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The Primacy of Control: A Risk-Centric TCO Framework for Generative AI and the Financial Irrelevance of Productivity

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Abstract

Generative AI is framed as a productivity enhancer in the prevailing narrative. This paper challenges this view as financially incomplete and potentially misleading for strategic investment. A new framework for financial evaluation was proposed, based on control and risk. Application Programming Interfaces (APIs) and fine-tuned Open-Source (OS) techniques were compared using a stochastic Total Cost of Ownership (TCO) framework that we developed and tested. To deconstruct the key drivers of financial performance, the model incorporates probabilistic estimates for operational and risk variables. These estimates were then analyzed using Monte Carlo simulation and Sobol sensitivity analysis, and the classical value logic of Information Technology (IT) was fundamentally inverted. Sensitivity analysis demonstrates that traditional productivity gains are financially irrelevant in determining the optimal strategy. The model's result was mostly determined by the critical error probability and cost (λ, P). The simulation revealed that the OS strategy has a low likelihood of being financially superior (6.58%) due to the high cost of its insourced risk management (the HIL process), which significantly affects its total cost of ownership (TCO).

Keywords:
Generative AI, Investment Appraisal, Risk Management, Technology Strategy, Total Cost of Ownership (TCO)

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1. Introduction

Quick and widespread use of Generative Artificial Intelligence (Gen AI) is changing the face of modern business. According to Kshetri et al. (2024) and Marshall et al. (2024), GenAI is a general-purpose technology that has the potential to revolutionize operational efficiency, strategic innovation, and value creation. As a result, there is a growing feeling of strategic urgency around this technology across all industries. Consequently, corporate leaders are under immense pressure to invest in this transformative technology to secure a competitive advantage. Chief Financial Officers and strategic decision-makers face a significant problem in assessing the financial feasibility of GenAI initiatives due to the investment imperative. Traditional investment appraisal frameworks are not suitable for this type of work.

Deterministic, point-estimate inputs for costs and benefits are fundamental to traditional evaluation methods like Net Present Value (NPV) or basic Total Cost of Ownership (TCO). Since GenAI is a technology with its own distinct and complicated set of traits, this method is not suitable. Firstly, it's important to note that AI "hallucinations" result from its probabilistic rather than deterministic outputs, which adds an extra layer of performance uncertainty and risk (Kaate et al., 2025). The second issue is that human variables, such as review efficiency and rapid engineering competence, are highly variable, and the financial outcome depends on them because GenAI is often valued through a human-AI collaborative process. Lastly, current accounting regulations do not specifically address the classification, valuation, or amortization of a proprietary, fine-tuned GenAI model, despite the fact that it is a substantial, internally generated intangible asset (Leitner-Hanetseder and Lehner, 2023). Boone et al. (2025) noted that GenAI poses a new risk profile that includes security flaws, algorithmic bias, and data privacy breaches. These issues might lead to substantial financial liabilities that are hard to estimate.

Since these factors—probabilistic performance, human-in-the-loop relationships, unclear asset classification, and a new risk landscape—traditional financial models do not work anymore. Comparing the cost of an API subscription to an employee's compensation is a very incomplete way to look at the situation. We need a complete financial framework that can bring all of these different parts together. A well-tuned AI can be viewed as a capital-generating asset; the costs of human-AI interaction can be calculated, unique probabilistic risks can be taken into account, and deep uncertainty can be addressed. The lack of such a framework creates a big hole in both the academic literature and real-world financial management. This means that companies have to make decisions about investments worth millions of dollars based on limited information and wrong assumptions.

This study fills this important gap by creating and showing a stochastic Total Cost of Ownership (TCO) framework that is specifically made for figuring out the costs of corporate Generative AI. Our research is directed by the following inquiries:

RQ1: Is it possible to systematically integrate capitalizable intangible assets, variable operational costs, human-centric inefficiencies, and probabilistic risk provisions into the full lifecycle cost of enterprise GenAI?

RQ2: Considering uncertainty, what are the key financial drivers and risk factors that determine which GenAI implementation should be opted for: the operational expenditure-heavy (API-based) or the capital expenditure-heavy (fine-tuned)?

We create a multi-pillar TCO model that combines ideas from management accounting, corporate finance, and information technology to answer these concerns. We make a way to capitalize GenAI development costs that is in line with International Accounting Standard 38 (IAS 38). We also come up with new ways to figure out how much it costs to be inefficient right away and to account for mistakes made by AI that are very important. We choose a stochastic model that uses Monte Carlo simulation to account for uncertainty in key parameters over a deterministic method. This paper addresses this critical gap by developing a novel framework that makes three principal contributions to theory and practice. Primarily, it presents the initial stochastic Total Cost of Ownership (TCO) model tailored to simulate the "make" (Open Source) vs. "buy" (API) choice for generative AI. The model gives a systematic framework for managing capital allocation decisions in the face of extreme uncertainty by moving the analysis away from a single point estimate and toward a probability distribution of outcomes. Secondly, this study uses the framework to provide empirical support for a significant change in how technology is valued: moving away from the old "economics of speed" and towards a new "economics of trust and control." We argue that financial viability is governed not by productivity gains, but by the novel agency costs required to manage a probabilistic, non-human agent. Thirdly, this study provides a fresh perspective on business strategy by shedding light on the rationale behind the multi-billion-dollar valuations of AI safety corporations. These organizations were able to outsource the enormous monitoring expenses associated with the "make" strategy. Sobol sensitivity analysis is used in conjunction with this to determine which factors have the greatest impact on financial results.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature across four key domains to establish the theoretical foundations and identify the research gap. Section 3 describes how we made our stochastic TCO model. The stochastic TCO model is formally described in Section 4, including its components, capitalization, and probability methodology. Section 5 then applies this model in a comparative simulation, presenting the quantitative results of the Monte Carlo and Sobol sensitivity analyses. Our next section, Section 6, discusses the implications of these results for corporate governance and financial practices from a managerial, theoretical, and strategic standpoint. Finally, Section 7 concludes the paper with a summary of its primary contributions, a transparent acknowledgment of its limitations, and a proposal for future research avenues.

