

# Research Questions 4 & 5: Market Structure and Sustainability

## Research Question 4: Market Structure & Competitive Dynamics

What impact does the pricing model have on market concentration, barriers to entry for competitors, and the distribution of value between different stakeholder groups?

### Executive Summary

Per-token pricing in AI LLM markets interacts with network effects, economies of scale, and vertical integration to shape **market structure**. Evidence suggests that while **data and compute access** create barriers to entry, these are **surmountable** through partnerships and open-source alternatives<sup>[1] [2] [3] [4]</sup>. However, **pricing opacity** and **lock-in effects** contribute to **market concentration** by creating **information advantages** and **switching costs** that benefit incumbents<sup>[5] [6] [7]</sup>.

### Network Effects & Market Concentration

#### 1. Traditional Network Effects Theory

Network effects occur when a product becomes **more valuable as more people use it**<sup>[8] [6] [9]</sup>. Classic examples include:

- **Direct network effects:** Telephone networks (more users = more people to call)
- **Indirect network effects:** Operating systems (more users → more apps → more value)

Research shows network effects are **traditionally linked to**:

- **High market concentration** (winner-take-most dynamics)
- **Early-mover advantages** (first to achieve scale locks in users)
- **Barriers to entry** (new entrants cannot match incumbent's network value)<sup>[6] [7]</sup>

#### 2. AI LLM Market Characteristics

Do AI LLM markets exhibit strong network effects?

**Limited Direct Network Effects:** Unlike social networks, my use of GPT-4 doesn't make it more valuable to you. There are no "network externalities" between end-users.

#### Potential Indirect Effects:

- **Data flywheel:** More users → more usage data → better fine-tuning → better models → more users
- **Complementary services:** More users → more third-party tools → more ecosystem value

- **Talent attraction:** Market leaders attract better researchers → better models → market dominance [6] [1] [9]

However, research on AI markets suggests **data is NOT a significant barrier**:

- "Superior algorithms and preferred user experiences remain a far more significant competitive advantage than access to data" [3]
- "Continued and successful market entry by a range of firms... indicates a **fiercely competitive** and rapidly evolving generative AI and LLM market" [3]
- Top-performing models are frequently **newly launched or recently updated**, indicating that "training data cost or scarcity has **not been a barrier** to entry or innovation" [3]

### 3. Empirical Evidence: Cryptoasset Market Concentration

Research on token-based markets (cryptocurrencies) provides insights into concentration dynamics:

- Despite "fair launch" allocation mechanisms, **concentration persistently occurs** [10] [11]
- The "disease is **endogenous**"—concentration stems from **tokens' tradability**, not initial distribution [10] [11]
- Network effects **do exist** in crypto markets but **don't guarantee dominance**—Bitcoin's early-mover advantage is challenged by newer protocols [6] [7]

**Application to AI Token Pricing:** Even with "fair" pricing (same per-token rate for all users), **concentration can emerge** through:

- **Volume discounts** (large users pay less per token → economies of scale advantage)
- **Committed-use contracts** (enterprise customers lock in better rates → SMBs disadvantaged)
- **Information advantages** (sophisticated users optimize costs, naive users overpay) [12] [13]

## Barriers to Entry Analysis

### 1. Traditional Barriers in AI Markets

Concerns about AI market barriers focus on:

- **Data access:** Large datasets required for training [1] [2]
- **Compute resources:** Expensive GPU clusters for training and inference [1] [2] [3]
- **Talent:** Scarce AI researchers and engineers [1] [4]

### 2. Empirical Assessment: Barriers Are Declining

Recent analysis challenges these concerns:

**Data Access:** "There are several ways that new entrants can obtain data or the means of constructing datasets when entering generative AI markets" [3], including:

- **Web scraping** (publicly available data)
- **Licensed datasets** (commercial data providers)
- **Open-source datasets** (community contributions)

- **Synthetic data generation** (AI-generated training data)<sup>[3]</sup>

**Compute Access:** "New entrants can access capital funding through private and public markets"—independent LLM developers raise **hundreds of millions** or even **multibillion dollars** through institutional investors and venture capitalists<sup>[3]</sup>. Cloud providers offer on-demand compute, eliminating upfront infrastructure investment.

**Talent:** The **600% increase in AI companies** in the UK over the past decade provides empirical evidence of lowering barriers<sup>[4]</sup>. If talent were a binding constraint, this explosion of entrants would not be possible.

### 3. Partnership Models Reshape Entry Dynamics

Rather than vertical integration creating barriers, **partnerships** enable new entrants:

- **Amazon/Anthropic**: Cloud infrastructure provider partners with LLM developer
- **Microsoft/OpenAI**: Similar strategic partnership model
- Partnerships foster "**exchange of capital investment, cloud storage, access to computing power, and other resources**"<sup>[3]</sup>

This creates a **disaggregated industry structure** where firms can enter by specializing (e.g., model development) without controlling the entire stack (infrastructure + models + applications)<sup>[1] [4]</sup>.

### 4. Open-Source as Competitive Force

Open-source models (LLaMA, Mistral, DeepSeek) provide:

- **Transparency and adaptability** (vs. proprietary black boxes)<sup>[14]</sup>
- **Cost-effectiveness** (no API fees for self-hosting)<sup>[15] [3]</sup>
- **Customization** (fine-tune for specific domains)<sup>[14]</sup>

Research indicates "companies would have to spend **3.5 times more** if there were no open-source software," and "smaller companies, in particular, **use open-source AI more frequently** than larger ones"<sup>[15]</sup>. This suggests open-source **lowers barriers** and **increases competition**.

