Pricing Models for Agentic AI Systems: From Token-Based to Value-Based Approaches

AI-Generated Academic Thesis Showcase

Academic Thesis AI (Multi-Agent System)

January 2025

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Abstract

Research Problem and Approach: The rapid emergence of agentic AI systems and large language models (LLMs) presents a significant challenge in developing fair, transparent, and economically viable pricing models. Traditional software pricing often falls short, necessitating novel approaches that account for variable computational costs, dynamic capabilities, and profound ethical implications. This thesis investigates the evolution of AI pricing, from token-based to value-based strategies, and proposes an integrated framework for sustainable monetization.

Methodology and Findings: Employing a qualitative, theory-building approach, this research synthesizes extensive literature on AI economics, ethics, and digital monetization with conceptual comparative case studies of leading AIaaS providers. Key findings highlight the trade-offs between cost predictability, value capture, and ethical considerations across different models. The analysis reveals that hybrid pricing structures, which blend elements of usage-based, subscription, and outcome-based strategies, are most effective in balancing these competing demands.

Key Contributions: This thesis offers three primary contributions: (1) a comprehensive comparative analysis of prevailing AI pricing models, delineating their strengths, weaknesses, and applicability; (2) a novel, ethically-aware framework for designing AIaaS pricing strategies that integrate economic viability with principles of transparency, fairness, and sustainability; and (3) actionable recommendations for AI companies, policymakers, and researchers to navigate the complex landscape of AI commercialization responsibly.

Implications: The insights from this research are crucial for fostering an AI economy that is not only innovative and profitable but also equitable and trustworthy. By guiding the development of robust and ethical monetization strategies, this work helps ensure the long-term societal acceptance and widespread adoption of transformative AI technologies.

Future work should focus on empirical validation and the continuous refinement of ethical governance mechanisms.

Keywords: AI pricing, Token-based pricing, Value-based pricing, Agentic AI, Dynamic pricing, Freemium, Subscription models, Outcome-based pricing, Green AI, Data privacy, Algorithmic bias, Ethical AI, Monetization strategies, LLMs, AIaaS.

Humanized Introduction

AI has advanced rapidly, kicking off a new era of tech innovation that truly reshapes industries, economies, and societies (Korinek, 2025)(Lorente, 2025). From smart predictive analytics (Niharika et al., 2024) to self-governing decision systems, AI isn't just a futuristic idea anymore. It's a real, widespread force, driving efficiency, enabling new capabilities, and generating immense value (Fang & Zhou, 2025). But this powerful potential brings its own set of tough problems. One major issue? Figuring out how to accurately and fairly price AI-driven services and products (Kshirsagar et al., 2021). Traditional software and service models have clear pricing strategies (De, 2017)(Seufert, 2014). Yet, the emerging class of agentic AI systems poses a unique, tricky challenge. These systems—autonomous, goal-oriented, and always interacting with their surroundings—add deep complexity to how we assess value, attribute costs, and monetize ethically.

Our economy is seeing more and more AI agents. They can perform tasks with little human help, from automated customer service to tricky financial trading and even scientific breakthroughs (Korinek, 2025). These agents work on all sorts of platforms, using different resources, and often produce results tough to measure with old-school metrics (Barbere et al., 2024). Pricing these clever entities isn't just a business problem. It's a crucial academic and practical issue, touching on core economic ideas, ethical concerns, and the long-term health of the AI ecosystem (Mirghaderi et al., 2023)(Cody, 2000). Without solid, clear pricing frameworks, agentic AI systems might not be widely adopted. Value capture could stay out of reach, hindering the technology's full societal benefit.

Literature Review

The rapid advancement and widespread integration of Artificial Intelligence (AI) across various sectors have fundamentally reshaped economic landscapes, business operations, and the very nature of digital services (Korinek, 2025)(Lorente, 2025). As AI-powered services

and digital platforms become increasingly sophisticated and ubiquitous, understanding the underlying economic and business models, particularly concerning pricing, monetization, and ethical implications, becomes paramount. This literature review delves into the existing body of knowledge surrounding these critical areas, synthesizing foundational theories with contemporary applications to delineate the current state of research, identify key trends, and highlight significant gaps for future inquiry. The review begins by exploring established pricing paradigms in the digital economy, before transitioning to novel models necessitated by AI's unique characteristics, such as token-based systems. It then broadens the scope to encompass diverse monetization strategies, concluding with an examination of the pressing ethical considerations inherent in the design and implementation of AI business models.

The digital economy, characterized by its intangible assets, network effects, and low marginal costs, has long challenged traditional pricing theories (De, 2017). Early digital products often adopted subscription models or one-time purchase fees, but the rise of cloud computing and Software-as-a-Service (SaaS) ushered in an era dominated by usage-based pricing (Ladas et al., 2019). The advent of AI, particularly generative AI, has introduced further complexities, necessitating innovative pricing structures that account for computational resources, model complexity, and the perceived value generated for end-users (Barbere et al., 2024)(Satapathi, 2025). This evolution underscores a continuous adaptation of economic principles to technological shifts, where the core challenge remains balancing profitability with accessibility, fairness, and sustainability. Moreover, the integration of AI into decision-making processes, including pricing optimization, raises profound ethical questions regarding transparency, bias, and potential market manipulation (Mirghaderi et al., 2023)(Ayata, 2020). A comprehensive understanding of these interconnected facets is crucial for developing robust, equitable, and sustainable AI-powered business models. This review aims to provide such a foundation, setting the stage for a deeper exploration of these multifaceted challenges and opportunities.

Foundational Concepts in Digital Pricing Models

The digital economy operates under distinct economic principles compared to traditional markets, often characterized by zero marginal cost for replication, network effects, and the prevalence of intangible goods (De, 2017). These characteristics have necessitated the evolution of pricing models beyond simple cost-plus or competitive pricing strategies. Understanding these foundational concepts is essential before delving into the specifics of AI-powered services, as many contemporary AI pricing models are built upon or significantly adapt these established frameworks. Key among these are usage-based pricing and value-based pricing, each offering unique advantages and challenges in the context of digital and AI services.

Usage-Based Pricing: Evolution and Application

Usage-based pricing, also known as pay-per-use or consumption-based pricing, is a prevalent model in the digital economy, particularly for cloud services, APIs, and various software platforms (Ladas et al., 2019). This model charges customers based on their actual consumption of a service or resource, rather than a flat fee for access. The appeal of usage-based pricing lies in its perceived fairness and flexibility, allowing customers to pay only for what they use, which can be particularly attractive for businesses with fluctuating demand or those seeking to minimize upfront costs (Divakaruni & Navarro, 2024). The origins of usage-based pricing can be traced back to utilities like electricity and water, but its application in the digital realm gained significant traction with the rise of the internet and cloud computing (Ladas et al., 2019). Early examples include telecommunication companies charging per minute of call time or per megabyte of data used. With the proliferation of cloud infrastructure services (IaaS) and platform services (PaaS), models based on compute hours, data storage, data transfer, and API calls became standard (De, 2017). Major cloud providers such as Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure

have extensively adopted and refined usage-based pricing for their vast array of services, including machine learning capabilities (Satapathi, 2025).

The implementation of usage-based pricing in digital services typically involves metering and billing systems that accurately track customer consumption of specific metrics. These metrics can vary widely depending on the service. For instance, a cloud storage service might charge per gigabyte-month, while a computing service might charge per CPU-hour or GPU-hour (Satapathi, 2025). For API services, charges are often levied per API call or per volume of data processed through the API (De, 2017). The sophistication of these metering systems is crucial for the successful operation of usage-based models, as inaccuracies can lead to customer dissatisfaction or revenue leakage. Furthermore, providers often offer tiered pricing structures within a usage-based model, where the per-unit cost decreases as consumption increases, incentivizing higher usage and rewarding loyal customers (Satapathi, 2025). This approach allows providers to capture different segments of the market, from small-scale users to large enterprises, while maintaining profitability. The flexibility of such tiered structures allows businesses to scale their operations without incurring prohibitive fixed costs, making advanced AI services accessible to a broader range of enterprises, from startups to large corporations.

The advantages of usage-based pricing are manifold. For customers, it offers cost efficiency, scalability, and transparency regarding their expenditure relative to their actual needs (Ladas et al., 2019). This model reduces the barrier to entry for new users, as they do not need to commit to large upfront investments or long-term contracts. This "pay-as-you-go" approach democratizes access to powerful AI tools, enabling smaller entities to experiment and innovate without significant financial risk. For providers, usage-based pricing aligns revenue directly with customer value, encourages adoption, and can lead to higher customer lifetime value (CLV) as usage grows (Siddannavar et al., 2025). It also provides valuable data on customer behavior and service utilization, which can inform product development, resource allocation, and future pricing adjustments (Seufert, 2014). The continuous feedback loop

from usage patterns allows providers to optimize their infrastructure and service offerings, ensuring that resources are allocated efficiently to meet demand.

However, usage-based pricing also presents challenges. Customers may struggle to accurately predict their future usage, leading to unexpected costs or "bill shock" (Satapathi, 2025). This unpredictability can deter some users, particularly smaller businesses or individuals, who prefer fixed, predictable expenses for budget planning. Managing and communicating complex usage metrics can also be challenging for providers, requiring robust billing systems and clear documentation to ensure customer understanding and trust (Mirghaderi et al., 2023). The complexity can extend to understanding the various factors that contribute to usage, such as different types of API calls, data transfer rates, and storage tiers, which can make cost forecasting a daunting task for end-users. Moreover, for services with highly variable or bursty demand, designing a usage-based model that is both fair and profitable can be complex, potentially requiring sophisticated dynamic pricing mechanisms to manage network load and resource contention (Kshirsagar et al., 2021)(Niharika et al., 2024). The transition from traditional product-centric models to pay-per-use services requires a strategic shift in how value is perceived and delivered, emphasizing continuous service delivery over one-time transactions (Ladas et al., 2019). This transition involves educating customers on the benefits of flexible consumption and providing tools for effective cost management.

Value-Based Pricing: Theoretical Underpinnings and Digital Adaptation

Value-based pricing is a strategic approach that sets prices primarily based on the perceived or actual value that a product or service delivers to the customer, rather than on the cost of production or competitive prices (Maguire, 2021)(Lorente, 2025). This paradigm shifts the focus from internal costs to external customer benefits, aiming to capture a portion of the economic value created for the customer. The theoretical underpinnings of value-based pricing are rooted in economic concepts of consumer surplus and willingness to pay. If a product delivers significant value, customers are often willing to pay a higher price, provided they

understand and appreciate that value. This approach is particularly effective for innovative products or services that offer unique benefits, solve critical problems, or significantly improve efficiency or outcomes for the customer (Maguire, 2021). In essence, it reorients the pricing discussion from "what does it cost us to make?" to "what is it worth to you, the customer?"

In the context of the digital economy, and especially for AI-powered services, value-based pricing takes on particular significance due to the intangible nature of many offerings and their potential for transformative impact (Lorente, 2025). Unlike physical goods, the "cost" of producing another instance of a digital service is often negligible, making cost-plus pricing less relevant. Instead, the value derived from an AI model's insights, automation capabilities, or predictive power can be immense, far outweighing the operational costs (Lorente, 2025). For instance, an AI system that improves a company's sales conversion rate by 10% or reduces operational errors by 20% creates substantial economic value, and pricing should reflect this impact rather than merely the computational resources consumed. This is particularly true for AI solutions that provide strategic advantages, unlock new markets, or significantly enhance decision-making capabilities, where the return on investment can be exponential (Hinterhuber, 2023). The challenge, however, lies in accurately quantifying and communicating this often-abstract value to the customer.

Implementing value-based pricing for AI services requires a deep understanding of customer needs, business processes, and the specific problems that the AI solution addresses (Maguire, 2021). This often involves close collaboration with customers to quantify the return on investment (ROI) or other tangible benefits. Such a collaborative approach ensures that the pricing model is not just theoretical but grounded in the real-world impact the AI solution delivers. Methods for assessing value can include: 1. **Economic Value to the Customer (EVC):** This involves calculating the total savings or additional revenue a customer can expect by using the AI service compared to their next best alternative. This requires a detailed analysis of the customer's current operations, identifying pain points, and projecting the financial benefits of the AI solution. 2. **Perceived Value:** Understanding how customers

subjectively weigh the benefits, brand reputation, and convenience of the AI service (Fang & Zhou, 2025). This often involves market research, customer surveys, and understanding psychological factors affecting customer adoption and satisfaction. Perceived value can be influenced by factors beyond pure economic gain, such as ease of use, reliability, and the prestige associated with using advanced technology. 3. **Performance-Based Pricing:** Tying the price directly to the outcomes or performance metrics achieved by the AI. For example, an AI fraud detection system might charge a percentage of the fraud prevented, or an AI-powered marketing tool might charge based on the number of qualified leads generated (Halidias, 2022). This model directly aligns the vendor's revenue with the customer's success, creating a strong incentive for the AI solution to perform optimally.