2. Literature review

2.1. The TCO paradigm: a foundation and its deterministic limitations

The Total Cost of Ownership (TCO) framework has long been the most important way to judge technology expenditures. It is a strategy that looks at the whole financial picture, not just the original purchase price (Ellram, 1995). TCO includes all direct and indirect expenses throughout an asset's existence, improving long-term financial analysis (Saccani et al., 2017; Subiyanto and Asadi, 2023). The TCO framework, however, is more than just an accounting exercise; it is the theory of Transaction Cost Economics (TCE) put into practice. TCE explains why a corporation chooses to create or buy, depending on the situation (Friese et al., 2020). TCE posits that this decision is driven by minimizing both production costs and the transaction costs of using a market, such as searching, bargaining, and enforcement (Den Butter and Linse, 2008).

The TCO paradigm has been used in Information Technology (IT) to evaluate large-scale projects such as Enterprise Resource Planning (ERP) systems, as well as to compare the Operational Expenditures (OpEx) of cloud computing versus the Capital Expenditures (CapEx) of on-premise applications (Hanane et al., 2024).

However, a critical review of this literature reveals a significant limitation: traditional TCO models are predominantly static and deterministic, relying on single-point estimates for future costs (Gyarmathy et al., 2020). This approach is insufficient for environments characterized by high uncertainty. Therefore, there has been a growing chorus of academics calling for the addition of cutting-edge quantitative methodologies to TCO. Avenali et al. (2024) and Wang et al. (2023) used Monte Carlo simulations to simulate the distributions of uncertain cost variables, while Avenali et al. (2023) used real options analysis to value managerial flexibility. In addition to the asset specificity and the uncertainty inherent in AI, the choice between buying a third-party API ("buy") and building your own AI system poses a classic TCE dilemma (Gyarmathy et al., 2020). This framework is directly applicable to modern strategic decisions.

These improvements are a subtle way of saying that a deterministic TCO isnot a good way to evaluate the financial performance of innovative, complex technology. This inherent limitation is particularly problematic when assessing a new class of enterprise technology defined by probabilistic behavior and novel risk profiles: Generative AI.

2.2. The accounting challenge: classifying and valuing AI as an intangible asset

Accounting rules outline how technology investments should be recognized and accounted for financially. One of these rules is IAS 38, which establishes a framework for capitalizing expenses incurred to create measurable intangible assets expected to generate future economic benefits (Mazzi et al., 2022). Research is expensed, whereas development can be capitalized if technical feasibility is established (Oswald, 2008). Conditional capitalization contrasts with the instant expensing of all Research and Development (R&D), which might disguise asset creation and lead to underinvestment (Lev and Sougiannis, 1996).

However, the discretion afforded by these standards creates a central tension. A project's capitalization of development costs can act as a reliable indicator for investors (Oswald and Zarowin, 2007). On the other hand, subjectivity can be exploited for opportunistic profit management, generating an agency problem in which accounting choices are influenced by managerial incentives (Markarian et al., 2008; Dinh et al., 2016). The most relevant precedent for GenAI is software development, where capitalization is common once technological feasibility is established (Canace et al., 2022). Intangible assets such as GenAI models are created through data curation, model training, and workflow integration, just like proprietary software.

Despite the fact that they are in sync, current accounting standards do not provide GenAI with any clear direction. This gives rise to critical valuation challenges: at what point does an AI project meet "technical feasibility" for capitalization? For amortization, how should the "useful life" of a rapidly evolving AI model be determined? How can its "useful life" be determined? The emerging literature recognizes that digital assets, particularly those driven by AI, are poorly represented on traditional balance sheets, creating a gap between book and market values (Moro-Visconti, 2024). From the perspective of the Resource-Based View (RBV), this capitalized model is an investment in a competitive advantage. However, the true inimitable asset is not the AI model itself, but the organizational dynamic capability to control it and manage its risks (Wang et al., 2025), a capability whose substantial cost must be recognized. This absence of a clear framework for capitalizing and valuing proprietary AI assets highlights a critical gap that a robust TCO model must address.

2.3. Generative AI: the duality of productivity and peril

Scholars have discussed GenAI in a dualistic way that describes it as both a powerful tool for increased productivity and a potential source of new and significant risks.

Chelliah et al. (2025) reference comprehensive research that identifies GenAI as a transformative factor in generating value for enterprises. Budhwar et al. (2023) and Heitmann (2024) say that the key selling point is that it can make operations much more efficient by automating boring chores like making code and content. This will free up human capital to focus on more strategic endeavors. GenAI is not just a tool for automating tasks, but it is also a strong instrument for boosting human creativity and working with people in the creative process (Chu et al., 2025). Sometimes human-AI collaboration is so successful that AI-generated content performs "superhuman" (Hartmann et al., 2025). Jobstreibizer et al. (2025) and Ruokonen and Ritala (2024) say this functional enhancement allows companies to innovate their business models and gain a sustainable competitive advantage.

Parallel to the discourse on productivity, a growing body of research is dedicated to the novel risks inherent in GenAI adoption (Boone et al., 2025). The most fundamental challenge is the threat to information integrity posed by AI "hallucinations," the generation of plausible yet factually incorrect outputs (Lee et al., 2025). This lack of dependability adds a high hidden cost to proof, forcing companies to buy pricey systems with a person in the loop (Collier et al., 2021). The algorithms' use of huge training datasets enhances data leakage and introduces prompt injection (Zhou and Wu, 2025; Choudhary and Kar, 2025). Meanwhile, corporations risk legal and reputational problems when models trained on raw data duplicate and exacerbate preexisting social biases (Sadeghiani, 2025). Lastly, the research points out that relying too much on GenAI could make people less able to think critically, which is a long-term strategic danger of "deskilling" the workforce (Eisikovits et al., 2025).