## Pricing Model Effects on Market Structure

### 1. Token Pricing as Competitive Baseline

Token-based pricing has become the **industry standard** for foundation model APIs:

- **OpenAI**: \$0.03/\$0.06 per 1K tokens (GPT-4o input/output)<sup>[16] [17]</sup>
- **Anthropic**: \$3/\$15 per 1M tokens (Claude 3.5 Sonnet)<sup>[16] [17]</sup>
- **Google**: Competitive per-token rates for Gemini<sup>[16]</sup>

This **standardized approach** facilitates **price comparison** (all else equal), potentially **increasing competition** by making switching easier.

### 2. However: Opacity Undermines Comparison

As established in RQ1, **per-token price is misleading** because:

- **Tokens per task varies** dramatically across providers [18] [19] [20] [21]
- **Tokenization algorithms differ** (same text = different token counts) [20] [21]
- **Quality/capability differences** make direct price comparison impossible [14] [16]

This **restores information asymmetry**, reducing effective competition despite nominal price transparency.

### 3. Lock-In Through Pricing Complexity

Research on platform competition shows that **switching costs** created by pricing models affect market structure:

- When switching costs are **high**, platforms can **exploit** locked-in users through price increases<sup>[5]</sup> [22] [23]
- **Proprietary metrics** (provider-specific tokenization) create incomparability → switching costs → market power [20] [21]
- **Volume commitments** require long-term contracts → lock-in → reduced competition [13]

### 4. Two-Sided Market Dynamics

AI platforms exhibit **two-sided market** characteristics:

- **Side 1**: End-users (enterprises, developers, consumers)
- **Side 2**: Complementors (third-party app developers, tool builders)

Research on two-sided markets demonstrates that pricing strategies must balance **both sides**:

- **Subsidize** one side to attract participation (e.g., low API rates for complementors)
- **Monetize** the other side (e.g., charge end-users premium rates)
- Optimal pricing is **not** cost-based but rather reflects **cross-side externalities** [24] [25] [26] [27]

Token-based pricing, being **cost-based**, may **fail to optimize** two-sided markets—it doesn't strategically price to balance ecosystem participation [24] [25].

## Value Distribution Across Stakeholders

### 1. Provider Capture vs. User Surplus

Under perfect competition, **consumer surplus** (value received minus price paid) is maximized. Under monopoly, providers capture this surplus through higher prices.

Token pricing affects value distribution:

- **Sophisticated users** (who optimize consumption) retain more surplus
- **Naive users** (who don't optimize) transfer surplus to providers [12]
- **High-value users** (deriving large business benefits) retain excessive surplus (underpaying relative to value) [28] [29]

This creates **inefficient value distribution**—not aligned with social welfare maximization [12] [28].

## 2. Complementor Value Capture

Research on platform ecosystems shows that **pricing to complementors** (API rates for third-party developers) affects value distribution:

- **High API prices** → Providers capture value, complementors struggle to profit → limited ecosystem
- **Low API prices** → Complementors capture value, ecosystem thrives, but platform foregoes revenue [8] [30]

Optimal strategy depends on **ecosystem multiplier**:

- If complementors create **10x value** (through apps, integrations, tools), provider should price low to enable ecosystem
- If complementors create **1.2x value**, provider should price high to capture direct value [8] [30]

## 3. End-User Value Distribution

Research on distributive justice in algorithmic decision-making emphasizes that **fair outcomes** require consideration of multiple principles:

- **Equality**: Equal treatment absent justification for differentiation
- **Desert**: Rewards proportional to contribution
- **Need**: Prioritize those with greater need
- **Efficiency**: Maximize total welfare [31] [32] [33]

Token pricing achieves **formal equality** (same per-token rate) but fails on:

- **Desert**: No alignment between payment and value created
- **Need**: No accommodation for users with high social value but low ability to pay (nonprofits, educators)
- **Efficiency**: Information asymmetries prevent welfare-maximizing allocation [31] [32] [33]

## Research Question 5: Long-Term Sustainability & Systemic Risks

**What are the long-term implications of the pricing model for provider viability, infrastructure investment, resource allocation efficiency, and systemic risks?**

### Executive Summary

Per-token pricing creates **long-term sustainability challenges** across multiple dimensions: (1) **revenue unpredictability** undermines business planning, (2) **infrastructure investment incentives** may be misaligned, (3) **environmental costs** are externalized, and (4) **access inequality** is exacerbated. These systemic risks threaten the **long-term viability** of usage-based pricing models in AI services.