Challenges in implementing value-based pricing for AI services are substantial. Quantifying the precise value generated by an AI can be difficult, especially for complex or nascent applications where the full impact is not immediately clear (Lorente, 2025). The long-term effects of AI integration might take time to materialize, making upfront value assessment speculative. Customers may also be skeptical or unable to fully grasp the long-term benefits, leading to resistance to higher prices. This is particularly true for innovative AI solutions where there are no clear benchmarks or comparable alternatives. Furthermore, the value proposition of AI can evolve rapidly as technology progresses and market needs change, requiring continuous reassessment of pricing strategies. The ethical implications of value-based pricing also warrant consideration, particularly if it leads to differential pricing that disproportionately impacts certain customer segments or if the perceived value is artificially inflated through aggressive marketing (Ayata, 2020). Despite these challenges, value-based pricing remains a powerful strategy for AI providers to capture a fair share of the value they create, moving beyond mere transactional exchanges to genuine partnerships focused on mutual benefit (Maguire, 2021). It emphasizes the strategic importance of AI as a value driver rather than a cost center, aligning the interests of providers and users in maximizing the utility and impact of intelligent systems (Lorente, 2025).

Emerging Pricing Paradigms for AI Services

The unique characteristics of AI, particularly large language models (LLMs) and complex machine learning algorithms, have necessitated the development of novel pricing paradigms that move beyond traditional usage-based or value-based models. These emerging approaches aim to account for the specific computational demands, intellectual property embedded, and the diverse ways in which AI is consumed and integrated into workflows. Among these, token-based pricing has rapidly become a standard for generative AI, while dynamic and AI-powered pricing strategies represent a broader trend towards intelligent, adaptive monetization.

Token-Based Pricing: The LLM Revolution

The advent of Large Language Models (LLMs) and other generative AI models has introduced a new and increasingly dominant pricing metric: the token (Barbere et al., 2024)(Rudnytskyi, 2022). Token-based pricing, exemplified by major AI service providers like OpenAI and Anthropic, charges users based on the number of "tokens" processed by the model. A token typically represents a piece of a word, a single word, or a sequence of characters, and models are trained and operate on these fundamental units (Barbere et al., 2024). For instance, the word "apple" might be one token, while "unbelievable" might be two or three tokens depending on the tokenizer used. This approach emerged as a practical solution to quantify the computational effort and output size associated with LLM interactions, which can vary dramatically based on the complexity of prompts and the length of generated responses (Rudnytskyi, 2022). It provides a more granular measurement than a simple "per query" charge, reflecting the actual work performed by the underlying AI model.

The rationale behind token-based pricing is multifaceted. Firstly, it directly correlates with the computational resources consumed. Processing longer inputs (prompts) and generating longer outputs requires more computational power and time, thus incurring higher costs

for the AI service provider (Barbere et al., 2024). Training and inference for LLMs are notoriously resource-intensive, demanding significant GPU utilization and energy consumption. By charging per token, providers can align their revenue with their operational expenses more accurately than with a flat-rate or per-query model, especially given the varying nature of LLM interactions. This ensures that the cost structure scales with the actual computational load, making the business model sustainable for the provider. Secondly, token-based pricing offers a granular and transparent metric for users. While the exact definition of a token can vary slightly between models and providers, it provides a quantifiable unit that users can understand and, to some extent, control. This allows developers to optimize their prompts and manage the length of generated content to control costs (Rudnytskyi, 2022). For example, if a user needs a concise summary, they can specify parameters to limit the output length, thereby reducing the token count and cost. This level of control empowers users to manage their budgets effectively, especially for applications with high volume or varying requirements.

The implementation of token-based pricing typically involves different rates for input tokens (prompts sent to the model) and output tokens (responses generated by the model). This distinction is important because the computational load and associated costs for generating output can often be higher than merely processing input, as the model has to actively synthesize new information (Barbere et al., 2024). Furthermore, different LLM models within a provider's ecosystem may have different token pricing, reflecting their varying capabilities, sizes, and underlying computational requirements. For instance, a more advanced or larger model designed for complex tasks (e.g., GPT-4) might have a higher per-token cost than a smaller, faster model optimized for simpler queries or specific tasks (e.g., GPT-3.5 Turbo) (Satapathi, 2025). Some providers also offer specialized models or fine-tuned versions with distinct pricing structures, reflecting the added value or specific use cases they address, such as models optimized for code generation, medical applications, or multilingual tasks (Satapathi, 2025). These tiered offerings cater to diverse customer needs and budget constraints, enabling a broader adoption of AI technologies.

The emergence of token-based pricing has had several significant implications for the development and adoption of AI services. It has driven innovation in prompt engineering, as developers seek to maximize the value extracted per token (Barbere et al., 2024). Techniques such as chain-of-thought prompting, few-shot learning, and contextual compression are not only aimed at improving model performance but also at optimizing token usage by making prompts more efficient and informative. Moreover, the concept of "dynamic token hierarchies" has been proposed to enhance LLM efficiency, suggesting that not all tokens are equal in terms of their informational value or computational cost (Barbere et al., 2024). Such approaches could lead to more sophisticated token-based pricing models that differentiate based on semantic density, contextual importance, or the complexity of the processing required for specific tokens, moving beyond a simple count (Barbere et al., 2024). This would allow for a more nuanced reflection of the value generated by different parts of an AI interaction.

However, token-based pricing is not without its challenges. One significant issue is the difficulty for users to accurately estimate costs, especially for complex applications or dynamic interactions where the number of input and output tokens can vary unpredictably (Rudnytskyi, 2022). This unpredictability can lead to "bill shock," similar to the challenges faced with general usage-based cloud services, particularly for developers integrating LLMs into applications with unpredictable user input. To mitigate this, providers often offer tools for cost estimation, usage monitoring, and budget caps, allowing users to set spending limits and receive alerts (Satapathi, 2025). Another challenge lies in the potential for "token inflation," where models might generate verbose or redundant output, increasing token counts without necessarily adding proportional value. This necessitates careful prompt design and output parsing by developers to ensure cost-effectiveness and extract only the most relevant information. Furthermore, the intellectual property implications of token usage, particularly regarding the training data embedded within models and the generated output, present complex legal and ethical questions that are still being navigated, especially concerning copyright and fair use (Ali, 2025). Despite these challenges, token-based pricing has become

a cornerstone of the generative AI economy, reflecting a pragmatic approach to monetizing highly resource-intensive and versatile AI capabilities. Its continued evolution will likely involve greater granularity, intelligence, and transparency to meet the diverse needs of the burgeoning AI ecosystem (Barbere et al., 2024). This includes developing more intuitive cost estimation tools and potentially integrating value-based components into token pricing.

Dynamic and AI-Powered Pricing Strategies

Beyond fixed or tiered pricing models, the digital and AI landscape is increasingly characterized by dynamic pricing strategies, where prices fluctuate in real-time based on a multitude of factors (Kshirsagar et al., 2021)(Niharika et al., 2024). This approach is not entirely new, with airlines and ride-sharing services having long employed surge pricing or demand-based pricing to optimize revenue and manage capacity (Divakaruni & Navarro, 2024). However, the proliferation of big data, advanced analytics, and AI algorithms has significantly enhanced the sophistication and potential of dynamic pricing, allowing for unprecedented levels of optimization and personalization (Niharika et al., 2024). AI-powered dynamic pricing models leverage machine learning to analyze vast datasets, including market demand, competitor pricing, customer behavior, inventory levels, time of day, and even external factors like weather or news events, to determine optimal prices at any given moment (Bhuram, 2025)(Niharika et al., 2024). The ability to process and act upon these diverse data streams in real-time gives AI-driven systems a significant advantage over traditional static pricing methods.

The core objective of dynamic pricing is to maximize revenue and profitability by adjusting prices to match supply and demand fluctuations, segment customers, and capture the maximum willingness to pay from different market segments (Niharika et al., 2024). For AI services, this can involve real-time adjustments to token prices, API call rates, or subscription tiers based on network congestion, computational resource availability, or the perceived urgency of a user's request (Kshirsagar et al., 2021). For instance, a cloud-based AI

service might offer lower prices during off-peak hours to incentivize demand shifting, thereby optimizing resource utilization and reducing overall operational costs (Kshirsagar et al., 2021). This "Green AI" approach not only seeks economic efficiency but also aims to minimize the environmental footprint by distributing computational loads more evenly, thus reducing peak energy consumption (Kshirsagar et al., 2021). This dual benefit of economic efficiency and environmental sustainability makes AI-powered dynamic pricing particularly attractive for large-scale AI infrastructure providers.

The methodology for implementing AI-powered dynamic pricing often involves several key components (Niharika et al., 2ar): 1. **Data Collection and Aggregation:** This involves continuously gathering real-time data from various sources, including market conditions (e.g., competitor prices, economic indicators), customer interactions (e.g., browsing history, purchase patterns), internal costs (e.g., compute utilization, energy prices), and external factors (e.g., seasonal trends, social media sentiment). The quality and breadth of this data are paramount for the accuracy of pricing predictions. 2. **Predictive Analytics:** Using advanced machine learning models (e.g., regression, time-series forecasting, neural networks) to predict future demand, price elasticity, and competitive responses (Niharika et al., 2024). These models analyze historical data to identify patterns and forecast future market behavior under different pricing scenarios. For example, an AI might predict how a 5% price increase will impact demand for a specific AI API during a particular time slot. 3. **Optimization Algorithms:** Employing sophisticated algorithms (e.g., reinforcement learning, genetic algorithms, linear programming) to determine the optimal price point that maximizes a specific objective function, such as revenue, profit, or market share (Kshirsagar et al., 2021). These algorithms consider the predictions from the analytical models and the defined business objectives to make real-time pricing decisions. Reinforcement learning, in particular, allows the system to learn from its pricing actions and continuously refine its strategy. 4. **Automated Execution:** Integrating these models into automated pricing engines that seamlessly adjust prices across various sales channels or service interfaces (e.g., API gateways, cloud dashboards). This

automation ensures that pricing changes are implemented instantaneously in response to market shifts, without human intervention.

Examples of AI-powered dynamic pricing extend beyond traditional e-commerce. In the automotive aftermarket, edge-cloud AI systems are being developed to optimize pricing for spare parts and services, taking into account vehicle age, mileage, service history, and local market conditions (Bhuram, 2025). This allows for highly personalized and localized pricing, reflecting the unique value proposition for each customer. Similarly, in digital advertising, real-time bidding (RTB) platforms use AI to dynamically price ad impressions based on user profiles, ad context, and predicted conversion rates, ensuring that advertisers pay an optimal amount for maximum impact. For AI-as-a-Service (AIaaS) offerings, dynamic pricing could involve adjusting the cost of specific model inferences based on the complexity of the input, the latency requirements, or the current load on the inference servers (Kshirsagar et al., 2021). This allows providers to manage their infrastructure more efficiently, ensuring quality of service while maximizing revenue during periods of high demand, and conversely, offering discounts during low-demand periods to encourage usage.

Despite its significant potential, dynamic and AI-powered pricing also presents considerable challenges and ethical dilemmas (Mirghaderi et al., 2023). One major concern is the potential for price discrimination, where different customers are offered different prices for the same service based on their inferred willingness to pay, potentially leading to unfair outcomes (Ayata, 2020). This can erode customer trust and lead to regulatory scrutiny, especially if pricing algorithms exhibit biases against certain demographic groups (e.g., based on inferred income, location, or ethnicity) by leveraging data proxies (Mirghaderi et al., 2023). Transparency is another critical issue; customers often find it difficult to understand *why* prices are changing, leading to frustration and a perception of being exploited (Mirghaderi et al., 2023). The "black box" nature of some AI algorithms further exacerbates this problem, making it hard to explain pricing decisions in a way that is comprehensible and reassuring to consumers. Furthermore, aggressive dynamic pricing can lead to price wars, market instability,

or even accusations of anti-competitive behavior if dominant platforms leverage their data advantage to unfairly squeeze competitors or create insurmountable barriers to entry (Ayata, 2020). Therefore, while AI-powered dynamic pricing offers powerful tools for optimization, its implementation requires careful consideration of fairness, transparency, and regulatory compliance to ensure long-term sustainability and maintain customer goodwill (Mirghaderi et al., 2023). The ethical frameworks for AI must extend to its economic applications, ensuring that pricing strategies are not only profitable but also equitable and socially responsible (Ayata, 2020)(Mirghaderi et al., 2023).