In conclusion, this duality creates a new and unique agency problem for the company. In conventional agency theory, costs come from getting a human agent and a principal to agree on what to do. In this case, the "agent" is a non-human, probabilistic entity. Its risks stem not from self-interest, but from stochastic failure. Consequently, the firm (the principal) must incur a new class of agency costs to govern this agent. The extensive Human-in-the-Loop (HIL) processes and continuous verification required to manage hallucinations (Collier et al., 2025) can be framed as direct and substantial monitoring costs to control the AI agent's behavior. Simultaneously, the potential for catastrophic financial, legal, or reputational damage from an undetected AI error due to data leakage, bias, or factual inaccuracy represents a significant residual loss. Financial provisions or other investments made to mitigate the consequences of this fallibility are therefore analogous to bonding costs incurred by the principal (Florackis, 2008).

2.4. Addressing uncertainty: the case for stochastic and sensitivity analysis

Investing in an uncertain environment requires a method of evaluating investments beyond the deterministic approach. A lot of research in corporate finance and operations management has shown that random modeling is necessary for making good decisions (Kozlova et al., 2022).

Among stochastic techniques, Monte Carlo Simulation (MCS) has emerged as a dominant framework for capital budgeting under uncertainty (Pawlak, 2024). In order to provide a better picture of the risk profile of a project, MCS changes static outputs into dynamic probability distributions by sampling from the distributions of important input variables multiple times (Fiorentini et al., 2024). It is widely used, from assessing renewable energy assets with unpredictable power prices (Verstraten and Van der Weijde, 2023) to working with TCO models to make them dynamic (Cai et al., 2025). The research indicates that MCS is the benchmark for evaluating strategic investments in situations characterized by significant uncertainty.

The range of possible outcomes can be quantified using MCS, but the input variables that contribute most to the uncertainty cannot be identified. For this, a robust sensitivity analysis (SA) is required (Magni and Marchioni, 2020). Global Sensitivity Analysis (GSA) methods are more complex than basic "one-at-a-time" analyses, which do not account for interaction effects, according to the literature. Variance-based methods, such as Sobol indices, have become a benchmark, offering the ability to quantify both the direct effect of each variable and the effect of its interactions with others (Pannier et al., 2018). With its numerous stochastic and interdependent cost drivers, GenAI implementations require this more advanced GSA approach to identify the most influential parameters and guide effective risk management.

Due to the clear but incomplete image presented by the current literature, these strategies are essential. While TCE offers a theoretical perspective on the "make-or-buy" choice, TCO models tend to be overly prescriptive. IAS 38 permits the capitalization of AI assets, resulting in agency issues. Most crucially, the GenAI literature talks about big risks, but it doesnot put them in the context of agency costs, which is the usual way to talk about them in economics.

Even though TCO, accounting standards, and agency theory offer basic ideas, there is currently no framework that financially operationalizes the distinct agency costs of probabilistic technologies. This highlights a significant theoretical and practical gap. No model integrates the stochastic nature of AI risk (λ, P) into a TCO analysis, treats the corresponding control structures (HIL) as a component of a capitalizable intangible asset under IAS 38, and thereby allows for a theoretically grounded financial comparison of "make" (OS) versus "buy" (API) strategies. This paper develops such a framework to fill this critical gap.

2.5. Synthesis and research gap

A clear but incomplete picture is painted by the literature. The TCO framework is a basic way to figure out how much technology costs. While accounting standards have general rules for intangible assets, they do not go into detail about how to capitalize and amortize a private GenAI model. A lot of new research on GenAI shows that it has both a huge potential for output and a very complicated, multi-layered risk profile that is hard to quantify. Lastly, stochastic models and GSA are well-known as the best ways to make decisions when you do not know what will happen. However, they have not been put together yet in a way that makes sense for Generative AI's economic and accounting needs.

This reveals a critical, multi-faceted gap: there is no existing model that synthesizes these four domains. No framework (1) adapts the TCO paradigm for a probabilistic technology, (2) provides a clear method for capitalizing GenAI assets, (3) quantifies human-AI collaboration's unique operational costs and risks, and (4) accounts for pervasive uncertainty with a rigorous stochastic methodology. This paper aims to fill this gap by developing and presenting such a framework.

3. Research methodology

3.1. The TCO framework for generative AI: a formal Model

The TCO framework for generative AI is formally defined in this section. The framework is composed of three pillars: (1) Variable Operational Cost, (2) Capitalized Asset Cost, and (3) Indirect Operational Costs and Risk Provisions. Each pillar is represented by a set of formulas that quantify its financial impact.

3.2. Pillar 1: Per-unit variable operational cost (C_{var})

According to Table 1, this formula calculates the effective variable cost to produce one successful unit of output using a human-AI collaborative process. It represents the core operational efficiency of the AI implementation.

$$C_{var} = \frac{\left(\frac{W}{\alpha L} + IC\right)}{p} \tag{1}$$

Objective: A fully-loaded variable cost should be calculated per successful AI-assisted output, including human review, API costs, and AI's quality failure rate.

Table 1. Per-Unit variable operational cost (C_{var}) component breakdown.

