Valuation Gap:

Produced from Industrial Revolution Accounting

Abstract

A company can spend heavily on AI and still leak payroll every day through unarchitected information files. The leak hides in search time, duplicated work, unclear source material, stale content, token waste, support escalation, and AI rework. In knowledge-heavy companies, this can reach an estimated 20 percent of employee time spent looking for information instead of using it.

This paper names that hidden cost as unmanaged knowledge debt. It shows why technical writing, documentation architecture, taxonomy, metadata, and lifecycle governance now belong in the AI investment case. When companies treat governed knowledge as infrastructure, AI has better context, employees spend less time reconstructing answers, and finance leaders get a clearer path from AI spend to operating leverage.

Introduction

When a CFO asks where AI value is leaking, the answer may sit in ordinary files. The source of truth may be scattered across old documents, personal folders, duplicate drafts, stale pages, and content no one clearly owns.

BCG Group argues that CEOs and boards need a clear AI ambition focused on value, innovation, and competitive advantage. That ambition depends on the information layer underneath the tools. AI systems retrieve, summarize, and reuse what the company has already written, stored, tagged, approved, or left unmanaged.

This paper looks at the valuation gap through that lens. The issue is payroll leakage from unarchitected knowledge. Employees spend paid time searching, validating, recreating, and correcting information that should already be findable, current, and trusted.

For CFOs, Treasurers, boards, and technology executives, this is a measurement problem with a direct management action. Measure documentation debt as part of AI ROI. Track duplicated content, missing ownership, stale files, weak metadata, search time, rework, and AI correction cost. Then fund the knowledge architecture that turns AI spending into reusable operating capacity.

Projections

The valuation gap has become a knowledge readiness gap.

The original indexed chart shows both groups starting at 100 in 2019. By 2025, the AI-ready knowledge infrastructure group reaches 194, while the legacy documentation cost model reaches 166. This paper extends that view to 2026p and 2027p. In the projection, the AI-ready group reaches 237 in 2026p and 303 in 2027p. The legacy documentation cost model reaches 177 in 2026p and 188 in 2027p.

The spread matters because AI depends on the information layer underneath it. The green path represents companies that have structured content, clear ownership, useful metadata, source validation, lifecycle status, and human review. Once those pieces are in place, each new AI workflow can use the same governed knowledge base.

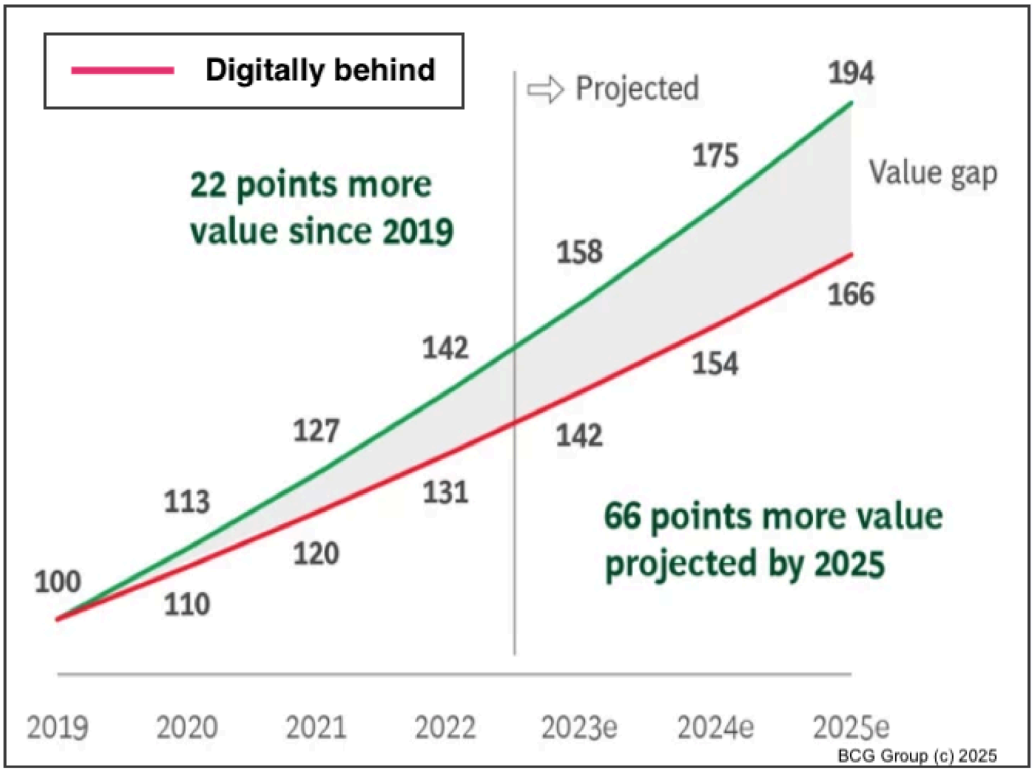
The red lines in Figures 1 and Figure 2 represent companies that still carry scattered files, duplicate drafts, stale pages, unclear ownership, and local file habits. These companies spend time and money working around weak contexts. That is the business point of the projection.