Monetization Strategies Beyond Direct Pricing

While pricing models dictate the specific charges for AI services, monetization strategies encompass the broader business frameworks through which digital platforms and AI providers generate revenue (De, 2017). These strategies often combine various pricing models with other value-capture mechanisms, reflecting the diverse ways in which value is created and consumed in the digital economy. Understanding these broader approaches is crucial for developing sustainable and competitive AI business models, as a holistic strategy often involves more than just setting a price per unit.

One prominent monetization strategy is the **Freemium model**, which offers a basic version of a service for free while charging for premium features, enhanced capabilities, or higher usage tiers (Seufert, 2014). This model is particularly effective for digital products with low marginal costs, as it allows providers to attract a large user base without significant upfront investment. The free tier acts as a powerful marketing tool, enabling users to experience the value of the service firsthand, thereby reducing adoption barriers and fostering trust (Seufert, 2014). For AI services, a freemium model might offer a limited number of free tokens, access to a smaller AI model, or restricted functionality (e.g., fewer API calls per month, slower processing speeds), with premium tiers unlocking larger, more capable models, higher token limits, advanced features (e.g., fine-tuning capabilities, dedicated support, custom

integrations), or faster processing speeds (Satapathi, 2025). The success of a freemium model hinges on the ability to convert a sufficient percentage of free users into paying subscribers, which requires a compelling value proposition for the premium features and an effective "paywall" strategy (Seufert, 2014). Analytics play a critical role in optimizing freemium models, helping providers identify conversion points, understand user behavior, and refine their offerings to maximize conversion rates.

Subscription models represent another foundational monetization strategy, providing recurring revenue streams in exchange for continuous access to a service or a bundle of features (De, 2017). While often combined with usage-based or tiered pricing, pure subscription models offer predictability for both providers and customers. Customers benefit from predictable budgeting, while providers gain a stable revenue base that facilitates long-term planning and investment. For AI services, subscriptions can be tailored to specific user needs, offering different levels of access, processing power, or model capabilities (Satapathi, 2025). For example, a business might subscribe to an AI analytics platform for a fixed monthly fee, gaining access to a suite of tools regardless of their specific usage within certain parameters. The appeal of subscriptions lies in their ability to foster long-term customer relationships and provide a stable revenue base, which is crucial for investing in ongoing AI research and development (Siddannavar et al., 2025). However, maintaining subscriber loyalty requires continuous innovation and value delivery to prevent churn, as customers can easily switch providers in the competitive digital landscape.

Beyond direct service charges, **platform monetization** strategies are highly relevant for AI, especially as many AI capabilities are delivered through developer platforms or integrated into broader ecosystems. These strategies include: 1. **Transaction Fees:** Charging a percentage or fixed fee on transactions facilitated by the AI platform. For example, an AI-powered marketplace connecting developers with businesses seeking custom AI solutions might take a commission on each successful project (De, 2017). This model aligns the platform's success directly with the value it creates for its users. 2. **Advertising:**

While less common for core AI services themselves, platforms that integrate AI for content generation, personalization, or user engagement might monetize through targeted advertising. Leveraging AI to improve ad relevance and effectiveness can increase advertising revenue by delivering more impactful ads to users (Peng & Chao, 2020). This is particularly prevalent in consumer-facing AI applications or content platforms. 3. **Data Monetization:** An ethically complex but potentially lucrative strategy involves anonymizing and aggregating user data (with explicit consent) to derive insights that can be sold to third parties or used to develop new, value-added services (Kaaniche & Laurent, 2018). For instance, aggregated usage patterns of an AI service could reveal market trends valuable to other businesses. However, this approach is fraught with privacy concerns, regulatory hurdles (e.g., GDPR, CCPA), and potential reputational risks, necessitating robust ethical guidelines and transparent data governance practices (Mirghaderi et al., 2023). The balance between data utility and privacy protection is a delicate and ongoing challenge. 4. **Value-Added Services and Ecosystems:** Offering a core AI service at a competitive price and then monetizing through supplementary services, integrations, or a marketplace for AI plugins and custom models. This strategy aims to build an ecosystem around the AI, increasing switching costs and fostering deeper engagement (Lorente, 2025). Examples include offering premium support, consulting services, custom model training, or a marketplace where third-party developers can sell AI extensions. This expands the revenue potential beyond the core AI offering by creating a comprehensive solution environment.

The strategic choice of monetization models for AI-powered services is critical for long-term success. It requires a careful balance between attracting users, demonstrating value, ensuring profitability, and addressing ethical responsibilities (Lorente, 2025). The dynamic nature of the AI market means that monetization strategies must be flexible and adaptive, capable of evolving with technological advancements and changing customer expectations. For instance, as AI models become more commoditized, the focus might shift from selling raw computational power (tokens) to monetizing the curated data, specialized knowledge, or

integrated workflows that leverage AI (Jessen & Roshchin, 2025). This continuous evolution underscores the need for a holistic approach to monetization, considering not just the immediate transaction but the entire customer journey and the broader ecosystem of value creation (Lorente, 2025). A successful strategy will often combine elements of several models, creating a flexible and resilient revenue generation framework.

Ethical Considerations and Societal Impact of AI Business Models

The rapid proliferation of AI-powered services and digital platforms, while offering unprecedented opportunities for economic growth and innovation, simultaneously introduces a complex array of ethical considerations and potential societal impacts (Mirghaderi et al., 2023)(Ayata, 2020). These concerns are not merely peripheral to business models but are deeply embedded in the design, pricing, and monetization strategies of AI, necessitating a proactive and responsible approach from providers and regulators alike. Ignoring these ethical dimensions risks eroding public trust, fostering market inequities, and inviting significant regulatory backlash (Mirghaderi et al., 2023). The ethical implications span across fairness, transparency, privacy, market dynamics, and broader societal welfare, demanding a comprehensive and interdisciplinary examination.

One of the most pressing ethical concerns in AI business models relates to **transparency and fairness in pricing**. As discussed in the context of dynamic and AI-powered pricing, algorithms can segment customers and adjust prices based on their inferred willingness to pay, potentially leading to price discrimination (Ayata, 2020). While dynamic pricing can optimize resource allocation and revenue, it can also result in situations where individuals are charged different prices for the same service without clear justification, raising questions of fairness (Mirghaderi et al., 2023). If these algorithms inadvertently (or intentionally) use proxies for protected characteristics (e.g., location, browsing history that correlates with socioeconomic status, or even device type), they could perpetuate or exacerbate existing societal inequalities, leading to digital redlining or other forms of discrimination (Mirghaderi

et al., 2023). The "black box" nature of many AI algorithms further complicates this, making it difficult for consumers to understand how prices are determined or why they are being charged a particular amount (Mirghaderi et al., 2023). This lack of transparency can lead to a perception of manipulation and erode trust, which is crucial for the long-term adoption and success of AI services (Fang & Zhou, 2025). Regulatory bodies are increasingly scrutinizing such practices, with some jurisdictions exploring legislation to ensure algorithmic transparency and prevent discriminatory pricing, demanding explainability in automated decision-making processes (Ayata, 2020).

Data privacy and security represent another fundamental ethical challenge (Kaaniche & Laurent, 2018). AI models are inherently data-hungry, relying on vast datasets for training and operation. Business models that leverage user data for personalization, optimization, or even direct monetization raise significant privacy concerns, especially when personal data is involved (Kaaniche & Laurent, 2018). While anonymization and aggregation techniques are employed, the risk of re-identification or data breaches remains a constant threat, potentially exposing sensitive personal information. Ethical AI business models must prioritize robust data governance frameworks, ensuring informed consent, secure data handling, and transparent policies regarding data usage. This includes clear communication about what data is collected, how it is used, and who has access to it (Kaaniche & Laurent, 2018). The tension between maximizing value from data and protecting individual privacy is a continuous balancing act that requires stringent ethical guidelines and legal compliance, as exemplified by regulations like GDPR and CCPA (Mirghaderi et al., 2023). Furthermore, the potential for AI models to infer sensitive attributes from seemingly innocuous data raises additional privacy challenges, even with anonymized datasets.

The potential for **market concentration and excessive pricing by dominant platforms** is also a significant ethical and economic concern (Ayata, 2020). As AI capabilities become increasingly centralized within a few large technology companies, often due to the immense resources required for R&D and infrastructure, there is a risk that these dominant

players could leverage their market power and data advantages to stifle competition, dictate terms, and engage in anti-competitive pricing practices (Ayata, 2020). This could lead to monopolies or oligopolies in key AI sectors, limiting consumer choice, hindering innovation, and potentially extracting excessive rents from users and smaller businesses reliant on their platforms. The ethical responsibility of these dominant firms extends beyond mere legal compliance to fostering a healthy, competitive ecosystem that benefits all stakeholders, including developers and end-users. Regulators are actively examining these issues, drawing parallels to antitrust concerns in traditional industries and exploring new frameworks for digital markets that account for the unique characteristics of AI and data-driven economies (Ayata, 2020). This includes scrutinizing mergers and acquisitions in the AI space and evaluating platform policies that might disadvantage smaller competitors.

Furthermore, the **societal impact of AI automation on employment and economic distribution** is an overarching ethical consideration that influences the perception and acceptance of AI business models. While AI promises increased productivity, new job creation, and economic growth, it also poses a significant threat to existing jobs through automation, particularly in routine and predictable tasks (Selesi-Aina et al., 2024). Business models that aggressively pursue automation without considering the broader societal implications can exacerbate economic inequality and social displacement, leading to widespread unemployment and social unrest. Ethical AI development and deployment require a commitment to reskilling and upskilling workforces, investing in social safety nets, and ensuring that the benefits of AI are broadly distributed across society, rather than concentrating wealth and power in the hands of a few (Shuford, 2024). This necessitates collaboration between governments, industry, and educational institutions to prepare the workforce for the future of work in an AI-driven economy.

Finally, the **environmental impact of AI** is an emerging ethical concern, particularly relevant for computationally intensive models that underpin many AI services. The energy consumption associated with training and running large AI models contributes significantly

to carbon emissions, raising questions about the sustainability of current AI development practices (Kshirsagar et al., 2021). Ethical AI business models should therefore incorporate principles of "Green AI," striving for energy efficiency, optimizing resource utilization, and exploring sustainable computing practices, such as using renewable energy sources for data centers (Kshirsagar et al., 2021). This includes designing pricing models that incentivize efficient usage and penalize wasteful consumption, aligning economic incentives with environmental responsibility (Kshirsagar et al., 2021). For instance, offering lower prices for off-peak usage can help distribute computational load and reduce reliance on peak energy generation, which is often carbon-intensive.

Addressing these ethical considerations is not merely a matter of compliance but a strategic imperative for the long-term viability and public acceptance of AI-powered services (Mirghaderi et al., 2023). Companies that proactively embed ethical principles into their AI business models, prioritize transparency, fairness, and accountability, and engage in meaningful stakeholder dialogue are more likely to build trust, foster loyalty, and achieve sustainable success in the evolving AI economy (Fang & Zhou, 2025). This requires a shift from purely profit-driven optimization to a more holistic framework that balances economic objectives with social responsibility, acknowledging AI's profound impact on individuals and society at large.

Comparative Analysis and Identified Gaps

The preceding sections have explored various pricing and monetization strategies for AI-powered services, from foundational usage-based and value-based models to emerging token-based and dynamic AI-driven approaches, alongside critical ethical considerations. A comparative analysis of these models reveals their distinct strengths, weaknesses, and suitability for different AI service contexts, while also highlighting significant gaps in the current literature and practical implementation. This synthesis is crucial for identifying areas ripe for further research and development in the rapidly evolving field of AI economics.