Symbol	Name & Description	Unit
C_{var}	*Per-Unit Variable Operational Cost:* The final calculated cost for one usable output.	Currency/Output
W	*Wage Rate of Human Reviewer:* Human reviewers can produce one hour's worth of output without using artificial intelligence. This should include salary, benefits, and overhead.	Currency/Hour
L	*Baseline Human Productivity:* Without AI assistance, the number of outputs the human reviewer can create in an hour. The term $\frac{W}{\alpha L}$ represents the baseline human-only cost per output.	Outputs/Hour
α	*Human Productivity Multiplier:* A dimensionless number that shows how much more efficient it is to work with AI and humans together. It tells you how much faster an employee can check and fix an AI output than make it from scratch. For example, if an employee takes 1 hour to write a report but only 15 minutes to review an AI draft, $\alpha = 4$.	Dimensionless Ratio
IC	*Inference Cost:* It's the direct cost per request charged by the 3rd-party AI model provider (OpenAI, Anthropic). This is a pure variable cost associated with each API call.	Currency/Output
p	*AI Quality Rate (Yield):* After a standard human review, the probability that the output of an AI system will be of sufficient quality (from 0 to 1) for use. It represents the "yield" of the AI system. An output that is so poor it must be discarded contributes to a lower p.	Dimensionless Probability

Derivation and Interpretation: The numerator, $\left(\frac{W}{\alpha L} + IC\right)$, represents the total cost incurred for each *attempted* AI-assisted output. This comprises the human review cost ($\frac{W}{\alpha L}$) and the machine cost (IC). The formula divides this cost by the quality rate, p, to account for failures. In production, the cost of a good unit must include the cost of units that were thrown away, which is similar to this. Since it typically takes two tries to get a single successful output at a quality rate of 50% (0.5), the effective cost quadruples.

3.3. Pillar 2: Capitalized AI asset cost ($CAPEX_{AI}$)

This pillar explains how much money is needed to put up front to make a proprietary or improved open-source model. IAS 38 counts these costs as intangible assets and am,ortizes them over time.

Formula 2: Data asset acquisition & preparation cost (C_{data})

$$C_{data} = C_{lic} + (H_{clean} \cdot W_{label}) + C_{storage} \qquad (2)$$

Objective: To quantify the total cost of sourcing and preparing the data corpus required for model training, which forms the foundational component of the intangible asset (Table 2).

Table 2. Data asset acquisition & preparation cost (C_{data}) component breakdown

Symbol	Name & Description	Unit
C_{lic}	*Data Licensing Cost:* Direct costs for purchasing or licensing external datasets.	Currency
H_{clean}	*Human Hours for Data Curation:* Total person-hours spent on data cleaning, labeling, de-duplication, and formatting.	Hours
W_{label}	*Wage Rate of Data Curators:* The fully-loaded hourly wage of employees or contractors performing data curation tasks.	Currency/Hour
$C_{storage}$	*Data Storage Cost:* Costs associated with storing the prepared dataset during the development phase.	Currency

Formula 3: Model training & fine-tuning cost (C_{train})

$$C_{train} = (H_{gpu} \cdot Cost_{gpu}) + (H_{eng} \cdot W_{eng}) \quad (3)$$

Objective: To quantify the direct development costs associated with the computational and engineering effort to train or fine-tune the AI model (Table 3).

Table 3. Model training & fine-tuning cost (C_{train}) component breakdown

Symbol	Name & Description	Unit
H_{gpu}	*Graphics Processing Unit (GPU) Compute Hours:* Total high-performance compute hours (e.g., NVIDIA H100-hours) consumed during the training process.	Hours
$Cost_{gpu}$	*Cost per GPU Hour:* The rental cost of a specialized GPU from a cloud service provider (e.g., AWS, Azure).	Currency/Hour
H_{eng}	*Machine Learning (ML) Engineer Hours:* Total person-hours from specialized machine learning engineers for setting up, monitoring, and validating the training run.	Hours
W_{eng}	*Wage Rate of ML Engineer:* The fully-loaded hourly wage of scarce, high-cost ML engineering talent.	Currency/Hour

Formula 4: Per-unit amortization cost (C_{amort})

$$C_{amort} = \frac{C_{data} + C_{train}}{T_{useful\_life}} \quad (4)$$

Objective: To allocate the total capitalized cost of the AI asset ($CAPEX_{AI} = C_{data} + C_{train}$) to individual outputs over the asset's useful life, in accordance with the matching principle (Table 4).

Table 4. Per-unit amortization cost (C_{amort}) component breakdown

Symbol	Name & Description	Unit
$T_{useful\_;ife}$	*Useful Life of the AI Asset:* A critical management estimate of the asset's productive life. This can be expressed in time (e.g., years) or, more appropriately for a units-of-production method, in the total expected number of outputs the model will generate before becoming obsolete.	Total Outputs or Years

3.4 Pillar 3: Indirect operational costs & risk provisions ($C_{indirect}$)

This pillar quantifies the often-hidden ongoing costs related to operational inefficiency and risk management. These are operational expenses that must be tracked and provisioned for.

Formula 5: Cost of prompt inefficiency ($C_{badprompt}$)

This formula calculates the total cost of wasted effort within a given period due to poorly constructed prompts that fail to yield a usable output.

$$C_{badprompt\_period} = N_{prompts} \cdot R_{bp} \cdot \left(IC + (T_{reprompt} \cdot W_{user})\right) \quad (5)$$

Objective: To quantify the "cost of poor quality" stemming from user inefficiency, providing a financial justification for employee training and prompt engineering standards (Table 5).

Formula 6: Provision for AI-Generated risk ($Prov_{risk}$)

This formula calculates the amount that should be provisioned per output to cover potential future costs arising from critical AI errors (e.g., legal liabilities, reputational damage, financial misstatements).

$$Prov_{risk} = \lambda \cdot P \quad (6)$$

Table 5. Cost of prompt inefficiency ($C_{badprompt}$) component breakdown

Symbol	Name & Description	Unit
$N_{prompts}$	*Total Prompts:* The total number of prompts sent to the AI model in an accounting period.	Prompts/Period
R_{bp}	*Bad Prompt Rate:* The proportion of total prompts that are deemed "bad" (i.e., they fail to elicit a useful response and must be re-engineered). This is a key operational Key Performance Indicator (KPI).	Dimensionless Ratio
IC	*Inference Cost:* The direct API cost wasted on the initial failed prompt.	Currency/Prompt
$T_{reprompt}$	*Time to Reprompt:* The average time a user spends diagnosing the failure and rewriting a bad prompt.	Hours/Bad Prompt
W_{user}	*Wage Rate of End-User:* The fully-loaded hourly wage of the general employee using the AI tool.	Currency/Hour

Objective: To apply a systematic, risk-based approach to financial provisioning, converting an unquantified risk into a managed operational expense based on expected value (Table 6).