## Provider Revenue Stability

### 1. Forecasting Challenges

Research on usage-based pricing identifies **revenue predictability** as a major challenge:

- "**Forecasting** variable costs is inherently difficult" for CFOs [34]
- "**Revenue recognition**, especially for public companies, can be tricky, requiring **real-time data pipelines** and precise accounting controls" [34]
- Budgeting becomes "a **headache**" when usage fluctuates unpredictably [34]

### 2. Customer Churn Risk

Unpredictable bills lead to churn:

- "**Unpredictable bills can lead to customer churn** if the perceived value doesn't match the cost" [34]
- "**Bill shock**" generates disproportionate negative sentiment despite initial pricing appeal [35] [36] [37]
- Users experiencing unexpected costs are likely to **cancel** or **switch** to competitors with more predictable pricing [34]

### 3. Mitigation Strategies

Providers address instability through:

- **Committed-use discounts**: Customers commit to annual volume, creating predictable revenue floor [13]
- **Prepaid credits**: Upfront payment improves cash flow and reduces churn risk [13] [34]
- **Usage caps & alerts**: Prevent extreme bill shock that drives cancellations [35] [36]

## Infrastructure Investment Dynamics

### 1. Capacity Planning Under Uncertainty

Token-based demand is **highly variable**:

- **Viral adoption** of new capabilities (e.g., ChatGPT launch) creates **demand spikes**
- **Seasonal patterns** (e.g., enterprises reducing usage during holidays)
- **Competitive dynamics** (users shift to competitors after price increases) [15] [38]

This variability creates **infrastructure challenges**:

- **Over-provisioning** (excess capacity to handle peaks) → Higher costs, lower profitability
- **Under-provisioning** (insufficient capacity) → Service degradation, customer dissatisfaction [39] [38]

### 2. Energy Infrastructure Constraints

Research on digital infrastructure sustainability reveals **critical bottlenecks**:

**Energy Costs:** "40-60% of OPEX" for AI infrastructure is energy costs<sup>[38]</sup>. This creates:

- **Pricing pressure** to pass energy costs to customers
- **Dependence** on energy infrastructure that may not scale at required pace
- **Regulatory risk** (governments restrict data center expansion due to grid constraints)<sup>[38]</sup>

**Government Constraints:** "Singapore increased sustainability standards. They said **no more investments in data centers** unless the DC meets certain minimum requirements"<sup>[38]</sup>. Similar constraints emerging globally as energy demands grow.

**Green Energy Challenges:** "Utilities (providers) are faced with the need to **green the grid** because governments have made commitments to reduce CO2 emissions"<sup>[38]</sup>. This creates **triple pressure**:

- Provide **additional power** for AI infrastructure
- Ensure this power is **green** (renewable)
- Adapt to **intermittent renewable energy** (solar/wind variability)<sup>[38]</sup>

### 3. Pricing Models for Sustainability

Research on infrastructure investment pricing explores alternatives:

- **Carbon pricing** embedded in infrastructure costs (make environmental impact visible)<sup>[40] [41]</sup>
- **Differentiated pricing** for green vs. non-green energy consumption<sup>[41] [38]</sup>
- **Time-of-use pricing** to shift demand to renewable energy availability windows<sup>[38]</sup>

None of these are well-integrated into current token-based pricing models, creating **externalities** where environmental costs are borne by society rather than users<sup>[41]</sup>.

## Access Inequality & Digital Divide

### 1. Structural Barriers to Access

Research on digital divide and pricing models reveals **profound inequalities**:

**Language Barriers:** As established in RQ1, **tokenization inefficiencies** create 5-25x cost differences for non-English languages<sup>[20] [21]</sup>. This **systematically disadvantages** non-English speakers and exacerbates global inequality.

**Income-Based Barriers:** Research on bridging the digital divide demonstrates that making access **affordable** for low-income populations requires dramatic price reductions:

- In **Mexico**, providing ICT access to the poorest 20% would require reducing prices to **13% of current levels** (from \$244/year to \$35/year)
- In **Brazil**, the poorest 20% can afford only **\$9 per year** (\$0.75/month), requiring prices to drop to **4% of current levels**<sup>[42]</sup>

Alternatively, **subsidies** equivalent to **6.2% of GDP** (Uruguay example)—equal to total public spending on education + health—would be required<sup>[42]</sup>.

### 2. Implications for AI Access

If AI services are priced via **usage-based tokens**:

- **High-income users/countries** can afford extensive usage → Derive compounding benefits (productivity, learning, competitive advantages)
- **Low-income users/countries** are priced out or severely limited → Fall further behind
- **Digital divide** is **exacerbated** rather than mitigated<sup>[43] [42] [44]</sup>

### 3. Policy Interventions

Research on addressing digital inequality identifies several approaches:

#### Tiered Pricing by Segment:

- **Educational discounts** (students, teachers, researchers)
- **Nonprofit pricing** (subsidized rates for social-benefit use cases)
- **Geographic discounts** (adjusted for purchasing power parity)<sup>[43]</sup>

#### Public Sector Provision:

- **Government-funded AI access** for public services (education, healthcare)
- **Public-private partnerships** to subsidize access for underserved populations<sup>[45] [43]</sup>

#### Universal Service Obligations:

- Analogous to telecom universal service requirements
- Providers must offer **affordable basic tier** as condition of market participation<sup>[43] [44]</sup>

Currently, **none of these** are systematically implemented in AI token pricing, creating **systemic access inequality**.

## Systemic Risks & Market Stability

### 1. Boom-Bust Cycles

Usage-based pricing can **amplify economic cycles**:

- **Boom periods**: Enterprises increase AI usage aggressively → Provider revenue surges → Over-investment in capacity
- **Bust periods**: Budget cuts → Sudden usage collapse → Provider revenue crashes → Infrastructure stranded<sup>[34]</sup>

This creates **volatility** that threatens long-term sustainability of business models built on usage-based revenue<sup>[34]</sup>.

