# Intangible Assets: The Input and the Output of the Artificial Intelligence Revolution – Part I

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## Highlights

- Artificial Intelligence (AI) is forcing companies to confront the fact that most enterprise value now comes from intangible assets. Around 90 percent of the value of the S&P 500 is attributable to assets such as data, software, know-how, relationships, approvals, and brand, yet most of these assets are not recognized on the balance sheet under current accounting rules.

- In the AI era, intangible assets are both the inputs and the outputs of value creation. AI systems rely on proprietary data, expertise, software, content, approvals and relationships as their raw material, and in turn generate new data, software, insights, and capabilities, meaning the strength of a firm's intangible asset base largely determines the results it can obtain from AI.

- This input-output relationship creates a flywheel in which AI strengthens the intangible asset base, which then enables more powerful AI. Each cycle of the fly wheel increases competitive advantage and future earning power. However, because the assets being created sit largely off-balance sheet, traditional ROI and financial reporting often understate both the value being built and the risks being taken.



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## 1. The Intersection of Intangible Assets and Artificial Intelligence

In 1975, tangible assets accounted for 83 percent of the S&P 500's total value. When investors purchased equities, they were mostly buying a claim on tangible corporate assets. Today, tangible assets account for only 10 percent of the value of the S&P 500. So, exactly what are investors paying for?

The answer is intangible assets—and increasingly, the artificial intelligence systems that consume and produce them. As Nobel Laureat and Andersen Institute Advisor Myron Scholes observes: *"Intangible assets now account for the majority of enterprise value, yet they remain largely invisible in financial statements. AI systems consume these assets as core inputs and convert them into new sources of value. As AI becomes central to business performance, leaders must understand which intangible assets the enterprise controls and how they drive value creation. Without rigorous measurement of this AI–intangible asset relationship, capital allocation to AI will remain driven more by assumption than evidence."*

This paper addresses that relationship. It advances a unified argument across three interconnected threads: first, that intangible assets constitute the dominant but largely invisible source of modern enterprise value; second, that this invisibility creates profound problems for capital allocation, governance, and valuation; and third, that AI fundamentally transforms how these assets are created, enhanced, and deployed—while simultaneously depending on them for its own effectiveness.

These three threads must be treated together because AI is not merely a tool that operates on intangible assets. AI is a transformation engine that restructures how firms capture data, organize knowledge, and make decisions. Organizations that fail to understand their intangible asset base cannot effectively deploy AI; conversely, organizations that deploy AI without understanding its asset implications will systematically misallocate capital and underestimate risk. The relationship is reciprocal: intangible assets fuel AI, and AI produces new intangible assets, creating a flywheel effect that compounds competitive advantage for those who manage it well—and accelerates decline for those who do not.

Until recently, companies generated cash flows primarily by using tangible assets. A company might own a factory to produce widgets, or a railroad and locomotives it utilized to sell tickets, thereby generating cash flows for investors. Companies with more assets, or better quality, or better-utilized tangible assets produced more cash flows and were rewarded with higher stock prices.

Today, companies generate a much larger share of their cash flows from intangible assets. Unlike tangible assets such as plant, property, and equipment, intangible assets cannot be touched or seen, yet they are typically the foundation of a company's ability to compete, innovate, sustain cash flow and profit growth, and ultimately investor returns. They range from what people have traditionally considered intellectual property, such as patents and trademarks, to less formally recognized items such as business relationships, regulatory approvals, or network effects that are not classified as "intellectual property" per se but are nonetheless among the most valuable assets an enterprise can possess.

Despite their ubiquity and value, intangible assets remain among the most complex of all assets to identify, manage, and value. More problematically, they are largely ignored in modern financial statements, and management and investors are essentially left to infer their impact. This invisibility is not a minor accounting nuisance—it is a structural impediment to effective capital allocation. When 90 percent of enterprise value cannot be seen on the balance sheet, decisions about investment, risk, and strategy are made with systematically incomplete information.

Intersecting directly with these highly valuable yet poorly understood assets is another phenomenon that is similarly valuable and poorly understood: Artificial Intelligence. While it is clear that AI will revolutionize business and society, the optimal commercial applications of these technologies are uncertain. Likewise for organizations investing in AI, reliable methods for calculating Return on Investment remain elusive. This is problematic, as the sums involved are substantial and stakeholders rightly expect to understand what potential returns might be.