Usage-based pricing excels in its simplicity and perceived fairness for services where consumption can be easily metered and directly correlates with resource cost (Ladas et al., 2019). It is highly scalable, democratizes access, and reduces entry barriers for users. Its strength lies in its direct link to operational cost, making it a sustainable model for providers of raw computational power or basic API access. However, its primary weakness lies in cost unpredictability for customers, potentially leading to "bill shock," and its inherent disconnect from the actual *value* delivered by complex AI outputs (Satapathi, 2025). While suitable for infrastructure-level AI services (e.g., raw compute, data storage for models), it struggles to capture the nuanced value of intelligent insights, creative outputs, or strategic decision support generated by advanced AI.

Value-based pricing, conversely, directly addresses the issue of value capture, aligning price with the tangible or perceived benefits an AI service provides (Maguire, 2021)(Lorente, 2025). It is ideal for highly differentiated AI solutions that solve critical business problems or generate significant ROI. This model positions AI as a strategic asset rather than a commodity, allowing providers to capture a larger share of the economic value created. Its challenges, however, include the difficulty of accurately quantifying value, potential customer skepticism regarding claimed benefits, and the risk of perceived unfairness if value assessments are opaque or inconsistent (Ayata, 2020). For many generic or widely available AI services, a pure value-based approach might be impractical due to the high effort required for individual value assessment and the difficulty in differentiating offerings.

Token-based pricing, a specialized form of usage-based pricing, has become the de facto standard for generative AI, particularly LLMs (Barbere et al., 2024)(Rudnytskyi, 2022). Its strength lies in providing a granular metric that correlates with computational effort and output length, offering some level of transparency and control for developers who can optimize their prompts. Yet, it shares the drawback of cost unpredictability, especially for complex or iterative interactions. Furthermore, current token definitions may not adequately capture the *semantic value* or cognitive complexity of information processed (Barbere et al.,

2024). A short, highly impactful output might cost the same as a long, verbose one that provides less utility, indicating a potential misalignment between token count and actual value delivered. This highlights a limitation in current tokenization methods for measuring true "AI work."

Dynamic and AI-powered pricing strategies offer the most sophisticated approach to optimization, leveraging real-time data and machine learning to adjust prices based on demand, supply, and granular customer segmentation (Kshirsagar et al., 2021)(Niharika et al., 2024). This model maximizes revenue, optimizes resource efficiency, and can adapt to rapidly changing market conditions. Its significant weaknesses, however, are ethical in nature: the potential for pervasive price discrimination, a profound lack of transparency in algorithmic decision-making, and the inherent risk of algorithmic bias leading to unfair or inequitable outcomes (Mirghaderi et al., 2023)(Ayata, 2020). Implementing these models responsibly requires robust ethical frameworks and regulatory oversight that are still in nascent stages, alongside advanced explainable AI techniques for pricing decisions.

Several critical gaps emerge from this comparative analysis, indicating rich avenues for future research:

1. **Bridging Cost, Usage, and Value in Integrated Pricing Models:** A significant gap exists in developing comprehensive pricing models that seamlessly integrate the cost of underlying computational resources (as reflected in usage or tokens), the actual usage patterns, and the perceived or quantifiable value delivered by AI services (Lorente, 2025). Current models often prioritize one dimension over others, leading to suboptimal outcomes for either providers or consumers. Future research needs to explore sophisticated hybrid models that dynamically adjust pricing based on a combination of token count, the complexity of the AI task, the quality of the output, and the measurable business outcomes for the user (Kumari & Raj, 2025). This could involve performance-based pricing mechanisms that are triggered by specific AI achievements

rather than just raw usage, or tiered value-based subscriptions that scale with the demonstrated impact.

2. **Developing Ethical AI Pricing Frameworks and Governance:** While ethical concerns are widely acknowledged (Mirghaderi et al., 2023)(Ayata, 2020), the literature lacks detailed, actionable frameworks for designing and implementing AI pricing models that are demonstrably fair, transparent, and non-discriminatory. There is a pressing need for robust methodologies to audit AI pricing algorithms for bias, ensure explainability in pricing decisions, and establish governance structures that incorporate diverse stakeholder input and oversight. Research into effective regulatory approaches, industry best practices, and technological solutions for "ethical pricing by design" is crucial to build public trust and ensure responsible AI adoption (Eriksson, 2024). This includes developing metrics for fairness in pricing and mechanisms for redress when perceived unfairness occurs.
3. **Impact of AI on Market Structures and Competition:** The long-term implications of various AI pricing and monetization strategies on market concentration, competition dynamics, and the potential for monopolistic practices require deeper investigation (Ayata, 2020). How do different pricing models affect the entry and survival of new competitors in the AI market? Do token-based models inadvertently favor large incumbents with economies of scale, or do they enable smaller players to compete on specific niche offerings? Research should explore the economic dynamics of AI ecosystems, including platform effects, the emergence of data moats, and the role of open-source AI initiatives, to understand their competitive implications and inform antitrust policy.
4. **Customer Psychology and Adoption of AI Pricing:** While some research touches on customer lifetime value (Siddannavar et al., 2025) or online purchase intention related to AI technology (Yin & Qiu, 2021), there is a need for more granular studies on how customers perceive and respond to novel AI pricing models, especially token-based

and dynamic pricing. What psychological factors drive trust or distrust in AI-driven pricing? How can providers effectively communicate value, manage expectations, and mitigate "bill shock" or perceptions of unfairness when prices fluctuate or are based on abstract units like tokens? Understanding these cognitive and emotional factors is vital for successful market adoption and sustained customer loyalty (Fang & Zhou, 2025).

5. **Sustainability and "Green AI" in Monetization:** While `cite_001` introduces Green AI in the context of congestion control, its integration into broader monetization strategies beyond specific resource optimization requires further exploration. How can pricing models actively incentivize energy-efficient AI development and deployment across the entire AI lifecycle, from training to inference? What are the economic levers that can drive sustainable AI practices across the value chain, and how can these be reflected in pricing structures to promote environmentally responsible consumption and production of AI services? This includes exploring carbon-aware pricing models or incentives for using renewable energy-powered AI infrastructure.

These gaps represent fertile ground for interdisciplinary research combining economics, computer science, ethics, and business strategy. Addressing them is essential for fostering an AI economy that is not only innovative and profitable but also equitable, transparent, and sustainable.

Conclusion

The landscape of economic and business models for AI-powered services and digital platforms is rapidly evolving, driven by unprecedented technological advancements and shifting market dynamics. This literature review has systematically examined foundational pricing concepts, including usage-based and value-based strategies, and explored emerging paradigms such as token-based and dynamic AI-powered pricing. It has also highlighted the critical ethical considerations and societal impacts that are inextricably linked to the design and implementation of these models.

From the granular, resource-aligned nature of token-based pricing for large language models to the sophisticated optimization capabilities of AI-driven dynamic pricing, the industry is continually innovating to capture value and manage costs in a complex digital environment. These innovations reflect a profound adaptation of economic principles to the unique characteristics of AI, offering both immense opportunities for efficiency and new forms of value creation. However, this evolution is not without its challenges. Issues of cost predictability, transparency, fairness, and the potential for algorithmic bias loom large, necessitating a robust ethical framework alongside economic analysis. The review underscores that while AI offers immense potential for value creation (Lorente, 2025), its monetization must be approached with a keen awareness of its broader societal implications, ensuring that economic gains do not come at the expense of equity, privacy, or trust (Mirghaderi et al., 2023)(Ayata, 2020).

Crucially, significant gaps remain in the current body of knowledge, indicating vital avenues for future inquiry. There is a pressing need for integrated pricing models that effectively balance cost, usage, and value, moving beyond single-metric approaches to capture the multifaceted nature of AI's contribution. The development of actionable ethical AI pricing frameworks and governance mechanisms is paramount to ensure fairness, prevent discrimination, and foster public confidence in AI-driven markets. Furthermore, deeper investigations into the long-term impact of AI business models on market structures, competition dynamics, customer psychology, and environmental sustainability are essential to guide responsible innovation. Addressing these gaps requires interdisciplinary research that bridges economic theory with ethical considerations, technological capabilities, and regulatory foresight. The future success and societal acceptance of AI-powered services will depend not only on their technical prowess but also on the integrity, equity, and sustainability of the business models that underpin them. This paper aims to contribute to filling these identified gaps by proposing novel approaches that integrate these multifaceted considerations, thereby advancing the discourse towards more responsible and effective AI monetization strategies.

Methodology

The development of a robust and ethically sound pricing framework for Artificial Intelligence as a Service (AIaaS) necessitates a rigorous and systematic methodological approach. Given the nascent and rapidly evolving nature of the AIaaS market, coupled with the inherent complexities introduced by ethical considerations, a qualitative research design centered on theoretical synthesis and comparative conceptual analysis is most appropriate (Korinek, 2025). This section outlines the research design, detailing the framework employed for comparing existing AIaaS pricing models, the criteria for selecting illustrative case studies, and the analytical approach utilized to synthesize findings and construct the proposed framework. The objective is to move beyond a mere descriptive account of current practices, aiming instead for a prescriptive and normative framework that integrates economic viability with fundamental ethical principles.

Research Design and Approach

This study adopts a qualitative, theory-building approach, leveraging conceptual analysis and a form of comparative case study methodology to explore the multifaceted landscape of AIaaS pricing. Unlike empirical studies that focus on data collection and statistical inference, this research is fundamentally theoretical, aiming to develop a novel conceptual framework based on a systematic review and synthesis of existing knowledge and practices (Godfrey, 1998). The choice of a qualitative design is justified by the exploratory nature of the research question, which seeks to understand complex phenomena (AIaaS pricing and ethics) in a holistic and nuanced manner, rather than quantifying relationships between variables (Fletcher, 2017).

The research process is iterative, commencing with an extensive literature review to identify current AIaaS pricing models, their underlying economic rationales, and the emerging ethical challenges associated with AI deployment (Mirghaderi et al., 2023). This initial phase

informs the development of a structured framework for comparing these models. Subsequently, illustrative case studies of prominent AIaaS providers are selected based on specific criteria to ground the theoretical analysis in real-world applications. The data derived from these cases, primarily public documentation and academic analyses, are then systematically analyzed using a qualitative content analysis approach. The insights gained from this comparative analysis, alongside the theoretical foundations established in the literature review, are synthesized to construct the proposed ethically-aware pricing framework. This iterative refinement process ensures that the framework is both theoretically grounded and practically relevant, addressing both economic imperatives and ethical responsibilities (Lorente, 2025).

The theoretical grounding for this methodology draws upon several established economic and ethical theories. From an economic perspective, concepts such as value-based pricing (Maguire, 2021), transaction cost economics (Ladas et al., 2019), and platform economics (De, 2017) provide lenses through which to understand how AIaaS providers capture value and structure their offerings. The unique characteristics of AI, such as its data intensiveness, computational demands, and potential for rapid evolution, also necessitate consideration of cost structures related to green AI (Kshirsagar et al., 2021) and dynamic resource allocation (Barbere et al., 2024)(Bhuram, 2025). Ethically, the research is informed by principles of fairness, transparency, accountability, and data privacy, which are critical in the context of AI systems (Mirghaderi et al., 2023)(Kaaniche & Laurent, 2018). By integrating these diverse theoretical perspectives, the methodology aims to provide a comprehensive and robust foundation for developing a holistic pricing framework that transcends purely economic optimization.

Framework for Comparing AIaaS Pricing Models

To systematically evaluate the diverse array of pricing models currently employed in the AIaaS landscape, a comprehensive comparative framework was developed. This framework is designed to move beyond a superficial comparison of price points, delving into the underlying

structures, economic rationales, ethical implications, and operational complexities of each model. The necessity for such a structured approach stems from the unique characteristics of AIaaS, which include variable computational costs, reliance on vast and often sensitive data, continuous model improvement, and the profound societal impact of AI applications (Kshirsagar et al., 2021)(Mirghaderi et al., 2023). Without a multidimensional framework, a comprehensive assessment of how different pricing strategies align with both business objectives and ethical responsibilities would be challenging. The framework comprises four key dimensions: Economic Viability and Value Capture, Ethical Considerations, Technical and Operational Feasibility, and Strategic Alignment. Each dimension is further broken down into specific criteria, allowing for a granular and nuanced analysis.

Economic Viability and Value Capture

This dimension assesses how effectively a pricing model enables AIaaS providers to capture value while remaining economically viable and sustainable. It considers both the cost recovery mechanisms and the value perceived by the customer.