### 2. Competitive Instability

**Price wars** in token-based markets:

- Per-token prices have dropped **dramatically** (€36 to €0.07 per million tokens)<sup>[15]</sup>
- This **30-fold decrease** creates **margin pressure** for all providers

- Some providers may **exit** (cannot sustain profitability at current prices)
- Market **concentration** may increase as weaker players fail [15]

**Race to the bottom:** If competition focuses on **per-token price** (ignoring tokens-per-task), providers compete on a **misleading metric**, potentially destroying value [18] [19] [15].

### 3. Environmental Sustainability

**Energy consumption** of AI models is **growing exponentially**:

- Larger models consume more energy per inference
- More users generate more inferences
- **Rebound effect:** As prices fall, usage increases, potentially **offsetting** efficiency gains [15] [41]

Research on digital infrastructure sustainability emphasizes:

- **Embedding carbon costs** in pricing to internalize externalities [41]
- **Circular economy approaches** (extending hardware lifecycles, refurbishment) [41]
- **Renewable energy procurement** directly by data center operators (not just grid reliance) [38]

Current token pricing **externalizes** these costs—users don't see or pay for environmental impact, creating **unsustainable consumption patterns** [41].

## Recommendations for Long-Term Sustainability

### 1. Hybrid Revenue Models

Combine **predictable base** (subscriptions, committed-use) with **variable component** (usage-based) to:

- Stabilize provider revenue (enable infrastructure investment planning)
- Maintain fairness (users pay for what they use beyond base)
- Reduce churn (predictability improves customer satisfaction) [13] [34]

### 2. Infrastructure Investment Frameworks

**Public-private partnerships** for infrastructure:

- Shared investment in energy infrastructure (renewables + grid capacity)
- Risk-sharing between providers, cloud platforms, and governments
- Long-term contracts enabling financing of sustainable infrastructure [46] [47] [38]

### 3. Equity-Focused Pricing

**Differential pricing** that reflects social value:

- **Cost-based pricing** for commercial users (token-based or outcome-based)
- **Subsidized pricing** for educational, nonprofit, public-sector users

- **Language-normalized pricing** (same cost for equivalent outcomes regardless of tokenization efficiency) [43] [20] [31]

#### 4. Environmental Pricing

**Carbon-adjusted pricing:**

- **Display carbon footprint** alongside token costs
- **Offer green premium tier** (guaranteed renewable energy, higher price)
- **Incentivize efficiency** through carbon pricing (more efficient models cost less due to lower carbon footprint) [41] [38]

#### 5. Regulatory Frameworks

**Sustainability standards:**

- **Mandatory disclosure** of energy consumption per token
- **Carbon reporting** requirements for AI providers
- **Infrastructure efficiency benchmarks** (minimum PUE—Power Usage Effectiveness—standards) [41] [38]

**Access equity requirements:**

- **Universal service obligations** (affordable basic tier)
- **Language fairness audits** (ensure tokenization doesn't create structural discrimination)
- **Geographic equity** (adjust pricing for purchasing power parity) [43] [20] [31]

### Conclusion

**Market Structure:** Token-based pricing interacts with network effects and switching costs to create **moderate concentration** but not insurmountable barriers. **Open-source alternatives** and **partnership models** enable competitive entry, but **pricing opacity** and **lock-in** create incumbent advantages [5] [6] [3].

**Sustainability Risks:**

- **Revenue unpredictability** undermines provider viability and infrastructure investment [34]
- **Energy constraints** create bottlenecks that may limit growth [38]
- **Access inequality** is exacerbated by usage-based pricing without equity mechanisms [43] [42] [20]
- **Environmental externalities** are not priced in, creating unsustainable consumption patterns [41]

**Path Forward:** Sustainable pricing models must:

1. **Stabilize revenue** through hybrid approaches [13]
2. **Internalize environmental costs** through carbon pricing [41]
3. **Address access equity** through differential pricing and subsidies [43] [31]
4. **Enable infrastructure investment** through long-term contracts and partnerships [47] [38]

Current token-based pricing largely **fails** these sustainability criteria, suggesting that without significant evolution, the model may prove **unsustainable** in the long run.

## References

Citations embedded throughout using bracketed numbers corresponding to source IDs.

[48] [49] [50] [51] [52] [53] [54] [55] [56] [57] [58] [59] [60] [61] [62] [63] [64] [65] [66] [67] [68] [69] [70] [71] [72] [73] [74] [75] [76] [77] [78] [79] [80] [81] [82] [83] [84] [85] [86] [87] [88] [89] [90] [91] [92] [93] [94] [95] [96] [97] [98] [99] [100] [101] [102] [103] [104] [105] [106] [107] [108] [109] [110] [111] [112] [113] [114] [115] [116] [117] [118] [119] [120] [121] [122] [123] [124] [125] [126] [127] [128] [129] [130] [131] [132] [133] [134] [135] [136] [137] [138] [139] [140] [141] [142] [143] [144] [145] [146] [147] [148] [149] [150] [151] [152] [153] [154] [155] [156] [157] [158] [159] [160] [161] [162] [163] [164] [165] [166] [167] [168] [169] [170] [171] [172] [173] [174] [175] [176] [177] [178] [179] [180] [181] [182] [183] [184] [185] [186] [187] [188] [189] [190] [191] [192] [193] [194] [195] [196] [197] [198] [199] [200] [201] [202] [203] [204] [205] [206] [207] [208] [209] [210] [211]