The data

In Figure 1, the AI-ready green line uses an accelerating compound model because governed documentation architecture creates reusable AI infrastructure. Once taxonomy, metadata, ownership, source validation, and expert-human review exist, each new AI workflow can draw from the same knowledge layer.

The legacy red line uses a linear continuation model because legacy firms can still gain some surface benefit from AI tools, while payroll leakage, search drag, rework, support escalation, token waste, and weak documentation architecture constrain compounding returns.

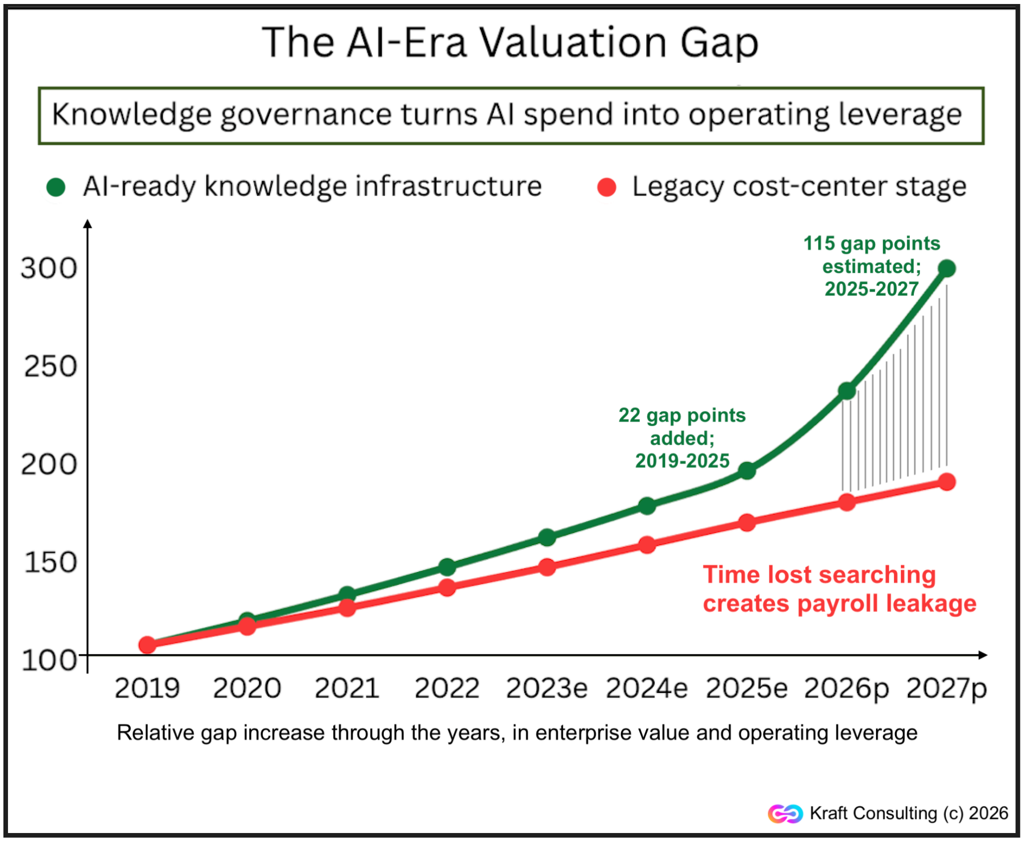
Figure 1. Previous valuation gap model estimations from BCG Group



In Figure 2 the calculated lines use the original indexed valuation-gap baseline for 2019 to 2025. The 2026p and 2027p values are Kraft Consulting scenario projections showing how governed knowledge compounds value while legacy documentation absorbs search drag, rework, token waste, support escalation, and payroll leakage.