Table 6. Provision for AI-Generated risk ($Prov_{risk}$) component breakdown

Symbol	Name & Description	Unit
λ	*Critical Error Detection Rate:* The probability that a *critical* error in an AI output will be detected by the firm's monitoring and control systems. The inverse, $1-\lambda$, represents the escape rate of critical errors. *Note: This formula can also be framed using the escape rate.*	Dimensionless Probability
P	*Cost per Critical Error:* A significant management estimate of the total financial impact if a single critical error is not detected and causes harm (e.g., legal settlement, client loss, regulatory fine). This is analogous to the "cost of failure" in risk analysis.	Currency/Error

3.5. A stochastic TCO model for generative AI strategy selection

A formal stochastic Total Cost of Ownership (TCO) model is presented here using the conceptual framework from Section 3. The model turns theoretical ideas into a computer structure that can be used to compare and analyze the two main ways that people use AI when they do not know what will happen:

API-Based Strategy: Primarily operating under an OpEx (operational expenditure) model, this approach relies on third-party generative AI APIs.

Fine-Tuned Open-Source (OS) Strategy: A CapEx (capital expenditure)-intensive model, involving the upfront investment required to develop and maintain proprietary, fine-tuned open-source models.

What makes this model different is that it does not use deterministic, point-estimate-based evaluations. Instead, it uses probabilistic distributions for important input variables. Instead, it uses probabilistic distributions for crucial input variables to make Monte Carlo simulations and Sobol sensitivity analyses realistically predict financial outcomes and hazards.

3.6. Core model structure

The TCO for each strategy is computed as the sum of its constituent cost components.

API-Based Strategy TCO is calculated as follows:

$$CO_{API} = C_{var,API} + C_{badprompt,API} + Prov_{risk,API} + \cdots \quad (7)$$

Additional amortization is factored into the total cost of ownership (TCO) for the fine-tuned operating system strategy:

$$TCO_{OS} = C_{var,OS} + C_{badprompt,OS} + Prov_{risk,OS} + C_{amort} + \cdots \quad (8)$$

We use the formulas from Section 3 to calculate each component. The principal decision-making metric is the difference in total cost of ownership between the two strategies:

$$\Delta TCO = TCO_{OS} - TCO_{API} \quad (9)$$

A negative ΔTCO value implies a cost advantage for the OS strategy.

Table 7. Maps each conceptual parameter to its computational counterpart, describing the assumptions and distribution applied.

Category	**Parameter**	**Symbol**	**Code Variable**	**Description**	**Distribution / Value**
General Context	Wage, Reviewer	$W_{reviewer}$	WAGE_REVIEWER	Fully-loaded hourly wage for reviewers	Fixed: $60/00
	Wage, End-User	W_{user}	WAGE_END_USER	Fully-loaded hourly wage for end-users	Fixed: $45/00
	Baseline Productivity	L	BASELINE_HUMAN_PRODUCTIVITY	Human output rate without AI	Fixed: 2
	Project Volume	T_{useful_life}	TOTAL_PROJECTED_OUTPUTS	Total expected outputs for amortization	Fixed: 500/000
API Strategy	Quality Rate	p_{API}	api_quality_rate	Probability that an API output is usable	PERT (0/90, 0/95, 0/98)
	Productivity Multiplier	α_{API}	api_prod_multiplier	Reviewer efficiency using API	PERT (3/0, 4/0, 6/0)
	Bad Prompt Rate	$R_{bp,API}$	api_bad_prompt_rate	Fraction of failed prompts	PERT (0/10, 0/15, 0/25)
	Critical Error Rate	λ_{API}	api_critical_error_rate	Frequency of critical errors per output	PERT (5e-5, 1e-4, 5e-4)
	Inference Cost	IC_{API}	API_INFERENCE_COST	Per-call API cost	Fixed: $0/05
OS Strategy	Quality Rate	p_{OS}	os_quality_rate	Probability that an OS output is usable	PERT (0/85, 0/90, 0/94)
	Productivity Multiplier	α_{OS}	os_prod_multiplier	Reviewer efficiency using the OS model	PERT (2/5, 3/5, 5/0)
	Bad Prompt Rate	$R_{bp,OS}$	os_bad_prompt_rate	Failed prompts under OS	PERT (0/15, 0/20, 0/30)
	Critical Error Rate	λ_{OS}	os_critical_error_rate	Frequency of critical errors	PERT (1e-4, 3e-4, 8e-4)
	Inference Cost	IC_{OS}	OS_INFERENCE_COST	Per-inference compute cost	Fixed: $0/01
Universal	Cost of Critical Error	P	cost_per_critical_error	Financial impact per critical error	PERT (50/000, 75/000, 200/000)
	Time to Reprompt	$T_{reprompt}$	*implicit*	Time to revise a bad prompt	API: 2 min; OS: 3 min

Note on λ: In this operational context, λ represents the expected occurrence rate of critical errors per output, directly informing the provision cost calculation. This differs from theoretical usage, where it might represent the error detection rate.

3.7. Parameterization and stochastic inputs

According to Table 7, to accommodate the inherent uncertainty in future costs and performance, key model parameters are specified as random variables, modeled using the PERT (Program Evaluation and Review Technique) distribution. PERT is advantageous in capturing expert judgment, requiring only three intuitive values: minimum, most likely (mode), and maximum.