- ***Cost-Based Elements.*** This criterion examines how pricing models account for the various costs associated with developing, deploying, and maintaining AI services. These include significant computational resources for model training and inference (Kshirsagar et al., 2021)(Barbere et al., 2024), data acquisition and curation costs, infrastructure expenses, and ongoing research and development investments to improve model performance and capabilities (Korinek, 2025). Green AI considerations, such as the energy consumption of large models, also fall under this category, influencing the true cost of service delivery (Kshirsagar et al., 2021).
- ***Value-Based Elements.*** This aspect focuses on how pricing reflects the value delivered to the customer (Maguire, 2021)(Lorente, 2025). It evaluates whether models attempt to quantify and charge based on the tangible outcomes or benefits users derive from the AI service, rather than merely the inputs consumed. This can include

performance-based pricing, where costs are tied to the accuracy or efficiency of the AI's output, or value-added services that enhance the core AI functionality. Perceived value, influenced by factors such as unique features, reliability, and brand reputation, is also critical here (Fang & Zhou, 2025).

- ***Market Dynamics.*** This criterion analyzes how pricing models respond to broader market forces, including competitive pressures, demand elasticity, and the presence of platform effects (De, 2017). It considers whether the pricing strategy facilitates market entry, sustains competitive advantage, or creates network effects that lock in users. Adaptability to changing market conditions and the ability to differentiate from competitors through pricing are key considerations (Divakaruni & Navarro, 2024).

Ethical Considerations

This dimension is crucial for evaluating whether pricing models promote fairness, transparency, and accountability in the deployment and use of AI, moving beyond mere compliance to proactive ethical design.

- ***Transparency.*** This evaluates the clarity and comprehensibility of the pricing structure and its underlying logic (Mirghaderi et al., 2023). It questions whether users can easily understand how their usage translates into costs, what data is being used, and how AI models arrive at their outputs. Lack of transparency can lead to distrust and perceived unfairness, especially concerning hidden fees or complex usage metrics (Ayata, 2020).
- ***Fairness and Equity.*** This criterion assesses whether pricing models inadvertently create or exacerbate inequalities, for instance, by making advanced AI capabilities inaccessible to smaller organizations or specific demographics. It also examines whether pricing mechanisms could lead to discriminatory outcomes based on usage patterns or user profiles. Equitable access and the avoidance of predatory pricing practices are central to this (Ayata, 2020).

- ***Accountability.*** This considers how pricing models implicitly or explicitly address the allocation of responsibility when AI systems produce errors, biases, or undesirable outcomes. It examines whether pricing structures incentivize providers to ensure model robustness and ethical performance, or if they merely shift all risk to the user (Mirghaderi et al., 2023). Data usage auditing, facilitated by technologies like blockchain, can play a role in ensuring accountability for data handling within pricing models (Kaaniche & Laurent, 2018).
- ***Data Privacy and Usage.*** Given that many AIaaS models are deeply intertwined with data, this criterion evaluates how pricing models reflect and communicate data handling practices. It assesses whether users are adequately informed about how their data is collected, used, and shared, and if pricing differentiates between services that require extensive personal data versus those that operate on anonymized or synthetic data (Kaaniche & Laurent, 2018).

Technical and Operational Feasibility

This dimension focuses on the practical aspects of implementing and managing a pricing model, including its technical complexity and operational efficiency.

- ***Granularity.*** This assesses the level of detail at which usage is metered and charged. Examples include token-based pricing (common for LLMs) (Barbere et al., 2024), request-based pricing (Satapathi, 2025), time-based usage, or feature-based pricing (Satapathi, 2025). The appropriate granularity depends on the AI service and its usage patterns, balancing precision with administrative overhead.
- ***Scalability.*** This criterion evaluates how well a pricing model adapts to varying levels of demand and usage. A scalable model should seamlessly accommodate growth in user base and usage volume without significant changes to its underlying structure or leading to disproportionate cost increases for users (Bhuram, 2025).

- ***Flexibility.*** This examines the extent to which a pricing model can be customized or offers different tiers and options to cater to diverse customer needs. This includes tiered pricing, freemium models (Seufert, 2014), or custom enterprise agreements that allow for tailored solutions.
- ***Implementation Complexity.*** This assesses the technical and administrative burden of implementing and managing the pricing model. This includes the ease of metering usage, generating accurate bills, and auditing service consumption (Kaaniche & Laurent, 2018). Overly complex models can lead to operational inefficiencies and customer confusion.

Strategic Alignment

This dimension evaluates how well the pricing model supports the overall business strategy of the AIaaS provider and its long-term goals.

- ***Business Model Fit.*** This criterion examines whether the pricing model is consistent with the provider's overarching business model, such as subscription services, pay-as-you-go, or a hybrid approach (Ladas et al., 2019). The pricing strategy should reinforce, rather than contradict, the core value proposition and revenue generation mechanisms.
- ***Customer Lifecycle Management.*** This assesses how pricing models support different stages of the customer journey, from acquisition and onboarding to retention and upselling (Siddannavar et al., 2025). Freemium models, for example, are often used for acquisition (Seufert, 2014), while tiered pricing can encourage increased usage and loyalty.
- ***Innovation Incentives.*** This criterion considers whether the pricing model encourages or discourages innovation, both on the part of the provider and its users. Pricing should ideally incentivize the adoption of new AI capabilities and foster an ecosystem of innovation, rather than creating barriers to experimentation or limiting access to cutting-edge technologies.

This comprehensive framework serves as the analytical lens through which existing AIaaS pricing models will be critically examined. Each criterion provides a specific point of inquiry, enabling a systematic and detailed comparison that highlights not only the economic implications but also the ethical and operational dimensions of each model.

Case Study Selection Criteria

To provide practical grounding for the theoretical framework and illustrate the application of the comparative dimensions, a selection of illustrative case studies was deemed essential. It is important to note that these are not empirical case studies in the traditional sense, aiming for generalizable findings through in-depth data collection, but rather conceptual case studies used to exemplify different AIaaS pricing strategies and their associated ethical considerations (Beckett & O'Loughlin, 2024). The selection criteria were designed to ensure a diverse and representative set of examples that cover various types of AI services, pricing models, and prominently feature relevant ethical challenges or solutions.

Inclusion Criteria

The following criteria guided the selection of AIaaS providers for conceptual case study analysis:

- ***Publicly Available Information.*** Priority was given to AIaaS providers whose pricing models, terms of service, and any associated ethical guidelines or controversies are well-documented and publicly accessible (Rudnytskyi, 2022). This ensures the feasibility of analysis without requiring proprietary data, aligning with the theoretical nature of this study. Examples include major cloud providers' AI services and prominent large language model (LLM) providers.
- ***Diversity of AI Services.*** To capture the breadth of the AIaaS market, cases were selected to represent different types of AI capabilities. This includes foundational models (e.g., large language models, multimodal agents) (Barbere et al., 2024)(Trad

& Chehab, 2024), specialized cognitive services (e.g., natural language processing, computer vision, speech-to-text) (Satapathi, 2025)(Rudnytskyi, 2022), and predictive analytics platforms (Niharika et al., 2024). This diversity allows for an examination of how pricing structures adapt to varying levels of complexity, resource intensity, and application domains.

- ***Variety of Pricing Models.*** The selected cases needed to demonstrate a range of pricing strategies. This includes traditional usage-based models (e.g., per request, per token, per hour) (Satapathi, 2025), subscription-based access, tiered pricing structures (Satapathi, 2025), value-based approaches, and hybrid models that combine elements of these strategies (Ladas et al., 2019). The inclusion of freemium models (Seufert, 2014) was also considered to analyze their impact on user adoption and long-term monetization.
- ***Representative of Ethical Challenges/Solutions.*** A critical criterion was the presence of explicit ethical considerations in the provider's pricing or service design, or instances where their pricing model has raised ethical questions (e.g., concerning fairness, transparency, data usage, or potential for misuse) (Mirghaderi et al., 2023)(Kaaniche & Laurent, 2018). Cases that have publicly articulated their approach to AI ethics or have been subject to academic or public scrutiny regarding their ethical implications were prioritized (Ayata, 2020).
- ***Market Prominence and Impact.*** Cases involving leading AIaaS providers or those with significant market impact were chosen to ensure that the analysis reflects current industry trends, challenges, and potential best practices. These providers often set benchmarks for pricing and service delivery, making their models particularly relevant for developing a universally applicable framework.

Exclusion Criteria

To maintain focus and ensure the relevance of the selected cases, certain types of AI offerings were excluded:

- ***Proprietary/Undisclosed Pricing Models.*** AI services with highly customized, enterprise-specific pricing that is not publicly disclosed were excluded, as they do not offer sufficient transparency for comparative analysis within this theoretical study.
- ***Non-AI-as-a-Service Offerings.*** On-premise AI deployments or embedded AI solutions that are not offered as a scalable, cloud-based service were excluded to maintain a clear focus on the "as-a-Service" paradigm.

By adhering to these rigorous selection criteria, the chosen conceptual case studies will serve as concrete examples to illustrate the strengths and weaknesses of different AIaaS pricing models when evaluated against the proposed comparative framework. This approach bridges the gap between abstract theoretical concepts and their real-world manifestations, enriching the discussion and informing the development of the ethically-aware pricing framework.

Analysis Approach

The analysis approach for this theoretical paper is primarily qualitative, employing a synthesis of literature review and conceptual comparative analysis of selected AIaaS pricing models. This multi-pronged approach ensures that the resulting framework is both deeply rooted in existing academic discourse and informed by current industry practices.

Qualitative Content Analysis

The initial phase of analysis involves a comprehensive qualitative content analysis of the collected data. This data includes academic literature on AI economics, AI ethics, software pricing models, and digital platform economics (De, 2017)(Korinek, 2025)(Mirghaderi et al., 2023)(Ladas et al., 2019). Additionally, public documentation from selected AIaaS providers,

such as pricing pages, terms of service, white papers, developer guides, and relevant news articles or academic analyses of specific platforms, will be systematically reviewed.

- ***Data Collection and Review.*** Information related to AIaaS pricing models, their features, cost structures, and any stated ethical guidelines or reported controversies will be meticulously gathered. This includes details on how services are metered (e.g., tokens, requests, computation time) (Barbere et al., 2024)(Satapathi, 2025), the different tiers or subscription options available (Satapathi, 2025), and any explicit statements regarding data privacy or model fairness (Kaaniche & Laurent, 2018)(Mirghaderi et al., 2023).
- ***Coding and Categorization.*** The gathered information will be systematically coded and categorized against the four key dimensions of the comparative framework: Economic Viability and Value Capture, Ethical Considerations, Technical and Operational Feasibility, and Strategic Alignment. For instance, any mention of computational costs, data acquisition fees, or performance-based pricing will be coded under "Cost-Based Elements" or "Value-Based Elements." Similarly, discussions on transparency of pricing or data usage policies will be coded under "Ethical Considerations." This structured coding process ensures that all relevant aspects of each pricing model are identified and systematically organized for subsequent comparison.

Comparative Analysis

Following the content analysis, a detailed comparative analysis will be conducted across the selected AIaaS pricing models, utilizing the structured framework as the analytical lens.

- ***Identification of Similarities and Differences.*** The coded data for each case study will be compared to identify common patterns, emerging trends, and unique approaches in AIaaS pricing. This involves mapping how different providers address similar challenges (e.g., managing computational costs, ensuring data privacy) through

their pricing structures. For example, a comparison of token-based pricing models for LLMs might reveal variations in how different providers handle context windows or fine-tuning costs (Barbere et al., 2024)(Rudnytskyi, 2022).

- ***Assessment of Strengths and Weaknesses.*** Each pricing model will be critically assessed against the criteria within the comparative framework. For instance, a model might be strong in "Economic Viability" due to its ability to capture value effectively but weak in "Ethical Considerations" if its pricing is opaque or potentially discriminatory (Ayata, 2020). This assessment aims to uncover the inherent trade-offs associated with different pricing strategies.
- ***Analysis of Trade-offs.*** A key aspect of the comparative analysis is to understand the trade-offs that AIaaS providers make when designing their pricing models. For example, a highly granular, usage-based model might offer greater fairness in cost allocation but could lead to increased "Implementation Complexity" and reduced "Transparency" for end-users (Satapathi, 2025). Similarly, prioritizing "Economic Viability" might sometimes come at the expense of certain "Ethical Considerations" such as broad accessibility or data privacy (Kaaniche & Laurent, 2018)(Ayata, 2020). Identifying these trade-offs is crucial for developing a balanced and holistic framework.

Synthesis and Framework Development

The insights derived from the comparative analysis will then be synthesized to inform the development of the novel, ethically-aware AIaaS pricing framework. This phase involves moving from analysis to conceptual construction.