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1. <https://skywork.ai/skypage/en/Technical-Barriers-to-Entry:-Challenges-in-North-American-AI-Model-Localization-and-Implementation/1950070050110914560>
2. <https://competition-bureau.canada.ca/en/how-we-foster-competition/education-and-outreach/consultation-artificial-intelligence-and-competition-what-we-heard>
3. <https://www.mercatus.org/research/working-papers/data-really-barrier-entry-rethinking-competition-regulation-generative-ai>
4. <https://www.linkedin.com/pulse/global-ai-ilm-market-critical-analysis-through-five-uvwxyzyn-ph-d--is3dc>
5. <https://onlinelibrary.wiley.com/doi/10.1111/jems.12612>
6. <http://ledger.pitt.edu/ojs/ledger/article/download/226/214>
7. <https://arxiv.org/pdf/2101.06210.pdf>
8. <https://pubsonline.informs.org/doi/10.1287/mnsc.2023.4917>
9. <https://www.nfx.com/post/network-effects-manual>
10. <https://arxiv.org/pdf/2208.10271.pdf>
11. <https://dl.acm.org/doi/pdf/10.1145/3649318>
12. <https://www.tandfonline.com/doi/full/10.1080/01605682.2023.2269212>
13. <https://stripe.com/resources/more/token-pricing-how-it-works-and-how-to-make-the-most-of-it>
14. <https://ieeexplore.ieee.org/document/11170906/>
15. <https://www.fiegenbaum.solutions/en/blog/dramatic-drop-ai-token-prices-opportunities-challenges-sustainability>
16. <https://www.solvimon.com/pricing-guides/openai-versus-anthropic>
17. <https://www.aipricingcomparison.com/text-generation-api-pricing-calculator>
18. <https://www.ikangai.com/the-ilm-cost-paradox-how-cheaper-ai-models-are-breaking-budgets/>
19. <https://www.finops.org/wg/genai-finops-how-token-pricing-really-works/>
20. <https://arxiv.org/pdf/2305.13707.pdf>
21. <https://aclanthology.org/2023.emnlp-main.614.pdf>
22. <https://www.sciencedirect.com/science/article/abs/pii/S1059056022003112>
23. [https://conference.iza.org/DATA\\_2022/stenzhorn\\_e32647.pdf](https://conference.iza.org/DATA_2022/stenzhorn_e32647.pdf)
24. <https://dl.acm.org/doi/fullHtml/10.1145/3497701.3497733>

25. [https://en.wikipedia.org/wiki/Two-sided\\_market](https://en.wikipedia.org/wiki/Two-sided_market)
26. <https://competitionpolicyinternational.com/assets/Uploads/Autumn2014Schmalensee.pdf>
27. <https://academic.oup.com/jeea/article-pdf/1/4/990/10312916/jeea0990.pdf>
28. <https://sevenfigureagency.com/implementing-value-based-pricing-in-digital-agencies/>
29. <https://www.ibbaka.com/ibbaka-market-blog/pricing-patterns-for-generative-ai>
30. <https://www.getmonetizely.com/articles/how-to-design-effective-pricing-models-for-network-effects-and-platform-businesses>
31. <https://www.nature.com/articles/s41598-022-19792-3>
32. <https://www.frontiersin.org/journals/sociology/articles/10.3389/fsoc.2022.883999/full>
33. <https://onlinelibrary.wiley.com/doi/abs/10.1111/poms.13369>
34. <https://flexprice.io/blog/why-ai-companies-have-adopted-usage-based-pricing>
35. <https://stripe.com/resources/more/pricing-flexibility-in-ai-services>
36. <https://schematichq.com/blog/why-usage-based-billing-is-taking-over-saas>
37. <https://www.younium.com/blog/usage-based-pricing>
38. [https://www.ey.com/en\\_sg/media/podcasts/moneymultiple/2025/06/unlocking-value-in-growing-digital-infrastructure](https://www.ey.com/en_sg/media/podcasts/moneymultiple/2025/06/unlocking-value-in-growing-digital-infrastructure)
39. <https://www.tandfonline.com/doi/full/10.1080/13241583.2024.2393933>
40. <https://www.mdpi.com/1911-8074/17/4/133/pdf?version=1711119244>
41. <https://www.pwc.com/gx/en/industries/tmt/digital-infrastructures-defining-moment-on-climate.html>
42. [https://martinhilbert.net/CheapEnoughWD\\_Hilbert\\_pre-print.pdf](https://martinhilbert.net/CheapEnoughWD_Hilbert_pre-print.pdf)
43. <https://ctu.ieee.org/blog/2023/02/03/solutions-to-the-digital-divide-moving-toward-a-more-equitable-future/>
44. <https://www.brookings.edu/articles/fixing-the-global-digital-divide-and-digital-access-gap/>
45. <https://www.multiresearchjournal.com/arclist/list-2024.4.6/id-4262>
46. <https://www.mdpi.com/2071-1050/13/16/8996>
47. <https://www.adb.org/sites/default/files/publication/939786/source-multilateral-platform-sustainable-infrastructure.pdf>
48. <http://www.emerald.com/jeim/article/36/6/1533-1555/205340>
49. <https://onlinelibrary.wiley.com/doi/10.1002/mde.4472>
50. <https://www.frontiersin.org/articles/10.3389/fmars.2025.1601322/full>
51. <https://arxiv.org/abs/2410.13090>
52. <https://www.mdpi.com/0718-1876/19/2/61>
53. <https://www.frontiersin.org/articles/10.3389/fphy.2021.631659/pdf>
54. <https://arxiv.org/pdf/2307.16874.pdf>
55. <https://www.rairo-ro.org/articles/ro/pdf/2022/01/ro210226.pdf>
56. [https://backend.orbit.dtu.dk/ws/files/290548890/2022\\_TMG\\_PartC\\_1\\_.pdf](https://backend.orbit.dtu.dk/ws/files/290548890/2022_TMG_PartC_1_.pdf)
57. <https://arxiv.org/pdf/2410.19107.pdf>
58. [https://papers.ssrn.com/sol3/Delivery.cfm/SSRN\\_ID4437801\\_code2617082.pdf?abstractid=3613261&mirid=1](https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID4437801_code2617082.pdf?abstractid=3613261&mirid=1)
59. <https://www.sciencedirect.com/science/article/abs/pii/S0304405X23000715>
60. <http://arxiv.org/pdf/2502.16363.pdf>