Currently, most organizations evaluate AI initiatives using traditional ROI models that treat AI investments as discrete projects with defined costs, near-term benefits, and typical payback horizons. However, for reasons explained in this paper investments in AI do not necessarily behave the same as investments in traditional assets such as factories, or even more modern assets such as brands. Accordingly, to properly understand ROI in AI we must develop more sophisticated models that reflect the underlying economics of AI.

AI intersects with intangible assets in a distinct way: intangible assets are simultaneously *inputs to* AI workflows and *outputs of* AI investment and utilization. This creates a feedback loop—a flywheel—in which intangible assets generate proprietary data, AI consumes and learns from that data, AI outputs enhance intangible value through better decisions and new products, and enhanced intangibles generate richer data, continuing the cycle. Each AI initiative therefore generates not only immediate operational benefits but also residual intangible assets—particularly data, software, and know-how—that persist beyond the project horizon. This relationship amplifies the critical importance of understanding and accurately valuing intangible assets.

Andersen Consulting has developed a structured methodology to accurately quantify ROI in AI. By treating AI technologies as both a consumer and producer of intangible assets, we provide organizations with a disciplined way to model, measure, and monitor the impact of AI on enterprise value. This approach enables leaders to quantify both returns and risks from AI investment in ways that:

a) are not possible with current embryonic methodologies used to assess AI ROI; and
b) have the advantage of being sufficiently similar to traditional financial metrics that they are familiar to finance leadership teams.

The remainder of Part I of this report proceeds as follows:

- Section 2 defines intangible assets and explains why their absence from financial statements creates a structural blind spot—and why resolving this blind spot matters for capital allocation, governance, and AI readiness.

- Section 3 explores the reciprocal relationship between intangible assets and AI, including the feedback loop through which each enhances the other.

In Part II of the report, we examine how AI creates value, both directly and indirectly, and discuss the many issues this raises for firms as they incorporate AI as a fundamental new element of business processes and their overall strategic planning.

## 2. Defining Intangible Assets and Why Visibility Matters

### 2.1 What Are Intangible Assets?

At the most basic level, intangible assets are non-physical assets that underpin almost all modern enterprise value. Perhaps the simplest way to describe them is that they are "everything in the business you can't drop on your foot."

From an accounting perspective, under IAS 38 (International Accounting Standard 38), an intangible asset is defined as "an identifiable non-monetary asset without physical substance." For an intangible asset to be recognized on the balance sheet, it must meet three criteria: (i) Identifiable—either separable from the entity or arising from contractual or legal rights; (ii) Controlled—the entity has the power to obtain future economic benefits and restrict others' access; and (iii) Future economic benefits—the asset is expected to generate future cash flows or other measurable value.

Equally important are IAS 38's exclusions. Internally generated assets such as brands, publishing titles, databases, and internally developed goodwill are explicitly excluded from recognition on the balance sheet. In practice, this means that the majority of a company's most valuable assets—brand, data, software, relationships, and know-how—are absent from financial statements entirely.

Yet these assets do not create themselves. They emerge from the coordinated efforts of individuals and teams within the firm. When an engineer writes code, a salesperson builds a client relationship, a researcher documents a discovery, or a marketing team develops a new brand, they are creating intangible assets. These assets are not static stocks sitting in a warehouse; they are emergent products of human collaboration, continuously shaped by decisions, actions, and organizational learning.

This human dimension is essential to understanding intangible assets in the AI context. Like an orchestra, where individual sections (strings, brass, woodwinds) must coordinate—sometimes self-organizing, sometimes conductor-driven—the creation of intangible assets requires alignment across functions, incentives, and capabilities. AI does not replace this human activity; it interacts with and amplifies it. AI systems learn from human-generated outputs, and their outputs in turn inform human decisions, creating a collaborative cycle of value creation.

### 2.2 Why Intangible Assets Are Not the Same as Intellectual Property

Intellectual property (IP) rights—such as patents, trademarks, copyrights, registered designs, and trade secrets—are an important but narrower subset of the much broader category of “intangible assets”. “IP” refers to statutorily defined legal rights that grant exclusivity over certain creations of the mind. These rights are excludable, enforceable against third parties, and arise from specific IP legislation.

Intangible assets, by contrast, are primarily business assets, not legal constructs. They encompass a far wider array of value-creating resources, including software, data, brands, know-how, relationships, network effects, and regulatory approvals—some of which are not IP and cannot be enforced as legal rights, yet are nevertheless critical to enterprise value.