- ***Identification of Best Practices.*** Elements from existing pricing models that effectively balance economic objectives with ethical principles will be identified and highlighted as potential best practices. This includes transparent metering mechanisms, flexible pricing tiers that promote accessibility, and explicit communication of data usage policies (Kaaniche & Laurent, 2018)(Satapathi, 2025).

- ***Addressing Gaps and Proposing Solutions.*** The analysis will also reveal areas where current pricing models fall short, particularly concerning ethical implications. This could include a lack of mechanisms to prevent algorithmic discrimination through pricing, insufficient transparency regarding the environmental costs of AI (Kshirsagar et2021), or inadequate provisions for user data governance. The research will propose conceptual solutions and design principles to address these gaps within the new framework.
- ***Iterative Refinement.*** The proposed framework will be developed iteratively, with initial conceptualizations being refined based on the insights gained from each comparative case and the broader literature. This ensures that the framework is robust, comprehensive, and addresses the complexities identified throughout the research process. The goal is not merely to describe what exists but to prescribe a normative model for future AIaaS pricing (Beinhoff, 2019).
- ***Integration of Ethical Lens.*** Throughout the synthesis, ethical considerations will remain paramount. The framework will not merely append ethics as an afterthought but will integrate ethical design principles directly into the pricing structure, promoting responsible AI development and deployment (Mirghaderi et al., 2023). This involves considering the impact of pricing decisions on various stakeholders, including end-users, developers, and society at large (Fang & Zhou, 2025).

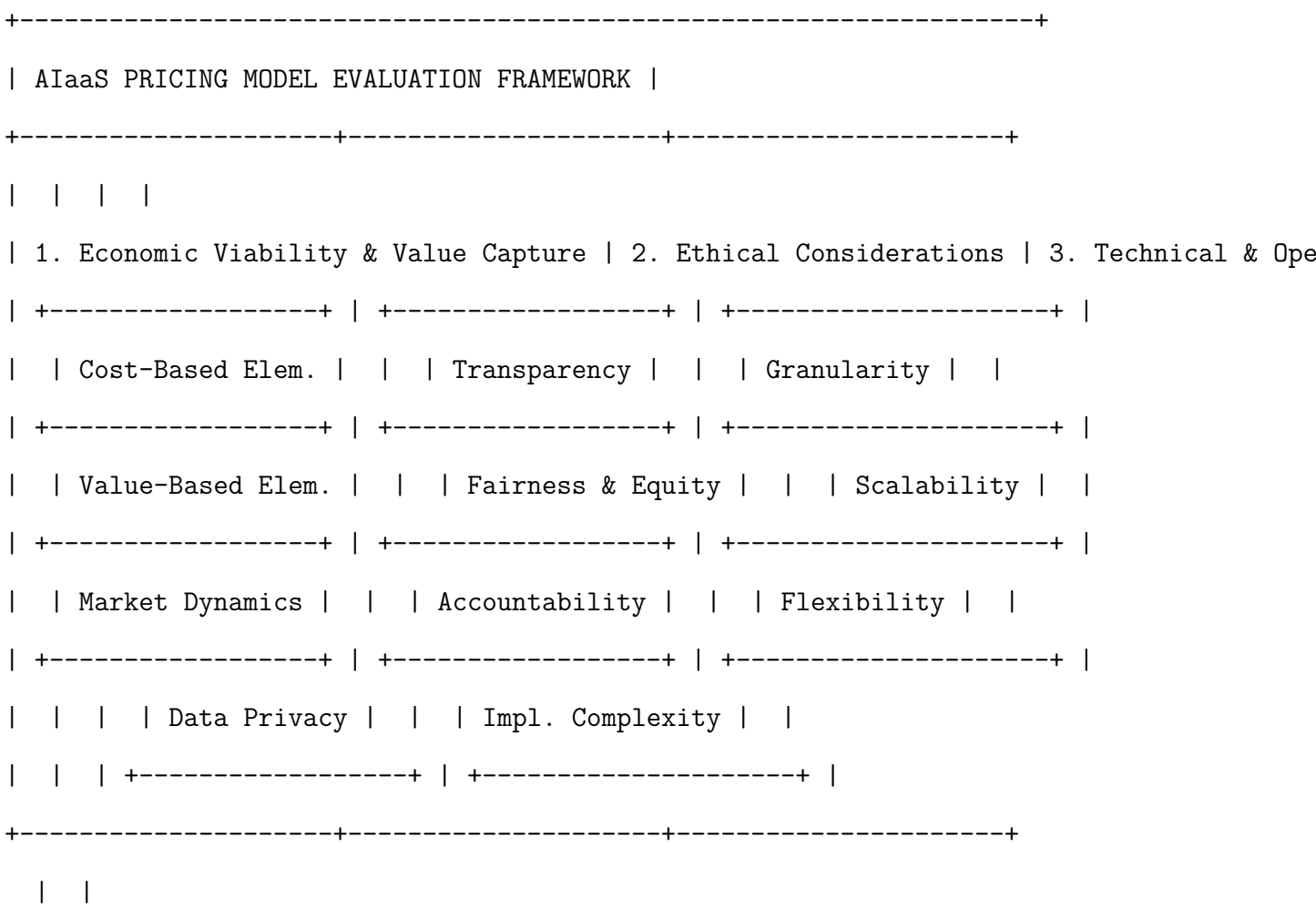
Limitations of the Theoretical Approach

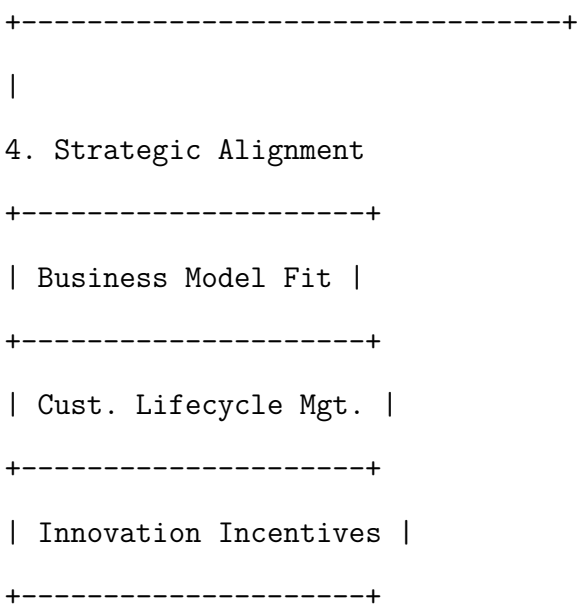
It is important to acknowledge the inherent limitations of this theoretical and qualitative approach. The reliance on publicly available information means that insights into proprietary pricing algorithms or internal cost structures are limited. The conceptual case studies are illustrative rather than empirically generalizable, meaning the proposed framework will be a theoretical construct, not one empirically validated through direct experimentation or large-scale data analysis. However, for a nascent field like ethically-aware AIaaS pricing, a robust theoretical framework is a crucial first step, providing a foundational structure for

future empirical research and practical implementation. The interpretive nature of qualitative analysis also means that the findings are subject to the researcher's interpretation, though this is mitigated by the use of a structured comparative framework and grounding in diverse theoretical perspectives.

Figure 1: Conceptual Framework for AIaaS Pricing Model Evaluation

This figure illustrates the multi-dimensional framework used to evaluate different AI-as-a-Service (AIaaS) pricing models. It highlights the interconnectedness of economic, ethical, technical, and strategic considerations.





Note: This framework provides a holistic lens for assessing AIaaS pricing, ensuring that models are not only economically sound but also ethically robust, technically implementable, and strategically aligned with long-term business goals. Each dimension and its criteria are crucial for a comprehensive evaluation.

Analysis

The economic landscape surrounding Artificial Intelligence (AI) services, particularly Large Language Models (LLMs), is characterized by a complex interplay of technological innovation, market dynamics, and evolving value propositions. This section undertakes a comprehensive analysis of the prevailing and emerging pricing models for AI, examining their comparative strengths, inherent disadvantages, and real-world applications. By dissecting the foundational economic principles and practical implications of various pricing strategies, this analysis aims to illuminate the strategic considerations for both AI providers and consumers, ultimately proposing a framework for understanding and implementing hybrid pricing approaches. The discussion will navigate through the intricacies of token-based,

subscription, outcome-based, and tiered pricing models, underpinned by examples from leading AI providers such as OpenAI and Anthropic, to provide a holistic understanding of the current state and future trajectory of AI monetization.

Comparison of AI Pricing Models

The monetization of AI services, especially those powered by sophisticated LLMs, necessitates the adoption of diverse pricing models that reflect the unique characteristics of AI consumption and value generation. Unlike traditional software, AI services often involve variable computational costs, continuous model improvements, and diverse application scenarios, demanding flexible and dynamic pricing structures (Kshirsagar et al., 2021). A critical comparison of the prominent pricing models reveals distinct advantages and disadvantages, shaping their applicability across different market segments and use cases. These models include token-based pricing, subscription models, outcome-based pricing, and tiered structures, each offering a unique approach to balancing cost recovery, value capture, and market penetration.

Token-Based Pricing Token-based pricing is arguably the most granular and widely adopted model for generative AI services, particularly LLMs (Satapathi, 2025). In this model, users are charged per "token," which represents a segment of text (e.g., a word, sub-word, or character sequence). The cost is typically differentiated between input tokens (prompts sent to the model) and output tokens (responses generated by the model), reflecting the varying computational demands of processing and generating information (Satapathi, 2025). This model offers a high degree of transparency and control for users, as costs are directly proportional to usage. For instance, a user generating a short response will incur a lower cost than one generating a lengthy document, providing a clear value-for-money proposition. The precision of this model allows for fine-grained cost allocation, making it particularly suitable for applications where usage patterns are highly variable and unpredictable, such as ad-hoc

content generation, conversational AI, or complex data analysis tasks where the length of queries and responses can fluctuate significantly (Rudnytskyi, 2022).

The fundamental appeal of token-based pricing lies in its direct correlation with computational resource consumption. Each token processed or generated consumes a certain amount of computational power, memory, and time. Therefore, charging per token allows AI providers to directly recover the variable costs associated with operating their models, including inference costs, data transfer, and infrastructure overhead (Kshirsagar et al., 2021). This direct cost recovery mechanism is crucial for the financial sustainability of large-scale AI operations, where the underlying compute infrastructure represents a significant ongoing expense. Furthermore, the model encourages efficiency from the user's perspective, prompting them to optimize prompts for conciseness and to manage the length of generated outputs, thereby reducing unnecessary computational load and associated costs. This user-driven optimization can lead to more efficient resource utilization across the entire AI ecosystem, benefiting both providers and the broader environment by potentially reducing energy consumption (Kshirsagar et al., 2021).

However, token-based pricing is not without its complexities and potential drawbacks. The concept of a "token" can be abstract for end-users, especially those without a technical background, making it challenging to estimate costs accurately before usage (Satapathi, 2025). Different models and languages may define tokens differently, leading to confusion and potential unexpected expenses. For example, a single word in English might correspond to one token, while in a language like Japanese or Chinese, it might require multiple tokens due to character encoding and segmentation rules. This variability necessitates clear documentation and potentially predictive cost calculators to help users manage their budgets. Moreover, for applications requiring very long contexts or extensive iterative interactions, token costs can accumulate rapidly, potentially making certain use cases economically unfeasible without careful optimization (Barbere et al., 2024). The challenge of accurately predicting token usage can also hinder budget planning for businesses integrating AI into their operations,

requiring sophisticated monitoring and control mechanisms to prevent cost overruns. This unpredictability can be a significant barrier for enterprise adoption, where budget certainty is often a paramount concern.

Subscription Models Subscription models, a staple in the software-as-a-service (SaaS) industry, involve users paying a recurring fee (e.g., monthly or annually) for access to AI services (De, 2017). These models typically offer different tiers, each providing a set amount of usage, specific features, or access to more advanced models. For example, a basic subscription might offer a limited number of tokens or requests per month, while a premium tier could provide unlimited usage, access to larger models, faster processing speeds, or dedicated support. This model is well-suited for users with predictable and consistent usage patterns, offering cost stability and simplifying budget management (De, 2017). The predictability of a fixed monthly or annual fee allows businesses to easily integrate AI costs into their operational budgets, removing the uncertainty associated with variable usage.