61. <https://ieeexplore.ieee.org/document/10172155/>
62. <https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2023&issue=027>
63. <https://ieeexplore.ieee.org/document/10380440/>
64. <https://ijsab.com/volume-32-issue-1/6438>
65. <https://www.mdpi.com/2071-1050/13/17/9762/pdf>
66. <https://www.frontiersin.org/articles/10.3389/fgwh.2022.696529/full>
67. [https://jaesj.journals.ekb.eg/article\\_398940.html](https://jaesj.journals.ekb.eg/article_398940.html)
68. <https://www.mdpi.com/1911-8074/17/4/133>
69. <https://fepbl.com/index.php/csitrj/article/view/577>
70. <https://www.mdpi.com/2071-1050/13/16/8996/pdf>
71. <https://www.mdpi.com/2071-1050/12/1/49>
72. <https://www.mdpi.com/2079-9292/5/4/65/pdf?version=1475056683>
73. <https://www.frontiersin.org/articles/10.3389/fpsyg.2022.821979/pdf>
74. <https://arxiv.org/pdf/2208.04710.pdf>
75. <https://www.mdpi.com/2071-1050/12/9/3893/pdf>
76. <https://www.bci.ca/adapting-risk-models-for-todays-infrastructure-investment-opportunities/>
77. <https://www.prompts.ai/en/blog/managing-token-level-costs-ai>
78. <https://daijobu.ai/2025/05/19/millions-of-tokens-the-invisible-unit-of-measurement-shaping-modern-ai/>
79. <https://www.getmonetizely.com/articles/should-your-ai-agent-use-token-based-or-subscription-pricing>
80. <https://arxiv.org/pdf/2402.09697.pdf>
81. <https://premierscience.com/wp-content/uploads/2024/11/pjcs-24-356-.pdf>
82. <https://www.sciencedirect.com/science/article/pii/S0148296323001157>
83. <https://www.linkedin.com/pulse/provisioned-capacity-ai-beginners-guide-dedicated-vs-asaf-liveanu-i1mhe>
84. <https://www.semanticscholar.org/paper/cef1b80bd30d8c31beb37bc73cf1f15a37962008>
85. <https://ieeexplore.ieee.org/document/10825591/>
86. <https://academic.oup.com/jamiaopen/article/doi/10.1093/jamiaopen/ooaf055/8161131>
87. <https://arxiv.org/abs/2508.19008>
88. <https://mededu.jmir.org/2025/1/e67244>
89. <https://www.mdpi.com/0718-1876/17/4/63/pdf?version=1664164923>
90. <https://ej-ai.org/index.php/ejai/article/view/82>
91. <https://www.cureus.com/articles/350635-preparing-for-vascular-surgery-board-certification-a-comparative-study-using-large-language-models>
92. <https://theaspd.com/index.php/ijes/article/view/10923>
93. [https://ascopubs.org/doi/10.1200/JCO.2025.43.16\\_suppl.e21598](https://ascopubs.org/doi/10.1200/JCO.2025.43.16_suppl.e21598)
94. <http://arxiv.org/pdf/2503.18129.pdf>
95. <https://arxiv.org/pdf/2502.07736.pdf>
96. <https://arxiv.org/html/2410.17950>
97. <https://arxiv.org/pdf/2407.10834.pdf>
98. <https://arxiv.org/pdf/2402.11754.pdf>