In short, "IP" does not describe the assets themselves, but rather the legal instruments used to protect some (but not all) categories of intangible assets. Confusingly, IP rights can cut across multiple types of intangible assets: copyright may protect software, data, and content; confidentiality may protect trade secrets, know-how, and relationships; and patents may overlap with software, hardware, or design-driven innovations. As a result, analyzing an enterprise's intangible assets primarily through an IP lens tends to shift attention to the legal right rather than the underlying business asset and the function it performs. For example, a discussion of "copyright" may obscure whether the asset in question is software, data, or content.

The proper lens is therefore commercial rather than legal: intangible assets, regardless of whether or not they are protected by formal IP rights, are business *assets* that create, sustain, and compound value.

### 2.3 The Twelve Categories of the Intangible Asset Model

At Andersen Consulting, we use a comprehensive model that defines twelve categories of Intangible Assets. This model is forward-looking, strategic, and economic in orientation, designed to help organizations identify, measure, and manage the assets that truly create value.

1. **Patents** — Legally protected inventions and processes granting exclusive rights to use and commercialize new technologies.
2. **Software** — Proprietary code, platforms, and algorithms used internally or licensed externally.
3. **Genetic Materials** — Unique biological, chemical, or genetic matter with proprietary commercial or scientific application.
4. **Trade Secrets** — Confidential technical know-how, formulas, processes, or methods that are not publicly disclosed.
5. **Data** — Proprietary databases, structured and unstructured datasets, and information repositories curated or generated by the entity.
6. **Know-How** — Tacit or codified organizational knowledge, accumulated experience, and specialized technical or managerial capabilities.
7. **Approvals & Certifications** — Regulatory licenses, approvals, accreditations, or certifications that permit or condition market participation.
8. **Brand & Reputation** — Distinctive names, marks, reputational goodwill, and consumer trust associated with a company or its offerings.
9. **Design** — Product, industrial, and creative designs that provide differentiation in appearance, function, or usability.
10. **Content** — Proprietary creative works, media assets, publications, and digital or informational materials.

11. **Relationships** — Established connections with customers, suppliers, distributors, partners, or other stakeholders that influence economic activity.
12. **Network Effects** — Value that increases with scale, where the utility of a product or service grows as more users participate.

Taken together, these twelve categories provide a comprehensive map for identifying and managing modern enterprise assets and correspondingly, the true drivers of value creation in the AI era. It should be noted that this model fundamentally differs from those used in purchase-price allocation (PPA) exercises. PPAs are largely accounting constructs designed to apportion acquisition consideration rather than to understand how the assets acquired actually create enterprise value. PPA frameworks tend to be retrospective, compliance-driven, and narrowly focused on amortization and impairment testing.

### 2.4 The Accounting Blind Spot: Why Intangible Assets Are Invisible

Even though these twelve intangible asset categories comprise the vast majority of modern enterprise value, they are almost entirely absent from financial statements. This invisibility is not a problem created by AI. It is a long-standing consequence of accounting standards that were designed for an industrial age in which physical assets were king.

The consequence of the IAS 38 Standard is that most intangible assets are either excluded from the balance sheet entirely, buried within the amorphous term "goodwill," or recorded at historical cost—a metric that bears little relationship to their actual economic value. Most activities that create intangible assets, including research and development, software engineering, data generation, branding and marketing, and strategic relationship-building, are treated as period expenses under IFRS and US GAAP. As a result, the very investments that in a modern company are central to long-term enterprise value tend to be immediately written off through the profit and loss statement rather than being capitalized as assets. Even if these assets are valued by an external valuation agency, under IAS 38 they generally cannot be placed on the balance sheet.

This invisibility is not merely an accounting curiosity. It has concrete, material consequences for how organizations allocate capital, make decisions, and compete.

*The Benefits of Visibility*

When intangible assets are identified, measured, managed and valued, organizations gain several critical advantages:

*Better Capital Allocation and Decision-Making.* When intangible assets are made visible, managers and investors can allocate capital with a clear understanding of which assets are being created, strengthened, or depleted. Projects that appear marginal on a short-term cash-flow basis may be highly attractive once their contribution to data assets, software infrastructure, regulatory positioning, or long-term capability is properly valued. Conversely, initiatives with strong near-term returns may destroy underlying asset value. Making these assets explicit allows decision-makers to weigh short-term operating performance against long-term asset formation and to govern accordingly.