The primary advantage of subscription models is the predictable revenue stream they provide for AI providers, facilitating long-term investment in research, development, and infrastructure (De, 2017). This stable income enables providers to plan for future advancements, attract top talent, and build robust, scalable systems without the constant pressure of fluctuating usage revenue. For users, subscriptions offer transparent and predictable costs, eliminating the uncertainty associated with variable usage charges. This predictability is particularly valuable for businesses integrating AI into core operations, allowing for easier budget allocation and financial planning. Furthermore, subscription tiers can be designed to cater to different user segments, from individual developers to large enterprises, offering tailored features and service levels. Higher tiers might include features such as custom model fine-tuning, dedicated API endpoints, enhanced security protocols, or even access to specialized domain-specific models, adding significant value beyond mere token access. The "all-you-can-eat" nature of some subscription tiers can also encourage greater exploration and

adoption of AI services, as users are not constantly calculating the cost of each interaction, fostering a more experimental and integrated approach to AI utilization.

However, subscription models can present significant challenges. If usage is highly variable, users might overpay for unused capacity in months of low activity or face additional charges for exceeding limits in months of high activity, leading to dissatisfaction and potential churn. The "fair use" policies often associated with unlimited tiers can also be vague, creating uncertainty for heavy users who might inadvertently violate terms and incur unexpected penalties (De, 2017). Moreover, subscription models might not adequately capture the differential value derived from various AI applications. A user generating a simple summary might pay the same as one performing complex scientific research, even if the latter derives significantly more economic value from the AI service. This can lead to a misalignment between price and perceived value, potentially deterring some users or encouraging others to seek more granular pricing alternatives. The challenge for providers is to design tiers that accurately reflect typical usage patterns and feature requirements without creating friction for users whose needs fall between defined tiers, requiring careful market research and iterative refinement of pricing strategies.

Outcome-Based Pricing Outcome-based pricing, also known as value-based pricing, represents a more advanced and potentially transformative model for AI services. Instead of charging for inputs (tokens) or access (subscription), this model ties the cost directly to the measurable business outcomes or value generated by the AI (Maguire, 2021). For example, an AI-powered marketing tool might charge a percentage of the increased sales revenue it generates, or an AI-driven fraud detection system might charge a fee based on the amount of fraud prevented. This model aligns the interests of the AI provider and the user, as the provider's revenue is directly linked to the user's success (Maguire, 2021). This creates a profound partnership where the AI provider is incentivized to ensure the AI's maximum

effectiveness, transforming the relationship from a vendor-client dynamic to a shared-success model.

The profound advantage of outcome-based pricing lies in its ability to directly address the perceived risk of AI adoption. Businesses are often hesitant to invest in new technologies without clear evidence of return on investment. By tying payment to tangible outcomes, AI providers essentially share the risk and reward with their clients, significantly lowering the barrier to adoption (Maguire, 2021). This model is particularly effective for high-value, mission-critical AI applications where the impact on business metrics is clear and quantifiable. It incentivizes AI providers to continuously improve their models and services to maximize client outcomes, fostering a symbiotic relationship. For instance, an AI for supply chain optimization could charge a percentage of the cost savings achieved through reduced logistics expenses or improved inventory management, motivating the AI provider to develop the most efficient algorithms possible (Bhuram, 2025). This model also shifts the focus from technology features to business solutions, making AI more accessible and appealing to decision-makers who are primarily concerned with results rather than technical specifications, thereby bridging the gap between technical capabilities and strategic business objectives.

However, implementing outcome-based pricing is fraught with challenges. Accurately measuring and attributing specific outcomes to the AI's contribution can be complex, especially in environments with multiple interacting variables and human intervention (Maguire, 2021). Establishing clear baseline metrics, defining success criteria, and agreeing on methods for calculating impact require robust data infrastructure, sophisticated analytics, and strong contractual agreements. There is also the potential for disputes over attribution, particularly when the AI works in conjunction with human teams or other technologies, making it difficult to isolate the AI's precise contribution. Furthermore, this model often requires a high degree of trust and partnership between the provider and the client, as sensitive business data may need to be shared to verify outcomes, raising concerns about data privacy and security. For AI providers, the revenue stream can be less predictable than subscription models, as it

depends on the client's performance and the AI's effectiveness, which can fluctuate. This model might also be less suitable for general-purpose AI services where the outcomes are diverse and less directly quantifiable, such as creative writing or general knowledge retrieval, where the value is more subjective or diffuse.

Tiered Pricing Structures Tiered pricing, while often integrated within subscription models, can also stand as a distinct strategy, offering different price points based on features, usage limits, or service levels (Satapathi, 2025). This model allows providers to segment their market and cater to diverse customer needs, from individual developers to large enterprises. Tiers can differentiate access to specific models (e.g., small, medium, large LLMs), advanced functionalities (e.g., fine-tuning capabilities, API access, custom model deployment), or support levels (e.g., community support, email support, dedicated account manager with guaranteed response times) (Satapathi, 2025). This approach is highly flexible and allows for dynamic adjustments based on market feedback and product evolution, providing a structured way to offer a range of options.

The primary benefit of tiered pricing is its ability to capture value from a broad spectrum of customers. A basic, low-cost tier can attract price-sensitive users and foster widespread adoption, serving as an entry point for experimentation and learning. Meanwhile, premium tiers with advanced features, higher performance guarantees, and enhanced service levels can cater to enterprise clients willing to pay more for enhanced capabilities, reliability, and security (Satapathi, 2022). This segmentation allows for optimized revenue generation across the entire customer base by matching price points to perceived value and budget constraints. Tiered pricing also provides a clear upgrade path for users as their needs evolve, encouraging them to move to higher-value tiers as they derive more utility and become more reliant on the AI service. It simplifies decision-making for customers by presenting distinct packages rather than a complex array of individual features. Moreover, it allows providers to test market demand for new features by introducing them in higher tiers before

potentially rolling them out more broadly, serving as a market validation mechanism for product development.

However, designing effective tiered pricing requires careful consideration to avoid "tier cannibalization" (where higher-value customers opt for lower tiers due to insufficient differentiation) or "feature bloat" (where tiers become too complex and confusing for customers to understand). The challenge lies in identifying the right features and usage limits that differentiate each tier meaningfully without creating significant gaps or overlaps in the value proposition (Satapathi, 2025). Customers may also feel constrained by fixed limits, especially if their usage fluctuates unpredictably, leading to frustration or the perception of being "locked in" to an unsuitable tier. The perception of value for each tier must be clearly communicated, and the incremental benefits of upgrading must be compelling enough to justify the higher price point. Furthermore, an overly rigid tiered structure might not accommodate highly specialized use cases that fall outside the predefined packages, potentially leading to customer dissatisfaction or the need for bespoke custom enterprise solutions, which can add complexity to a provider's sales and service operations.

Table 1: Comparative Strengths and Weaknesses of Core AI Pricing Models

This table provides a concise overview of the primary advantages and disadvantages associated with each of the core AI pricing models discussed.

Model	Primary Advantage (Max 50 chars)	Primary Disadvantage (Max 50 chars)	Key Applicability (Max 100 chars)	Ethical Concern (Max 100 chars)
Token-Based	Granular cost control	Cost unpredictability for users	Generative AI, variable workloads, ad-hoc content creation	Transparency of token definition, potential for "token inflation"

Model	Primary Advantage (Max 50 chars)	Primary Disadvantage (Max 50 chars)	Key Applicability (Max 100 chars)	Ethical Concern (Max 100 chars)
Subscription	Predictable revenue/costs	Mismatch with variable usage	Consistent usage, predictable needs, bundled features, enterprise	Value misalignment, "fair use" ambiguity
Outcome-Based	Strong alignment of interests	Measurement/attribution complexity	High-value, mission-critical AI, quantifiable ROI, risk sharing	Data sharing, potential for disputes, market power concentration
Tiered	Effective market segmentation	Complexity in tier design	Diverse user needs, feature differentiation, clear upgrade paths	Perceived fairness of tiers, access inequality

Note: The choice of pricing model is a strategic trade-off, balancing economic objectives with user experience and ethical considerations. Hybrid models often combine strengths.

Advantages and Disadvantages of AI Pricing Models

The choice of an AI pricing model is a strategic decision that profoundly impacts revenue generation, customer acquisition, and market positioning. Each model comes with a distinct set of advantages and disadvantages that must be carefully weighed against the specific characteristics of the AI service, target market, and business objectives. Understanding these trade-offs is crucial for optimizing monetization strategies and ensuring long-term sustainability (De, 2017). The intricate balance between cost recovery, value capture, market penetration, and user satisfaction drives the selection and refinement of these models.

Advantages Token-Based Pricing: * **Granular Cost Control and Transparency:** Users pay only for what they consume, offering high transparency and precise cost management, especially for variable workloads (Satapathi, 2025). This model is particularly appealing for developers and researchers who need fine-grained control over their expenditures and are sensitive to minute usage variations. The direct link between usage and cost fosters a sense of fairness and accountability, allowing users to optimize their interactions for cost-efficiency. * **Direct Cost Recovery for Providers:** Directly correlates revenue with computational resource usage, ensuring that providers recover the variable costs associated with inference and infrastructure (Kshirsagar et al., 2021). This predictability in cost recovery allows providers to manage their operational expenses more effectively and invest in scaling their infrastructure to meet demand, fostering long-term stability for their AI offerings. * **Flexibility for Diverse Use Cases:** Suitable for a wide range of applications, from short queries to extensive content generation, without requiring users to commit to fixed packages. This flexibility allows users to experiment with different applications and scale their usage up or down as needed, without being locked into a specific plan, which is crucial for rapid prototyping and evolving project needs. * **Encourages User Efficiency:** Promotes efficient prompt engineering and output management by users, as optimizing for conciseness directly translates to cost savings. This can lead to more focused and effective use of AI resources, benefiting both the user through lower costs and the provider through reduced unnecessary computational load.

Subscription Models: * **Predictable Revenue for Providers:** Generates stable and recurring income, enabling long-term financial planning, investment in R&D, and infrastructure expansion (De, 2017). This financial stability is crucial for sustained innovation and market leadership in the rapidly evolving AI landscape, allowing providers to focus on strategic growth rather than short-term revenue fluctuations. * **Predictable Costs for Users:** Offers budget certainty for businesses and individuals, simplifying financial planning and eliminating the worry of unexpected high charges (De, 2017). This predictability is a significant draw for enterprise clients who require stable operational costs for their AI

integrations, facilitating easier procurement and budget allocation. * **Simplified Access and Management:** Users gain continuous access to services without per-transaction billing, streamlining operational workflows and reducing administrative overhead. The "set it and forget it" nature of subscriptions can enhance user convenience and reduce friction in adopting and integrating AI services. * **Fosters Customer Loyalty and Retention:** Encourages users to remain engaged with the service to maximize the value of their recurring payment, fostering long-term relationships and reducing churn (De, 2017). The perceived value of continuous access at a fixed cost can be a strong driver of loyalty, especially when combined with consistent service improvement. * **Facilitates Tiered Feature Access:** Allows providers to segment the market and offer differentiated features, performance, or support levels to various customer groups (Satapathi, 2025). This enables providers to capture value from both casual users and high-value enterprise clients, optimizing revenue across the entire customer spectrum.

Outcome-Based Pricing: * **Strong Alignment of Interests:** Directly links provider revenue to client success, fostering a partnership approach and incentivizing continuous improvement of the AI service (Maguire, 2021). This creates a win-win scenario where both parties are motivated by the same goals, leading to deeper collaboration and shared innovation. * **Reduced User Risk:** Lowers the barrier to adoption for businesses hesitant to invest in unproven AI solutions, as payment is contingent on measurable results (Maguire, 2021). This is particularly valuable for innovative or disruptive AI applications where the ROI might be uncertain initially, allowing for more aggressive adoption. * **Focus on Value, Not Features:** Shifts the conversation from technical specifications to tangible business benefits, making AI more accessible and appealing to non-technical decision-makers (Maguire, 2021). This helps to bridge the gap between AI capabilities and strategic business objectives, emphasizing the "why" rather than just the "how." * **Potential for Higher Revenue per Outcome:** If the AI delivers significant value, the provider can capture a larger share of that value, potentially leading to higher revenue than fixed-cost models (Maguire, 2021). This

model rewards providers for delivering exceptional results, encouraging them to invest in highly effective AI solutions.