3.8. Capital expenditure and amortization

Model explicitly incorporates capital expenditures for the OS strategy amortized over projected output volume using the units-of-production method:

$$CapEx_{AI} = C_{data} + C_{train} \tag{10}$$

Where:

$$C_{data} = C_{lic} + (H_{clean} \cdot W_{label}) + C_{storage} \tag{11}$$

$$C_{train} = (H_{gpu} \cdot Cost_{gpu}) + (H_{eng} \cdot W_{eng}) \tag{12}$$

The budgeted project expenditures are set as fixed parameters in the model configuration.

The amortized cost per unit is then computed as:

$$C_{amort} = \frac{CapEx_{AI}}{T_{useful\_life}} \tag{13}$$

3.9. Analytical Output and Sensitivity Evaluation

Running the stochastic model across multiple simulation iterations yields a probability distribution rather than a single TCO estimate. Key decision-making metrics include:

Expected Value: The mean of the ΔTCO distribution, reflecting the average financial advantage or disadvantage of the OS strategy.

Probabilistic Breakeven: Proportion of iterations where the OS strategy is more cost-effective.

Variance and Risk: Based on the spread of the distribution, each strategy's uncertainty and financial risk are quantified. Unpredictability increases with wider spreads.

A Sobol Sensitivity Analysis is also supported, which uses Saltelli sampling to estimate the contribution of each input parameter to the output variance. This analysis identifies the most influential variables, such as P, α_{API}, and p_{OS} helping to prioritize risk mitigation and data collection efforts.

4. Results

This section presents the findings from the quantitative modeling designed to evaluate the competing technology investment strategies. The results are presented in two parts. First, we report the outcomes of the Monte Carlo simulation, which provides a probabilistic assessment of the overall financial viability and risk associated with each strategy. This analysis focuses on the distribution of the Total Cost of Ownership (TCO) differential. Second, we present the results of a variance-based Sobol sensitivity analysis to decompose the sources of this financial uncertainty and identify the most influential input parameters that drive the model's outcomes.

4.1. Stochastic financial viability analysis via Monte Carlo simulation

Under uncertainty, a Monte Carlo simulation (N=5,000) was conducted to assess the financial performance and risk profile of the two competing technology strategies. The simulation modeled the Total Cost of Ownership (TCO) per output for both the API-based and fine-tuned Open Source (OS) strategies by drawing input values from the nine specified stochastic parameters' PERT distributions. The principal outcome is the probability distribution of the TCO differential, defined as $\Delta TCO = TCO_{OS} - TCO_{API}$ in Figure 1. A positive ΔTCO indicates a cost advantage for the API-based strategy.

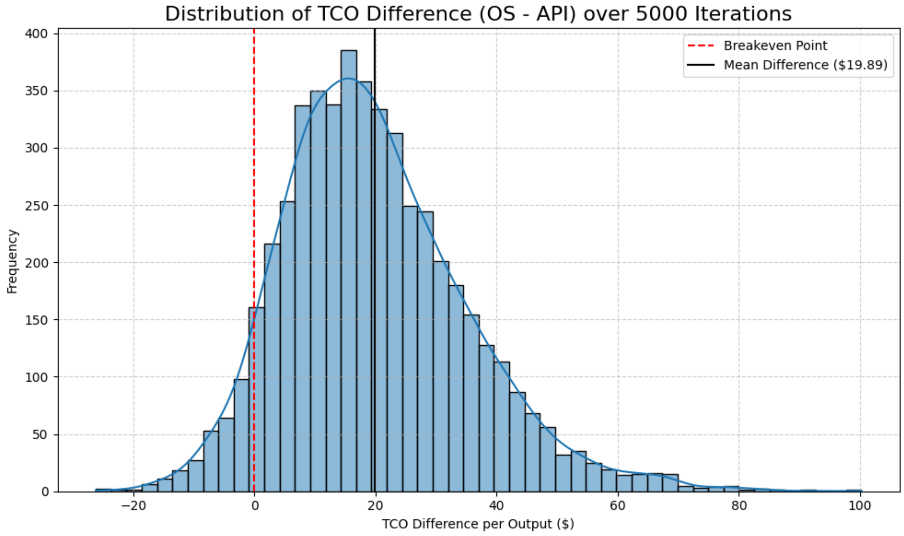

Figure 1. Distribution of TCO difference (OS - API) over 5,000 Iterations

The resulting distribution of ΔTCO, depicted in Figure 1, has a mean of $19.89. This positive anticipated value indicates that the API-based technique is, on average, the more cost-effective choice on a per-output basis. The mean shows the central tendency, but the main use of the simulation is to show how many different outcomes are possible. The distribution has a large standard deviation of $14.50, which means there is a lot of financial risk and uncertainty. The distribution also has a strong positive skewness (skewness = 1.24), which means that the OS strategy has a small chance of doing better than the API strategy (the left tail), but the danger of cost overruns is much greater than the API alternative.

The probability breakeven threshold is a very important number for making strategic decisions. The simulation indicates that the probability of ΔTCO being negative, a scenario where the OS strategy is more cost-effective, is only 6.58%. Consequently, the API-based strategy is projected to yield a lower TCO in 93.42% of the simulated scenarios. This result provides strong quantitative evidence in favour of the API-based approach. The OS plan requires a lot of money and work to put into action, and there is only a 6.58% chance that it will lead to better financial results. Real Options Theory can be used to explain this result. The lower initial investment and pay-per-use model of the API strategy protects strategic flexibility and limits downside exposure. This creates an option value that seems to be higher than the OS strategy's potential for lower marginal costs.