The source of truth lay hidden in amongst a massive set of scrambled files.

Figure 2 Current valuation gap model estimations



The data show the financial impact of knowledge governance, payroll leakage, search drag, token waste, rework, and support escalation.[1]

BGC reported most roadblocks involve people, organization, and processes.

The BSG chart is an indexed comparison, with 2019 set to 100 for both management models. The green path compounds because governed knowledge infrastructure can be reused across AI workflows, while the red path continues linearly because legacy firms capture some AI benefit while absorbing search drag, rework, token waste, support escalation, and payroll leakage.

[1] Source: 2019 to 2025 valuation-gap baseline from original chart. 2026p to 2027p are scenario projections based on the Valuation Gap 2026 article. See Statistical model in the backmatter of this paper,

AI use broke linear projections

AI has changed the timing of the valuation gap.

Earlier digital systems could hide weak documentation because people filled in the gaps. Employees knew who to ask, which folder to search, which old file to trust, and which answer needed a second look. That workaround had a cost, but the cost was scattered across payroll.

AI makes the same problem visible faster. It retrieves what the company gives it. It summarizes what it can find. It reuses the terms, files, versions, and source material available to it. When the underlying information is poorly named, duplicated, stale, or weakly governed, the cost shows up in prompt retries, review cycles, corrections, escalation, and model usage.

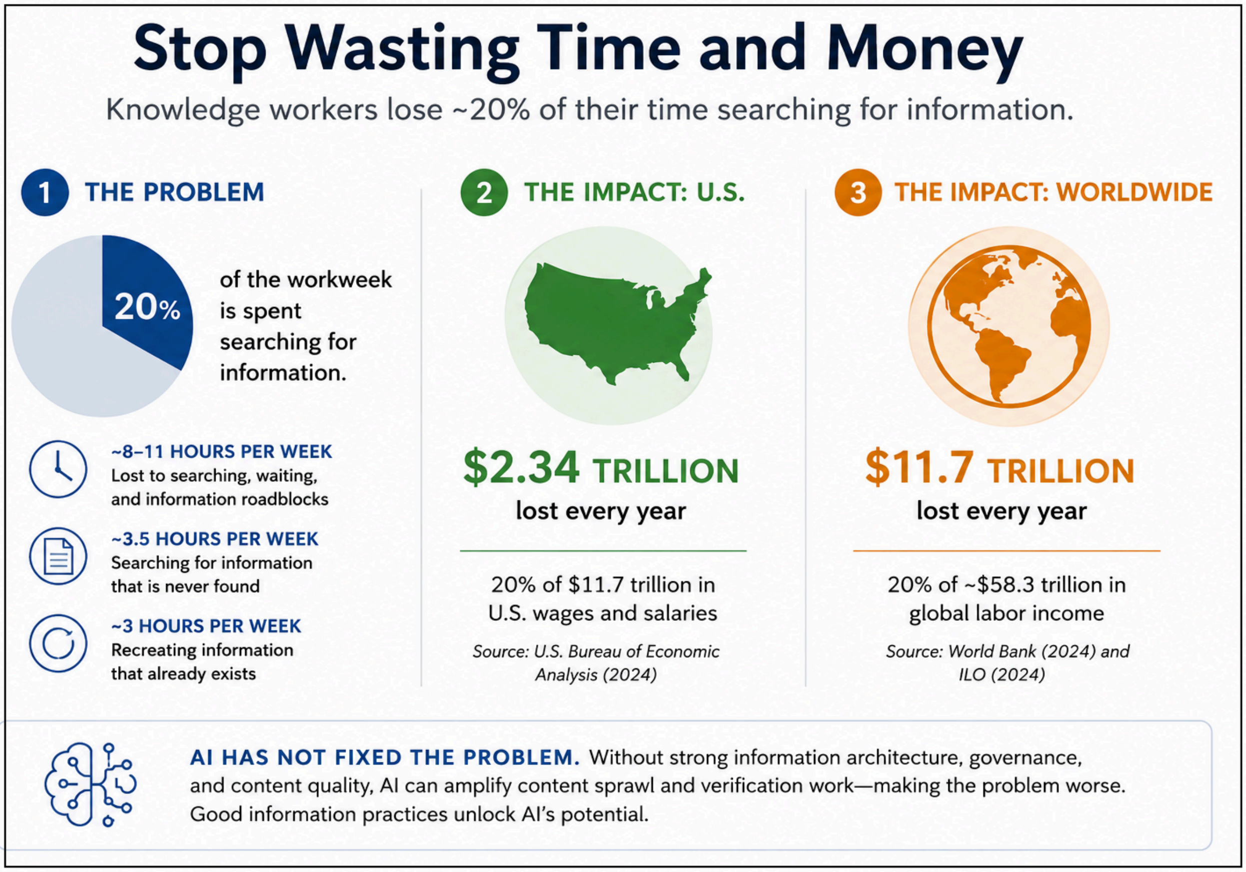
That is why the projection no longer behaves like a simple technology adoption curve. The AI-ready path compounds because the knowledge layer can be reused. The legacy documentation cost model continues to rise more slowly because value is still being absorbed by the work required to find, check, and correct information.