*AI Readiness.* As Section 3 will demonstrate, AI effectiveness depends critically on the quality, depth, and accessibility of intangible assets—particularly data. Organizations that have identified and organized their intangible asset base are better positioned to deploy AI effectively. Those that have not may invest heavily in AI systems yet lack the fuel to generate meaningful returns.

*Enhanced Valuation and Investor Communication.* When management can articulate the value of assets that do not appear on the balance sheet, they can communicate a more complete picture of enterprise value to investors, analysts, and regulators. This reduces information asymmetry and can materially affect market valuation.

*The Costs of Invisibility*

Conversely, when intangible assets remain unidentified, organizations suffer predictable consequences:

*Missed Cash Flows.* Assets that are not tracked may not be leveraged. A dataset sitting unused because no one knows it exists represents foregone revenue. Know-how that walks out the door with departing employees may materially impede cashflows.

*Undervaluation.* In transactions, businesses with strong intangible asset bases may be systematically undervalued if those assets are not identified and articulated. The buyer may not see them; the seller may not know to present them.

*Competitive Disadvantage.* Competitors who understand and manage their intangible assets will outperform those who do not. They will allocate capital more effectively, deploy AI more successfully, and compound their advantages over time.

This structural blind spot—where the assets that generate cash flows and competitive advantage are effectively below the financial waterline—off balance sheet, unrecorded, and unvalued —means that modern accounting tends to reveal what is visible but not what is valuable. The next section explores how AI both depends on and transforms this hidden intangible asset base.

## 3. The AI–Intangible Asset Flywheel

Having established what intangible assets are and why their visibility matters, we now turn to their relationship with AI. This relationship is not unidirectional. AI does not simply "use" intangible assets as inputs; nor does it simply "produce" intangible assets as outputs. The relationship is reciprocal and dynamic—a flywheel that, once spinning, compounds value for organizations that manage it effectively.

Viewed through the lens of ROI, input costs associated with AI produce defined operational outputs (e.g. productivity improvements) while simultaneously creating data and other intangible assets that can be retained, enhanced through AI, and reused to generate future cash flows thereby creating value that compounds over time beyond the scope of traditional project investment model horizons.

### 3.1 Intangible Assets as AI Inputs and Outputs

When an employee applies expertise or insight to create something new—whether software code, a product design, an analytical method, or a creative brand—they are generating new intangible assets. Companies employ smart people to come up with smart things. These people draw upon prior experience, ideas, and insights (intangible asset inputs) to create these smart things (intangible asset outputs).

If the company could get those smart things without the people, it would. Until the advent of applied AI, the creation of those smart things without people wasn't possible. That has now changed—AI can create valuable smart things. However, fundamentally AI is no different from human intelligence vis-à-vis this value creation process. AI uses intangible assets as its input and generates intangible assets as its output.

Viewed through the lens of the twelve intangible asset categories, intangible assets are *the* feedstock for AI. The foundational input is data. Software and system architecture form the next critical layer, defining how AI systems operate. Industry know-how (typically inside the heads of skilled employees) ensures that AI applications are relevant to domain-specific challenges, while competitive intelligence and proprietary algorithms create differentiation in how the AI system operates. Content, ranging from broad knowledge bases to highly specialized document libraries, further shapes system performance. Increasingly, synthetic data is central to AI effectiveness, particularly in contexts where privacy or data scarcity constrain the use of natural datasets. All of this is “fed into the machine” just as surely as coal is fed into a power station’s furnaces.

The outputs at the other end of the AI "machine" are new intangible assets. AI generates insights, optimizations, predictive models, and decision-support tools that extend organizational capabilities. As AI's capabilities grow, it is increasingly moving into new fields such as software generation, writing regulatory approvals, and the creation of content, designs, and even brands.

### 3.2 The Feedback Loop: How AI and Intangible Assets Compound Value

The relationship between AI and intangible assets is not a one-time transaction but a continuous cycle (the flywheel) with compounding effects:

**Stage 1: Intangible Assets Generate Proprietary Micro-Data.** The firm's existing intangible assets—its customer relationships, operational processes, domain expertise, content—generate streams of proprietary data. This is not the macro-data available to anyone (Wikipedia, public datasets, industry benchmarks) but micro-data specific to the firm: transaction patterns, customer behaviors, operational anomalies, decision histories. This distinction is critical. Generic AI trained on public macro-data provides capabilities that competitors can replicate. AI trained on proprietary micro-data generates differentiated insights that create sustainable competitive advantage.

