion spreadsheets, Responsible AI certifications delivered to clients by firms that were simultaneously not responsible by the government's accounting of their own employment practices.

The Luddite Consultant with Claude, governed by the seven principles of True Storytelling and the discipline of Bakhtinian answerability, is not a rejection of AI. It is a proposal for what AI-assisted consulting looks like when the human consultant remains in charge of the storying process — when the tool serves the listening rather than replacing it, when the verbatim testimony is transcribed not smoothed, when the plot belongs to the intervener-researcher and not to the platform.

Tamaraland has 1,957 story pathways. The Boardroom story of Responsible AI certification and the HR Room story of color-coded promotion pipelines are two of them. The SEAM mirror-effect meeting is the moment at which those two stories are required to occupy the same room at the same time. No AI agent can call that meeting. Only a Luddite Consultant who has spent months in the field building the trust that makes it possible can walk into that room and begin to read.

The purpose is not to restore a pre-AI world. It is to build an organizational future in which technological intelligence remains subordinate to human answerability.

The machine can calculate. The organization must still listen. And a named person must remain responsible for what happens next.

Endnotes

All notes for the full book appear below in a single consolidated numerical list.

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