For enterprise AI, the work system matters. Approved terminology, validated sources, metadata, ownership, version control, lifecycle status, modular content, and governance review help people and machines reach the same trusted answer faster.

Cost in payroll leakage

Payroll leakage is the hidden cost of unarchitected information. Trillions are draining from profit sheets world-wide.

Figure 3. Stop wasting time and trillions of dollars (data sources: BLS and ILOSTAT)



The leak appears when employees spend paid time looking for source material, recreating content, validating unclear answers, and correcting AI outputs that came from stale or duplicated files. In this paper, the current benchmark estimates that knowledge workers lose about 20 percent of their time searching for information.

This cost is easy to miss because it does not sit in one budget line. The employee is paid. The time is used. The work still moves forward. What disappears is capacity. Search time, review time, repeated work, escalation, and AI correction all draw from the same payroll base.

AI raises the importance of this issue because weak information now affects both people and systems. Poor taxonomy, missing ownership, stale versions, duplicate files, and unclear source authority increase the amount of checking required before a decision, answer, or customer response can be trusted.

There are two practical forms of leakage.

Direct labor leakage is paid employee time spent searching, validating, recreating, and correcting information.

AI execution leakage is model usage, token cost, rework, escalation, and delay caused by weak enterprise context.

For CFOs, Treasurers, boards, and technology executives, the action is direct. Treat documentation debt as part of the AI ROI model. Measure duplicated content, stale content, missing metadata, ownership gaps, review delays, search time, and AI rework.

The CFO question is simple: how much payroll is being spent to compensate for unmanaged knowledge?

Conclusion

CFOs should treat knowledge governance as an AI infrastructure investment and require a cost review of documentation debt before scaling AI spend.

The immediate action is to measure content duplication, metadata gaps, ownership gaps, stale content, search time, and AI rework cost as part of the AI ROI model.

The valuation gap now points to a finance opportunity. Companies that govern enterprise knowledge reduce hidden payroll leakage, improve AI execution, and turn documentation from residual overhead into measurable operating leverage.

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Projection Calculations

The data used in this article uses a directional projection; index values are a **scenario model** and explain assumptions.

The charts use unitless index points normalized to the first data point so that 2019 = 100. For each management group, the index value is calculated as $I(g,t) = [R(g,t) / R(g,2019)] \times 100$, where $R(g,t)$ is the raw value for group g in year t and $R(g,2019)$ is that group's 2019 base-year raw value. The public BCG materials provide the indexed baseline and current 2025 evidence for the widening AI value gap, but they do not disclose the raw 2019 denominator behind the older indexed series. The chart can therefore be validated as an indexed baseline and scenario extension, rather than as a reconstruction of BCG's proprietary raw dataset.

Data table for the graphic

Year	AI-ready knowledge infrastructure	Legacy documentation cost model	Data status
2019	100	100	Source baseline
2020	113	110	Source baseline
2021	127	120	Source baseline
2022	142	131	Source baseline
2023	158	142	Original projected baseline
2024	175	154	Original projected baseline
2025	194	166	Original projected baseline
2026p	237	177	KC scenario projection
2027p	303	188	KC scenario projection

Statistical model summary

NOTE: The **normalized index points**, with **2019 set equal to 100**.