4.2. Variance decomposition using Sobol sensitivity analysis

Following the quantification of output uncertainty, a Sobol sensitivity analysis was conducted to decompose the variance of the model output (ΔTCO) and identify the principal drivers of this variance. By calculating the Total-Order Sobol indices (ST), which account for each parameter's individual effect and its interactions with all other parameters, we can pinpoint the most influential variables. Rather than simply identifying if a risk exists, this analysis explains why it exists, helping to inform risk mitigation strategies. As shown in Figure 2, the results are summarized.

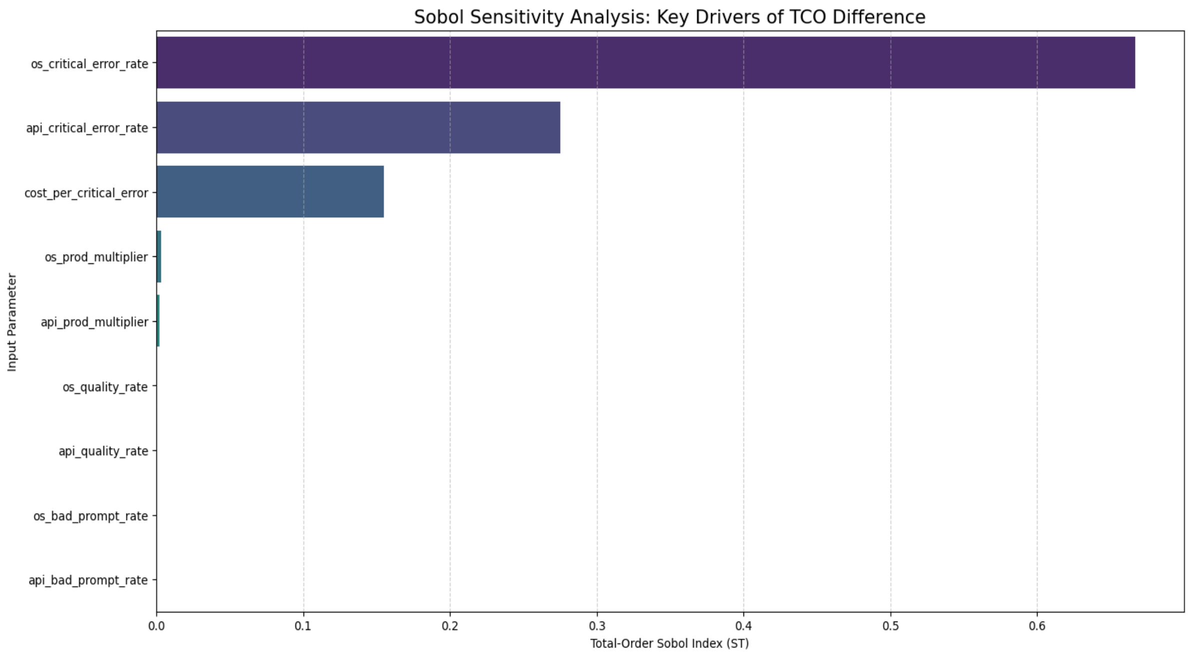

Figure 2. Sobol sensitivity analysis: key drivers of TCO difference

In the analysis, three parameters accounted for over 90% of the total variance, indicating a high concentration of variance attribution.

4.2.1. OS model critical error rate (os_critical_error_rate, ST ≈ 0.67)

The dominant source of uncertainty, contributing approximately 67% of the output variance, is the rate of critical failures in the fine-tuned OS model. This finding underscores the centrality of technical risk management in the evaluation of in-house AI solutions. The financial viability of the OS strategy is less dependent on operational efficiency metrics and more contingent upon the model's reliability and controllability. The high sensitivity is a result of the large uncertainty range and the substantial financial impact of each inaccuracy (P) for this parameter.

4.2.2. API model critical error rate (api_critical_error_rate, ST ≈ 0.28)

At 28%, the third-party API's critical error rate is the second most important variable. This highlights that the investment decision is fundamentally a *comparative risk assessment*. The financial outcome is highly sensitive to the *relative* reliability of the two platforms, shifting the focus from simply accepting a vendor's service-level agreements to actively monitoring and quantifying third-party platform risk.

4.2.3. Cost per critical error (cost_per_critical_error, ST ≈ 0.16)

The estimated financial consequence of a single critical error is the third substantive driver of variance. It's notable ST index validates the inclusion of the Prov_risk component within our TCO framework. It shows that when figuring out how much a technology investment is worth, you need to look at more than just the direct costs. You also need to make good guesses about the possible indirect costs that could come from operational failures. This is something that needs help from people in the legal, compliance, and operations areas.

One important finding is that standard measures of efficiency, like productivity multipliers and quality rates, have almost no effect (all ST < 0.01). Changes in these parameters do not have a statistically significant effect on the strategic choice within the uncertainty ranges given. This is because the risk parameters have a bigger effect. This finding goes against what most people think about evaluating IT projects, which is that they should focus on making things more efficient and saving money. Our analysis suggests that for complex AI systems, the focus of strategic financial evaluation should be reoriented from operational efficiency to a more comprehensive framework of financial risk management and model governance.

5. Discussion

Our stochastic TCO analysis quantifies two technical trajectories and reframes how generative AI investments should be evaluated. Based on our research, we propose a new paradigm that is risk-centric and is based on well-established accounting and economic theory; this paradigm shift would challenge orthodox IT value logic.

The major takeaway from this article is the complete reversal of traditional reasoning behind IT investment strategies. The Sobol sensitivity analysis (Figure 2) reached a clear conclusion: a handful of risk-related parameters (os_critical_error_rate, api_critical_error_rate, cost_per_critical_error) control the majority of the financial outcome of a strategic AI decision. These parameters account for more than 90% of the model's output variance. On the other hand, the strategic decision is not impacted by the conventional efficiency measures, including labor productivity multipliers (α) and output quality rates (p), which have been the focus of talks on IT value for many years. This proves with hard data that the outdated reasoning of calculating IT value by subtracting labor savings is seriously flawed when it comes to generative AI. It argues that the exponential cost of an uncontrolled AI-generated failure much outweighs the marginal value of making an employee progressively faster. As a result, the focus of strategic calculations should shift from the cost of speed to the cost of control.