99. <http://arxiv.org/pdf/2406.06565.pdf>
100. <https://arxiv.org/pdf/2409.01666.pdf>
101. [https://www.econtribute.de/RePEc/ajk/ajkdps/ECONtribute\\_258\\_2023.pdf](https://www.econtribute.de/RePEc/ajk/ajkdps/ECONtribute_258_2023.pdf)
102. [https://www.econstor.eu/bitstream/10419/171619/1/wp-13-176\\_rev.pdf](https://www.econstor.eu/bitstream/10419/171619/1/wp-13-176_rev.pdf)
103. <https://anotherwrapper.com/tools/llm-pricing>
104. <https://www.hec.ca/finance/Fichier/Mimra2013.pdf>
105. <https://arxiv.org/abs/2403.06150>
106. <https://langtail.com/llm-price-comparison>
107. <https://www.sciencedirect.com/science/article/pii/S0899825623000726>
108. <https://jurnal.unikal.ac.id/index.php/hk/article/view/3664>
109. <https://arxiv.org/abs/2509.06069>
110. <https://www.tandfonline.com/doi/full/10.1080/09537325.2022.2088342>
111. <https://link.springer.com/10.1007/s10479-021-04036-w>
112. <https://www.tandfonline.com/doi/full/10.1080/07421222.2023.2229122>
113. <https://www.ssrn.com/abstract=5218518>
114. <https://breached.company/red-sea-cable-cuts-the-hidden-crisis-threatening-global-internet-infrastructure/>
115. <https://journals.sagepub.com/doi/10.1177/1059147824130533>
116. <https://journal.uinjkt.ac.id/index.php/etikonomi/article/view/33892>
117. <https://www.semanticscholar.org/paper/f61fed43aa07694fa1df0a4ead140ed1ac39a4bf>
118. <https://www.semanticscholar.org/paper/e7fbad668e5b950d901cf706b8b300b2a28958c6>
119. <http://arxiv.org/pdf/1007.4586.pdf>
120. <https://linkinghub.elsevier.com/retrieve/pii/S0148296322005689>
121. <https://arxiv.org/pdf/1904.05656.pdf>
122. <http://www.scholink.org/ojs/index.php/ibes/article/download/4410/4994>
123. <https://arxiv.org/pdf/2303.13295.pdf>
124. [https://nottingham-repository.worktribe.com/preview/943810/Cred\\_SubEval\\_EJ-Style.pdf](https://nottingham-repository.worktribe.com/preview/943810/Cred_SubEval_EJ-Style.pdf)
125. <https://link.springer.com/10.1007/s10257-025-00702-9>
126. <https://downloads.hindawi.com/journals/jam/2023/4456931.pdf>
127. [https://aisel.aisnet.org/ecis2018\\_rp/147/](https://aisel.aisnet.org/ecis2018_rp/147/)
128. <https://conjointly.com/blog/willingness-to-pay/>
129. <https://journals.sagepub.com/doi/10.1177/20539517211069632>
130. <https://www.econstor.eu/bitstream/10419/238225/1/2020-01.pdf>
131. <https://www.quantilope.com/resources/how-to-conduct-pricing-research-using-conjoint-analysis>
132. [https://pure.mpg.de/pubman/item/item\\_3031522\\_6/component/file\\_3501197/2019\\_03online.pdf](https://pure.mpg.de/pubman/item/item_3031522_6/component/file_3501197/2019_03online.pdf)
133. <https://www.productfocus.com/willingness-to-pay-the-hidden-engine-behind-effective-pricing/>
134. <https://arxiv.org/pdf/2105.01441.pdf>
135. <https://labs.adaline.ai/p/token-burnout-why-ai-costs-are-climbing>
136. <https://kinde.com/learn/billing/billing-for-ai/ai-token-pricing-optimization-dynamic-cost-management-for-llm-power-red-saas/>

137. <https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2022.821979/full>
138. <https://www.abacademies.org/articles/pricing-strategies-in-a-digital-economy-a-microeconomic-perspective-17498.html>
139. <https://www.sciencedirect.com/science/article/abs/pii/S0377221724006362>
140. <https://www.getmonetizely.com/articles/understanding-token-based-pricing-for-agentic-ai-systems-a-new-paradigm-in-ai-economics>
141. [https://papers.ssrn.com/sol3/Delivery.cfm/SSRN\\_ID3358724\\_code2714802.pdf?abstractid=3108333&mirid=1&type=2](https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID3358724_code2714802.pdf?abstractid=3108333&mirid=1&type=2)
142. <https://instituteofinterneteconomics.org/behavioral-economics-of-subscription-pricing/>
143. <https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-025-12321-8>
144. <https://psychotricks.com/bounded-rationality/>
145. <https://www.tamarly.ai/blog-2-1/melvines-ai-analysis-12-understanding-tokens-and-the-costs-of-large-language-models-langs-for-enterprises>
146. <https://www.sciencedirect.com/science/article/abs/pii/S0925527321001225>
147. <https://ijsi.in/wp-content/uploads/2025/07/18.02.024.20251003.pdf>
148. <https://thedecisionlab.com/biases/bounded-rationality>
149. <https://cloudwars.com/ai/enterprise-ai-minute/breaking-down-token-based-pricing-for-generative-ai-large-language-models-langs/>
150. <https://www.investopedia.com/terms/a/asymmetricinformation.asp>
151. <https://ojs.apspublisher.com/index.php/amit/article/download/391/300/769>
152. <https://www.renascence.io/journal/bounded-rationality-customers-simplified-decision-making-processes>
153. <https://www.mdpi.com/0718-1876/20/3/201>
154. <http://www.emerald.com/jeim/article/34/5/1429-1451/216071>
155. <https://ieeexplore.ieee.org/document/9934060/>
156. <https://www.ijecs.in/index.php/ijecs/article/view/4447>
157. [https://noonomy-journal.ru/images/3\\_1\\_2024/3\\_1\\_10.pdf](https://noonomy-journal.ru/images/3_1_2024/3_1_10.pdf)
158. <https://www.mdpi.com/2071-1050/16/19/8545>
159. <https://ieeexplore.ieee.org/document/10502110/>
160. <https://bmchealthservres.biomedcentral.com/articles/10.1186/s12913-024-10777-8>
161. [https://link.springer.com/10.1007/978-3-031-43185-2\\_10](https://link.springer.com/10.1007/978-3-031-43185-2_10)
162. <https://journals.sagepub.com/doi/10.1177/10946705231173116>
163. <https://www.allsocialsciencejournal.com/search?q=SER-2025-3-064&search=search>
164. <http://arxiv.org/pdf/2404.00311.pdf>
165. [https://www.iiakm.org/ojakm/articles/2023/OJAKM\\_Volume11\\_2pp1-24.php](https://www.iiakm.org/ojakm/articles/2023/OJAKM_Volume11_2pp1-24.php)
166. <http://arxiv.org/pdf/1506.06648.pdf>
167. <https://journals.sagepub.com/doi/pdf/10.1177/10946705231173116>
168. <https://www.mdpi.com/2071-1050/14/19/11954/pdf?version=1663838570>
169. <http://arxiv.org/pdf/2503.21448.pdf>
170. <https://www.mdpi.com/2227-7072/6/4/87/pdf>
171. <https://www.mdpi.com/2071-1050/13/24/13701/pdf?version=1639475248>