The original BCG chart does **not** reveal the original raw measurement behind the index. BCG does not disclose the underlying 2019 raw values and coƒgamparison-group definitions.

Index point derivation

My prior answer was incomplete. It explained the normalization formula, but it did not clearly separate three different things:

- The **raw value** is the underlying measured variable before indexing.
- The **index value** is the normalized chart value after setting 2019 equal to 100.

The **public BCG PDF** supports the AI value-gap premise, but it does not disclose the raw 2019 denominator for the older indexed valuation-gap line that your article inherited.

Index point methodology

The index points were derived for the Figure 2 chart using normalized index points, with 2019 set to 100.[2] See Google sheet, Valuation Gap for data set.

- The chart uses **unitless index points normalized to the 2019 value**.

The index converts two different management paths into a common scale by setting each path's 2019 value equal to 100. Each later value then shows proportional change from that 2019 base.

Equation legend

Symbol	Definition
`t`	Year
`g`	Management group
`gA`	AI-ready knowledge infrastructure group
`gL`	Legacy documentation cost model group
`R(g,t)`	Raw value for group `g` in year `t`
`R(g,2019)`	Raw value for group `g` in the 2019 base year
`I(g,t)`	Normalized index value for group `g` in year `t`
`Gap(t)`	Index-point difference between the two groups in year `t`

Index equation

$I(g,t) = [R(g,t) / R(g,2019)] \times 100$

For the base year:

$I(g,2019) = [R(g,2019) / R(g,2019)] \times 100 = 100$

[2] The charts use normalized index points, with 2019 set equal to 100 for each line. A reader can recreate the plotted graph from the published index values, but cannot recreate the original BCG raw measurement as the underlying 2019 raw values and comparison-group definitions are not publicly available.

Gap equation

$Gap(t) = I(gA,t) - I(gL,t)$

Example:

$Gap(2025e) = 194 - 166 = 28$ index points

This is a **28 index-point gap calculated for 2025**; a gap between two normalized index values.

Significance of the 2019 raw value

The 2019 raw value is the denominator that anchors the index.

It represents the starting measurement for each group before the later divergence. In the chart, both groups begin at:

- $I(gA,2019) = 100$
- $I(gL,2019) = 100$

This does **not** mean both groups had the same dollar value, revenue, margin, market capitalization, or payroll base in 2019. It means each group was normalized to its own 2019 starting value so the chart can compare relative growth paths.

Mathematically, the raw 2019 values could differ:

$R(gA,2019) \neq R(gL,2019)$

Yet both indexed values equal 100 because each group is divided by its own 2019 base:

- $I(gA,2019) = [R(gA,2019) / R(gA,2019)] \times 100 = 100$
- $I(gL,2019) = [R(gL,2019) / R(gL,2019)] \times 100 = 100$

What the raw value measured

For the original baseline series, the public-facing chart gives normalized index values. It does not disclose the raw 2019 denominator. Therefore, the reader can recreate the **indexed graph** from the visible index values, but cannot reconstruct the undisclosed raw BCG dataset from the public chart alone.

The current BCG 2025 paper supports the wider value-gap premise with observed 2025 findings. BCG reports that only 5 percent of companies achieve AI value at scale, while 60 percent report minimal revenue and cost gains despite substantial investment. It also reports that future-built firms generate 1.7 times more revenue growth, 1.6 times higher EBIT margins, 2.7 times return on invested capital, and 3.6 times three-year TSR compared with lagging categories.

BCG also states that AI-driven value accrues over time through a compounding effect, and that future-built companies reinvest gains into stronger people, technology, and capabilities. This supports the shape of the green line as an accelerating scenario after 2025.

Projection equations for 2026p and 2027p

The green path applies rising compound multipliers because governed knowledge infrastructure can be reused across AI workflows, creating compounding operating leverage. The red path applies a fixed annual increment because legacy firms can still capture some tool-driven AI benefit, while search drag, rework, token waste, support escalation, and payroll leakage constrain compounding returns.

Green path:

- $I(gA,2026p) = 194 \times 1.22 = 237$
- $I(gA,2027p) = 237 \times 1.28 = 303$

Red path:

- $I(gL,2026p) = 166 + 11 = 177$
- $I(gL,2027p) = 177 + 11 = 188$