**Stage 2: AI Consumes and Learns from That Data.** AI systems ingest this proprietary micro-data, identifying patterns, relationships, and predictions that would be invisible to human analysts. The effectiveness of this learning depends critically on data quality, depth, and historical continuity. AI requires dynamic, time-series data—longitudinal records that capture how variables evolve over time—to benchmark performance, identify trends, and improve predictions. Point-in-time snapshots are insufficient.

Organizations that have systematically captured and retained historical data are positioned to extract far greater value from AI than those whose data practices have been episodic or fragmented.

**Stage 3: AI Outputs Enhance Intangible Value.** The outputs of AI—better decisions, new products, operational efficiencies, predictive capabilities—enhance the value of existing intangible assets and create new ones. A customer relationship becomes more valuable when AI-driven personalization increases retention. A dataset becomes more valuable when AI-generated insights reveal previously hidden commercial applications. Software becomes more valuable when AI optimizes its performance.

**Stage 4: Enhanced Intangibles Generate Richer Data.** The enhanced intangible assets in turn generate richer, more valuable data streams, feeding back into Stage 1. The customer relationship that has been strengthened by AI-driven personalization now generates more granular behavioral data. The optimized process now generates more precise operational telemetry.

**The Flywheel Accelerates.** Each rotation of this cycle compounds the firm's advantages and enhances the value of the firm's intangible assets. Organizations that activate the flywheel early and manage it well build increasingly insurmountable leads over competitors. Those that fail to activate the flywheel—or that initiate it with weak intangible asset foundations—find themselves progressively disadvantaged.

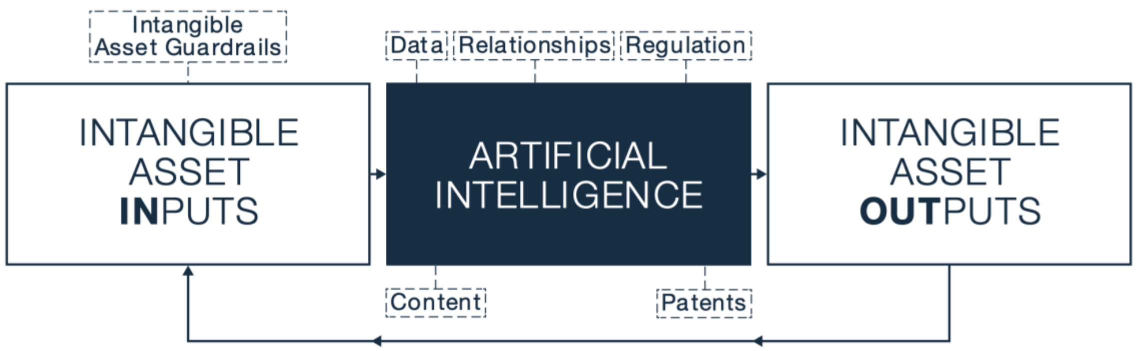


*Figure 1 – IA / AI / IA Relationship*

This flywheel effect explains why AI investment without intangible asset visibility is strategically perilous. If you do not know what assets you have, you cannot feed the flywheel effectively. If you do not capture and retain micro-data systematically, the flywheel cannot accelerate. And if you do not value the assets the flywheel produces, you will systematically underestimate its long-term value creation potential and correspondingly cannot allocate capital intelligently to sustain its momentum.

### 3.3 The Macro vs. Micro Data Distinction

The distinction between macro-data and micro-data deserves particular emphasis because it is central to understanding AI's value as a function of a firm's intangible assets.

**Macro-data** comprises the publicly available datasets—Wikipedia, web content, industry databases, academic publications—on which large language models and other AI systems are trained. This data is non-differentiating. Any competitor can access it. AI trained solely on macro-data therefore delivers commodity capabilities. As Myron Scholes observed: "There's only so much I can get out of Wikipedia."

**Micro-data** comprises proprietary, firm-specific data and is downstream of the firm’s existing intangible assets. It is generated by the organization’s unique operations, processes, relationships, systems, culture, and accumulated know-how. This includes transaction-level records, customer interaction histories, operational telemetry, internal communications, decision logs, and domain-specific measurements. In effect, micro-data is essentially an amalgam of key intangible assets made machine-readable. Because it arises from assets that competitors cannot replicate, this data is inherently differentiating and inaccessible to others.