172. <https://arxiv.org/html/2407.05484v1>
173. <https://verpex.com/blog/marketing-tips/price-discrimination-online-the-fairness-of-personalized-pricing-based-on-user-data>
174. <http://www.tandfonline.com/doi/abs/10.1080/00207543.2014.922707>
175. <https://easydigitaldownloads.com/blog/value-based-pricing-for-digital-products-and-services/>
176. <https://www.sciencedirect.com/science/article/abs/pii/S0278431924003268>
177. <https://sevenfigureagency.com/implementing-value-based-pricing-for-digital-agencies/>
178. <https://socsc.ktu.lt/index.php/Social/article/view/14247/7540>
179. <https://www.willingnesstopay.com/webinar/agentic-ai-pricing-4-of-6-ai-pricing-models---part-2-tokens-credit-systems>
180. <https://www.salesforce.com/sales/cpq/value-based-pricing/>
181. <https://journals.umcs.pl/h/article/download/1742/1357>
182. <https://www.youtube.com/watch?v=ZHIwPwAPzIA>
183. <http://mecs-press.org/ijieeb/ijieeb-v15-n3/v15n3-3.html>
184. <https://ges.jvolsu.com/index.php/en/component/attachments/download/1848>
185. <https://www.semanticscholar.org/paper/974665e62c139c842cb12359ea08e20222904f10>
186. <https://www.semanticscholar.org/paper/2875e7d26ede8bbc59a0d4bc2e187d369e72a15c>
187. <https://www.semanticscholar.org/paper/62d07091dfd8deb3f688b7599e563e04534ab415>
188. <https://journals.sagepub.com/doi/10.1016/j.ausmj.2019.07.002>
189. <https://www.emerald.com/insight/content/doi/10.1108/JIDE-08-2021-0004/full/pdf?title=the-achilles-tendon-of-dynamic-pricing-the-effect-of-consumers-fairness-preferences-on-platforms-dynamic-pricing-strategies>
190. <https://www.ccsenet.org/journal/index.php/ibr/article/download/66540/36058>
191. <https://arxiv.org/pdf/2311.00846.pdf>
192. <https://www.mdpi.com/0718-1876/18/3/60/pdf?version=1688609520>
193. <https://ejbe.org/EJBE2021Vol14No28p107-J-GOTMARE.pdf>
194. <https://asistdl.onlinelibrary.wiley.com/doi/10.1002/pra2.2015.145052010043>
195. <https://journals.sagepub.com/doi/10.1177/21582440241293304>
196. <https://www.tandfonline.com/doi/pdf/10.1080/1331677X.2020.1844587?needAccess=true>
197. <https://www.behavioraleconomics.com/mental-money-the-psychology-of-subscription-payment-options/>
198. <https://www.getmonetizely.com/articles/genai-pricing-models-from-tokens-to-outcomes>
199. <https://pmc.ncbi.nlm.nih.gov/articles/PMC10361766/>
200. <https://papers.ssrn.com/sol3/Delivery.cfm/fid/5251923.pdf?abstractid=5251923&mirid=1>
201. <https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2023.1162916/full>
202. <https://journals.sagepub.com/doi/10.3233/ISU-240230>
203. <https://techforward.io/the-token-economy-why-usage-based-ai-pricing-is-both-a-blessing-and-a-trap/>
204. <https://www.untaylored.com/post/demystifying-the-lock-in-business-model-a-comprehensive-explanation>
205. <https://bear.warrington.ufl.edu/brenner/mar7588/Papers/thaler-mktsci1985.pdf>
206. <https://www.sciencedirect.com/science/article/pii/S305070062500043X>
207. <https://www.ewadirect.com/proceedings/aemps/article/view/25070>

208. <https://onlinelibrary.wiley.com/doi/10.1002/mde.4460>
209. <https://pubsonline.informs.org/doi/10.1287/mnsc.2022.4530>
210. [https://s-lib.com/en/issues/eiu\\_2025\\_05\\_v8\\_a22/](https://s-lib.com/en/issues/eiu_2025_05_v8_a22/)
211. <https://www.mdpi.com/0718-1876/20/4/286>