Our approach determines the AI's critical mistake rate (λ) as the most sensitive parameter, necessitating a more profound analysis from the perspective of Agency Theory. The mistake rate is not a fixed characteristic of the AI model; rather, it is a result of its principal control mechanism—the Human-in-the-Loop (HIL) process. The high financial sensitivity to λ is really a sensitivity to the high costs of monitoring a non-human, probabilistic agent. When a company selects the OS strategy, it takes on all of this work itself, and its financial success depends directly on how well it can build an industrial-scale HIL process. The large range we see in os_critical_error_rate is the financial result of this huge operational problem.

This risk-centric paradigm finds powerful external validation in the recent strategic maneuvers within the AI industry. Meta recently signed a $14.8 billion deal with Scale AI, a company specializing in data labeling and human-led AI model refinement. According to Reuters, Scale AI now has a market valuation of nearly $14 billion. This event serves as a market-based confirmation of our central thesis. Scale AI's core business is not creating foundational models, but providing the industrial-scale HIL services required to make them safe and reliable. It is, in essence, a company that sells "error rate reduction as a service."

From the perspective of our TCO framework, the market's multi-billion-dollar valuation of this service can be understood not as speculative but as a financially rational price for certainty. Meta's cooperation acknowledges that the high cost to adopters to establish the HIL safety net is the main obstacle to these models' business viability. Within the Transaction Cost Economics (TCE) framework, these big collaborations can be thought of as complicated "make-or-buy" choices. A technology giant is paying a premium to "buy down" the single most volatile and financially significant variable in its TCO model, the error rate, λ, by outsourcing these immense and uncertain monitoring costs.

The validation of this paradigm has profound implications. For corporate governance, it demands that the board explicitly quantify its AI risk appetite. Our framework provides a financial reporting methodology that can be justified under IAS 38 for the purpose of capitalizing AI assets that are developed internally. The building of a control apparatus is the dominating cost being capitalized, which is a critical point. This observation is based on the Resource-Based View (RBV): the real, unique asset is not the AI model, but the organizational capacity to dynamically govern it. In management accounting, new measurements are needed beyond budget variance, such as tracking the observed critical error rate (λ_obs). Finally, the consistent financial superiority of the API strategy in our model is best explained through Real Options Theory (ROT). The API method is similar to having a call option on the technology, which keeps the huge financial value of management flexibility in an uncertain environment. This value is lost when the OS investment is high-cost and permanent.

6. Conclusion

This study addressed a significant issue at the convergence of technical innovation and financial management: the lack of a comprehensive framework to assess the considerable and intricate investments necessitated by generative AI. We filled this gap by creating and testing a stochastic Total Cost of Ownership (TCO) model that goes beyond simple, certain calculations and takes into account the uncertainty and many hazards that come with this new type of technology. The research sought not only to provide a practical tool for decision-makers but also to challenge the prevailing, efficiency-focused narrative surrounding the business value of AI.

6.1. Summary of contributions

This research makes three distinct contributions to the theory and practice of technology management, accounting, and corporate strategy.

First, it extends IT investment theory for the AI era. To evaluate generative AI, we introduce the first stochastic TCO framework that incorporates probabilistic variables. By doing so, our model moves beyond static analysis to provide a risk-adjusted comparison of OpEx-heavy (API) and CapEx-heavy (OS) strategies, empirically demonstrating that for GenAI, the traditional focus on production efficiencies must be replaced by a new paradigm centered on the agency costs of monitoring and control.

Second, it contributes to the accounting literature on intangible assets. We provide a rigorous and defensible methodology for applying IAS 38 to internally generated AI assets. By explicitly modeling the costs of data acquisition, model training, and the creation of control systems, we offer a practical pathway to move the valuation of these assets from speculative to auditable, addressing a critical gap in financial reporting for the digital economy (Leitner-Hanetseder and Lehner, 2023; Moro-Visconti, 2024).

In addition, a fundamental paradigm shift is validated through the strategic management of AI adoption. Our findings provide the formal financial logic for why the "economics of speed" must give way to the "economics of trust and control." We prove that corporate governance, risk management, and the development of control-oriented dynamic capabilities—not just the pursuit of productivity—are the primary and quantifiable levers for creating sustainable value from generative AI.

6.2. Limitations of the research

As with any modeling-based research, this study has limitations that present opportunities for future work. To begin, the reliability of the model's predictions relies on the precision of the parameters used to create them. Despite our use of PERT distributions for uncertainty management, the framework's usefulness depends on an organization's capacity to provide accurate estimates for critical variables, especially the cost per critical error (P), which is not always easy to measure in advance. Second, our TCO model is, by design, focused on the cost side of the equation. It does not explicitly model potential revenue generation, strategic differentiation, or other second-order network effects that might arise from adopting one AI strategy over another. Finally, the analysis does not incorporate the complex tax implications of capitalizing and amortizing intangible assets, which would vary significantly across jurisdictions.

6.3. Avenues for future research

The constraints of this study inherently indicate numerous potential directions for subsequent research. The next stage is to test the framework in real life by doing in-depth case studies with companies that are currently working on big AI projects. This kind of research could improve the model's parameters and show that its results are useful in the real world. A second useful addition would be to include the TCO model in a larger valuation framework, like a real options analysis or a Discounted Cash Flow (DCF) model, to take into account the strategic and revenue worth of AI. Lastly, more study is needed in the fields of accounting and law to develop standard rules for how to audit, report on, and tax these new AI-based intangible assets. Our framework gives a basic vocabulary for this area.

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