The value of AI therefore depends heavily on the enterprise’s micro-data and in turn its intangible assets. A generic chatbot trained on public data may reduce customer service costs, but it confers no durable advantage because competitors can deploy identical capabilities. By contrast, an AI system trained on decades of proprietary customer interaction data, product performance records, embedded workflows and domain-specific expertise leverages the firm’s underlying intangible assets to generate insights no competitor can replicate. In this sense, AI amplifies existing intangible assets rather than substituting for them.

This has profound implications for data strategy. Organizations must invest not merely in "data collection" in the abstract but specifically in the systematic identification, capture and retention of proprietary micro-data and in turn the intangible assets that underpin it. They must treat data not as a byproduct of operations but as a strategic asset—one whose value compounds over time and whose absence represents permanent competitive disadvantage.

### 3.4 Time-Series Data: The Temporal Dimension of AI Effectiveness

Effective AI requires not merely data but historical data—time-series records that capture how variables evolve over time. This temporal dimension is essential for three reasons:

*Benchmarking.* AI systems must compare current performance against historical baselines to identify anomalies, improvements, or deterioration. Without historical data, "good" and "bad" are undefined.

*Trend Identification.* Patterns that unfold over time—seasonal variations, gradual shifts in customer behavior, slow-moving competitive dynamics—are invisible in point-in-time snapshots. AI systems that lack access to historical time-series cannot identify these trends.

*Continuous Learning.* AI systems improve by learning from outcomes. A prediction made today can only be evaluated against actual results that emerge over time. Organizations that do not retain historical predictions alongside subsequent outcomes deprive their AI systems of the feedback necessary for improvement.

The implication is that data capture is not merely a present-tense activity. Organizations must think of data not as a snapshot *in time* but as an asset that appreciates *through time*. Every day that passes without systematic data capture is a day of value destruction—a gap in the time-series that cannot be retroactively filled.

### 3.5 Data Degradation and Asset Erosion

If data is an asset, then data that is not captured, retained, or maintained is an asset that is eroding. This phenomenon—data degradation—represents a form of intangible asset destruction. Returning to the accounting blind spot, if data and the intangible assets that generate and sustain it were recognized on the balance sheet and depreciated in the same manner as physical assets, their degradation would become financially visible. In practice, because these assets are not recognized, their erosion remains largely unacknowledged and unmeasured.

Data and other intangible assets degrade through multiple mechanisms:

*Non-Capture.* When operationally significant events occur but are not recorded, they disappear from the system. The customer interaction that was not logged, the operational anomaly that was not timestamped, the decision that was not documented—these represent permanent information loss.

*Decay.* Even data that is captured may degrade over time. Formats become obsolete. Storage systems fail. Metadata is lost. Context that would have made the data interpretable is forgotten.

*Departure.* When employees leave, they take tacit knowledge with them. If that knowledge has not been codified—captured in documentation, training materials, or AI-accessible formats—it is permanently lost.

AI systems can serve as a hedge against asset degradation. By systematically ingesting, processing, and retaining data and other intangible assets, AI infrastructure can prevent the information loss that occurs when capture is episodic or when knowledge resides only in human memory. But this hedge only functions if the organization recognizes degradation as a risk and invests accordingly.

Organizations that fail to address asset degradation face compounding disadvantage. Each year of loss represents a gap in the time-series that weakens AI effectiveness. Competitors who have maintained systematic intangible asset and in particular data hygiene practices accumulate increasingly insurmountable leads.

### 3.6 AI as a Transformation Engine, Not an Appendage

A final point on the AI–intangible asset relationship: AI is not a tool you add to existing operations. It is a force that restructures how the firm operates.

Deploying AI effectively requires changes to:

*Data Capture Processes.* Legacy systems often generate data as a byproduct, in formats optimized for operational rather than analytical purposes. AI-ready organizations redesign data capture to generate the clean, structured, time-stamped, contextual data that AI systems require.

*Storage Architecture.* The infrastructure that supports traditional reporting is rarely adequate for AI. AI systems require scalable storage, rapid retrieval, and the ability to handle the unstructured data that often accompanies intangible assets such as industry know how, relationships and customer interactions as well as more structured records.

*Reporting Structures.* AI generates insights that cut across traditional organizational silos. Organizations must develop new reporting mechanisms to surface these insights to decision-makers who can act on them.

*Organizational Roles and Decision-Making.* AI changes the division of labor between humans and machines. Roles that were previously entirely human become human-AI collaborations. Decision-making processes that were previously intuitive become data-informed. Organizations that fail to adapt their structures to accommodate these changes will not realize AI's potential.

This transformation dimension explains why so many AI initiatives fail to deliver expected returns. Organizations treat AI as an appendage—a capability bolted onto existing operations—rather than as a catalyst for organizational change. They underinvest in the infrastructure, process redesign, and organizational adaptation that AI effectiveness requires. The result is AI systems that are starved of fuel, isolated from decision-makers, and unable to generate the value they theoretically could.

### 3.7 Legal, Regulatory, and Strategic Guardrails

The impact of intangible assets on AI extends beyond functioning as inputs and outputs. Intangible assets also create guardrails and constraints on AI deployment. These constraints directly impact the economic outputs that can be expected from an AI investment.

**Patents.** Even at this early stage in AI's development, thousands of patents relating to AI have already been issued. An organization might invest to develop an AI product and then discover that it infringes patents belonging to a third party. The anticipated cash flows from that AI investment are likely to disappear or be materially reduced. Patent portfolios (an intangible asset) are thus a key risk to ROI and cash flow in the AI age.

**Regulatory Approvals.** While comprehensive global frameworks are still in development, most organizations deploying AI already operate under responsible use policies, ethical guardrails, and sector-specific compliance requirements. These determine what data may be used, how AI systems may function, and how outputs can be applied. Regulatory approvals (a core intangible asset) can restrict or altogether preclude an AI activity, directly impacting cash flow and ROI.

**Brand and Reputation.** Individuals and enterprises use systems such as ChatGPT or Gemini because of brand familiarity and trust. Would a U.S. Fortune 100 firm willingly use a Russian or Chinese agentic or generative AI system? Brand considerations shape AI adoption in ways that directly affect market access and revenue potential.

**Relationships.** Customer, supplier, and partner relationships moderate how AI providers gain access to critical inputs such as proprietary content and data, and the level of strategic reliance on external platforms.

**Network Effects.** As we have seen, the feedback loop created by customer and user interaction—the data flywheel—forms a critical intangible asset in itself. As organizations interact with AI systems, their prompts and judgments on outputs are stored, evaluated, and reintegrated into model training.

### 3.8 Encumbered Versus Unencumbered AI

Assessing the intangible assets surrounding an AI initiative provides a powerful methodology to determine how "encumbered" or "unencumbered" that initiative is. The degree of encumbrance has a material impact on the probability and scale of success—and ultimately the cash flows and ROI that the initiative is likely to generate.

Consider two AI initiatives (A) and (B) with ostensibly identical forecast financials. Deeper analysis of the intangible assets ultimately responsible for generating those cash flows tells a different story.

| Initiative A: encumbered (weak) Intangible Assets | Initiative B: unencumbered (strong) Intangible Assets |
|---|---|
| • **Patents**: Reliance on methods overlapping with third-party patents; high infringement risk.<br>• **Software**: Built on closed, licensed, or restrictive codebases; limited ability to modify or scale.<br>• **Genetic Materials**: Use of licensed or restricted datasets (e.g., biomedical/genomic) that limit downstream applications.<br>• **Trade Secrets**: Dependence on externally sourced know-how without clear ownership; leakage risk.<br>• **Data**: Licensed or purchased datasets with restrictive terms, or containing sensitive/regulated information (PII, health data, cross-border restrictions).<br>• **Know-How / Industry Expertise**: Scarce internal domain knowledge; over-reliance on outside consultants.<br>• **Approvals & Certifications**: Lack of compliance clearance for model outputs; regulatory hurdles.<br>• **Brand & Reputation**: Exposure to reputational damage if models are biased, inaccurate, or opaque. | • **Patents**: Proprietary, freedom-to-operate architecture secured with defensive filings.<br>• **Software**: Built on in-house or open-source codebases with permissive licenses, enabling scalability.<br>• **Genetic Materials**: Access to proprietary or ethically sourced datasets, free from encumbrances.<br>• **Trade Secrets**: Clear ownership of internal processes, algorithms, and methods with strong protection.<br>• **Data**: Large, high-quality proprietary datasets free of PII and sovereignty issues.<br>• **Know-How / Industry Expertise**: Deep internal expertise aligned with industry context, creating defensibility.<br>• **Approvals & Certifications**: Models already meeting or exceeding regulatory and ethical standards.<br>• **Brand & Reputation**: Trust enhanced by transparency, explainability, and ethical alignment.<br>• **Design**: Proprietary, differentiated interfaces and workflows that improve adoption. |

| | |
|---|---|
| • **Design**: User experience and interface constrained by licensed or protected frameworks.<br>• **Content**: AI-generated material dependent on copyrighted or third-party content; infringement liability.<br>• **Relationships**: Limited access to trusted data providers, regulators, or distribution partners; reliance on unfavorable contracts.<br>• **Network Effects**: Weak adoption and small user base; switching costs favor competitors with entrenched ecosystems. | • **Content**: Rights-cleared, original, or internally generated training and output materials.<br>• **Relationships**: Strong partnerships with regulators, ecosystem players, and key data providers.<br>• **Network Effects**: Expanding user base and integration into broader ecosystems, reinforcing adoption and defensibility. |

*Table 1: the dimensions of encumbered and unencumbered Intangible Assets.*

**Initiative A: Encumbered (Weak) Intangible Assets**
This initiative relies on methods read on by third-party patents (high infringement risk); is built on closed, licensed, or restrictive codebases; uses licensed or purchased datasets with restrictive terms or containing sensitive/regulated information; lacks internal domain knowledge and relies on outside consultants; has no compliance clearance for model outputs; generates AI content dependent on copyrighted third-party material; has limited access to trusted data providers; and faces weak adoption due to small user base and switching costs favoring entrenched competitors.

**Initiative B: Unencumbered (Strong) Intangible Assets**
This initiative has proprietary, freedom-to-operate architecture secured with defensive patent filings; is built on in-house or open-source codebases with permissive licenses; possesses large, high-quality proprietary datasets free of personally identifiable information and sovereignty issues; has deep internal expertise aligned with industry context; already meets or exceeds regulatory and ethical standards; uses rights-cleared, original, or internally generated training and output materials; maintains strong partnerships with regulators, ecosystem players, and key data providers; and benefits from an expanding user base reinforcing adoption and defensibility.

By examining the respective intangible asset constellations of each initiative, it becomes clear that *ceteris paribus* we can have more confidence in the cash flows from Initiative B than from Initiative A even when prima facie they are identical. In an ideal world, management or investors would routinely undertake this analysis, but as outlined in Section 2.4, they typically do not—or do not do so systematically.

It is for precisely this reason that Andersen Consulting developed our "AI Intangible Asset Stack Audit" framework. By systematically examining data rights, regulatory alignment, patent landscapes, relationships, and other intangible asset dependencies, we help organizations distinguish between unencumbered and encumbered pathways, quantify exposure, and design strategies that maximize value while minimizing risk. In turn these factors directly impact the cashflows from AI initiatives and ultimately ROI.

Having established the reciprocal relationship between AI and intangible assets, in Part II of this report we turn to how AI creates value. AI value creation can be both direct and indirect, and understanding both dimensions is essential to calculating true ROI.

**Please see *“Intangible Assets: The Input and the Output of the Artificial Intelligence Revolution – Part II”* which follows.**

**About the Authors:**

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Paul has been ranked among the world's top intellectual asset strategists 14 years consecutively and is globally recognized for his work on intangible assets and technology as core drivers of enterprise value. His experience spans senior leadership roles in global strategy firms, a NYSE-listed technology group and an international growth institution, alongside governance roles with high-growth companies, a major family office investor and a national ministerial appointment. A seasoned international speaker, he has delivered more than 250 keynotes and talks, including TEDx.

**Jason Strimpel** is a Global Managing Director at Andersen Consulting. He is a highly technical leader with over 20 years of experience delivering innovative technology solutions across financial services, commodities, and trading. Jason brings deep expertise in product engineering, data science, and advanced analytics, with a strong track record of building secure, scalable systems that drive commercial impact.

Jason has led the design and delivery of complex data platforms, machine learning systems, and risk management tools that have transformed business operations and decision-making processes. He has built and scaled cloud-based analytics solutions to improve revenue realization, enhanced trading and risk platforms to support new business opportunities, and developed AI-enabled strategies to improve pipeline performance and organizational insight.

Earlier in his career, Jason held leadership roles in global technology and innovation teams across the financial and energy sectors, where he developed quantitative models, automated credit risk systems, and real-time analytics platforms used in high-impact, high-volume environments. He was most recently a leader in Amazon Web Service's generative AI operations group. He is a frequent keynote speaker on topics related to emerging technologies and digital strategy.