Tiered Pricing Structures (as a standalone strategy or integrated): * **Effective Market Segmentation:** Effectively caters to diverse customer needs and budget constraints, from individual users to large enterprises, by offering a range of options (Satapathi, 2025). This broadens the total addressable market and optimizes revenue capture by matching offerings to specific customer segments. * **Clear Upgrade Path and Growth Incentive:** Provides a natural progression for users as their needs and usage grow, encouraging them to transition to higher-value tiers (Satapathi, 2025). This facilitates customer lifecycle management and maximizes customer lifetime value by providing clear incentives for growth. * **Robust Product Differentiation:** Allows providers to highlight and monetize specific features, performance levels, or support options, creating perceived value at different price points. This is crucial for competitive positioning in a crowded market, enabling providers to cater to niches and premium segments. * **Flexibility for Providers in Product Evolution:** Can be dynamically adjusted to introduce new features, respond to market demand, or optimize pricing strategies without overhauling the entire model. This adaptability is vital in the fast-paced AI industry, allowing for continuous refinement of offerings.

Disadvantages Token-Based Pricing: * **Cost Uncertainty for Users:** Difficult for non-technical users to accurately estimate costs upfront, leading to potential budget overruns or unexpected charges (Satapathi, 2025). The abstract nature of "tokens" can be confusing, requiring users to develop an intuitive understanding or rely on external tools for estimation. * **Complex Budgeting for Organizations:** Businesses integrating AI may find it challenging to forecast and budget for highly variable token usage, requiring sophisticated monitoring tools and potentially dedicated personnel (Satapathi, 2025). This can add an additional layer of operational complexity and cost. * **Optimization Burden on Users:** Places the onus on users to optimize prompts and manage output length to control costs, which can

detract from the user experience or lead to suboptimal AI interactions if users prioritize cost savings over comprehensive output. * **Scalability Challenges for Providers:** While cost-recovery is good, managing and billing millions or billions of granular token transactions can introduce significant operational overhead for providers, requiring robust and scalable billing infrastructure (Kshirsagar et al., 2021).

Subscription Models: * **Mismatch with Variable Usage:** Users with highly fluctuating usage patterns may find themselves overpaying for unused capacity in months of low activity or facing additional charges for exceeding limits in months of high activity (De, 2017). This can lead to dissatisfaction and customer churn if the tiers do not align with actual usage. * **Potential for Underutilization and Perceived Low Value:** Customers might pay for a subscription but not fully utilize the service, leading to perceived low value and potential churn (De, 2017). This requires providers to continuously demonstrate the value proposition and encourage engagement to retain subscribers. * **Ambiguity of "Fair Use" Policies:** Unlimited tiers often come with vague fair use policies, which can create uncertainty and frustration for heavy users who may unknowingly violate terms (De, 2017). Defining what constitutes "fair use" without alienating power users is a delicate balance. * **Value Misalignment Across Use Cases:** May not adequately capture the differential value derived from the AI service across diverse use cases, potentially leaving revenue on the table for high-value applications or deterring low-value but high-volume users who find the fixed cost prohibitive.

Outcome-Based Pricing: * **Measurement and Attribution Complexity:** Precisely quantifying the AI's contribution to a specific business outcome can be extremely difficult, especially in complex organizational environments with multiple interacting variables and human elements (Maguire, 2021). This often requires sophisticated analytics and robust data pipelines. * **Revenue Volatility for Providers:** Income streams can be unpredictable, directly tied to client performance and the AI's effectiveness, making financial forecasting challenging and potentially impacting a provider's ability to plan for future investments

and R&D (Maguire, 2021). * **High Trust and Data Sharing Requirements:** Often necessitates sharing sensitive business data and establishing deep partnerships, which can be a significant barrier for some clients due to concerns about data privacy, security, and competitive intelligence (Maguire, 2021). * **Limited Applicability:** Best suited for high-value, easily quantifiable applications; less practical for general-purpose AI services or those with intangible benefits where the value is subjective or difficult to measure directly. * **High Potential for Disputes:** Disagreements over outcome measurement, attribution, and payment calculation can lead to contractual disputes and strained client relationships, requiring strong legal frameworks and clear communication.

Tiered Pricing Structures: * **Complexity in Tier Design:** Requires careful balancing of features and limits to create compelling, distinct tiers without confusing customers or leading to cannibalization (Satapathi, 2025). Poorly designed tiers can lead to customer frustration and difficulty in choosing the right plan. * **"Goldilocks" Problem for Users:** Users may struggle to find a tier that perfectly matches their needs, feeling either overcharged for unused features or constrained by limits that are too restrictive (Satapathi, 2025). This can lead to churn if a suitable option isn't available. * **Perceived Value Gaps Between Tiers:** The jump in price and features between tiers might not always align with the perceived incremental value for some users, making upgrades less appealing and hindering customer progression. * **Increased Administrative Overhead:** Managing multiple tiers, features, and usage limits can add administrative complexity for providers, particularly in billing, customer support, and product management, requiring more sophisticated internal systems.

Real-World Examples of AI Pricing

Examining how leading AI providers implement their pricing models offers valuable insights into the practical application and strategic considerations discussed above. Companies like OpenAI, Anthropic, Google, and Microsoft have adopted various pricing strategies, often combining elements of different models to cater to their diverse user bases and product

offerings. These real-world examples illustrate the dynamic nature of AI monetization and the continuous refinement of pricing strategies in response to market demands and technological advancements, reflecting both the technical capabilities and business objectives of these industry leaders.

OpenAI's Pricing Strategy OpenAI, a pioneer in generative AI, primarily employs a **token-based pricing model** for its foundational models like GPT-3.5 and GPT-4 (Rudnytskyi, 2022). Users are charged per 1,000 tokens for both input (prompts) and output (completions), with different rates for various models and context window sizes. For instance, GPT-4 typically has a higher per-token cost than GPT-3.5, reflecting its superior performance, larger scale, and higher computational demands. Within GPT-4, models with larger context windows (e.g., 32k tokens vs. 8k tokens) also command different prices, acknowledging the increased computational resources required to process and generate longer sequences of text (Rudnytskyi, 2022). This granular approach allows OpenAI to directly recover the variable costs associated with operating these sophisticated models, which are substantial due to their scale and complexity, ensuring the economic viability of their cutting-edge research and development.

Beyond raw token usage, OpenAI also integrates elements of **tiered access** through its API plans and specific product offerings. While the core API pricing is token-based, access to certain models (e.g., the latest GPT-4 versions) might initially be restricted or offered through specific beta programs, creating a form of tiered access based on developer maturity, usage history, or specific application needs. Furthermore, for enterprise clients, OpenAI offers custom solutions that go beyond standard API pricing, potentially involving dedicated infrastructure, model fine-tuning services, and bespoke support, which implicitly incorporates elements of **subscription-like agreements** or **value-based consulting**. The evolution of OpenAI's pricing, including the introduction of models optimized for specific tasks (e.g., `gpt-3.5-turbo-instruct` for instruction following), demonstrates an attempt

to segment the market and offer more cost-effective options for common use cases, thereby catering to a broader range of developers and businesses, from individual innovators to large corporations (Rudnytskyi, 2022).

The introduction of ChatGPT Plus, a **subscription model** for its conversational interface, further exemplifies OpenAI's hybrid approach. For a flat monthly fee, subscribers gain access to ChatGPT even during peak times, faster response times, and priority access to new features and models (like GPT-4 access within ChatGPT). This subscription targets individual users and small businesses seeking a premium, reliable experience, providing predictable costs and enhanced service levels, while the API continues to serve developers with token-based pricing for programmatic access (Rudnytskyi, 2022). This dual strategy allows OpenAI to capture value from both direct end-users consuming the AI through a product interface and developers building innovative applications on top of their foundational models, maximizing market reach and revenue streams.

Anthropic's Pricing Strategy Anthropic, another prominent AI research company with a strong focus on AI safety and responsible development, also employs a **token-based pricing model** for its Claude series of LLMs. Similar to OpenAI, they differentiate pricing based on input and output tokens and offer different rates for their various models (e.g., Claude 3 Opus, Sonnet, Haiku), reflecting their respective capabilities and computational footprints. Claude 3 Opus, being their most powerful and intelligent model, commands a higher per-token price compared to Sonnet or Haiku, which are optimized for speed and cost-efficiency, respectively (Barbere et al., 2024). This differentiation allows users to select the most appropriate model for their specific task, balancing performance requirements with cost considerations, thereby offering flexibility and catering to diverse application needs.

Anthropic emphasizes the importance of context window size, offering significantly larger context windows (e.g., 200K tokens) compared to some competitors, which allows their models to process and reason over extremely lengthy documents and complex infor-

mation. While this provides unparalleled capability for tasks requiring extensive contextual understanding, it also impacts pricing, as processing larger contexts naturally incurs higher computational costs. Their token-based pricing directly reflects these resource demands, ensuring that the cost of advanced capabilities is appropriately captured. Anthropic also provides clear documentation on how tokens are counted, offering transparency to users and enabling better cost estimation (Barbere et al., 2024).

While their primary model is token-based, Anthropic, like OpenAI, also caters to enterprise clients with custom agreements that likely incorporate elements of **tiered access** and **subscription-based service level agreements (SLAs)**. These bespoke arrangements often include dedicated support, enhanced security features, custom deployments tailored to specific organizational needs, and potentially dedicated compute capacity, moving beyond simple per-token billing to a more holistic value proposition. The emphasis on responsible AI and safety, a core tenet of Anthropic, could also implicitly factor into enterprise pricing, as companies might pay a premium for models that prioritize ethical considerations and robust safety guardrails, offering an additional layer of value beyond raw performance (Mirghaderi et al., 2023). This strategic focus on safety and reliability can be a significant differentiator in enterprise markets, where trust and compliance are paramount.

Other Major Players (Google, Microsoft, AWS) Major cloud providers like Google Cloud (with its Vertex AI platform and Gemini models), Microsoft Azure AI (with Azure OpenAI Service and various proprietary models), and Amazon Web Services (AWS) with Amazon Bedrock, typically offer a sophisticated blend of **token-based pricing** and **tiered service offerings**, often integrated within their broader cloud ecosystems. Their strategies reflect a comprehensive approach to AI monetization, catering to a vast array of developers, startups, and large enterprises.

- **Google Cloud's Vertex AI** provides access to Google's foundational models, including the Gemini series, as well as a platform for building, deploying, and managing custom

machine learning models. Their pricing structure often involves token-based charges for model inference, with different rates for various models and context sizes, similar to OpenAI and Anthropic. Additionally, Vertex AI offers options for model fine-tuning, managed notebooks (e.g., for data scientists), and custom model deployment, which are priced separately, often on a **pay-per-use** or **resource-consumption basis** (e.g., per hour for GPU usage, per GB for storage) (Satapathi, 2025). This creates a comprehensive platform where users can choose between granular API access for pre-trained models and broader managed services for custom AI development and deployment, reflecting the full lifecycle of AI applications.

- **Microsoft Azure AI Language Service** and the **Azure OpenAI Service** similarly utilize token-based pricing for core LLM inference, providing access to OpenAI's models and Microsoft's proprietary AI capabilities (Satapathi, 2025). However, Azure's broader AI ecosystem integrates various cognitive services like speech-to-text, translation, and computer vision, each with its own pricing model, often based on **API calls**, **data volume processed**, or **compute time**. For enterprise customers, Azure offers comprehensive **subscription plans** and **enterprise agreements** that bundle various AI services, provide significant discounts, and include dedicated support, advanced security features, and compliance certifications. This multi-faceted approach allows Microsoft to serve a wide range of developers and large-scale corporate clients, offering both granular control over individual AI components and integrated solutions for complex business needs (Satapathi, 2025).
- **AWS with Amazon Bedrock** offers a similar paradigm, providing access to foundational models from various providers (including AI21 Labs, Anthropic, Cohere, Stability AI, and Amazon's own Titan models). Bedrock's pricing is primarily **pay-per-use** for inference, typically measured in tokens for LLMs, with variations based on the specific model used and input/output sizes. For fine-tuning custom models, charges are based on the **compute resources consumed** during training and the storage of the

resulting model. This approach aligns with AWS's broader cloud philosophy of utility computing, where users pay for the resources they provision and consume, offering maximum flexibility and scalability (Satapathi, 2025). Furthermore, AWS leverages its extensive ecosystem to integrate AI services with other cloud offerings, allowing for seamless data pipelines and complex architectural deployments, all under a unified billing system.

These examples highlight a prevailing trend: while token-based pricing remains the bedrock for direct AI model consumption, providers increasingly integrate elements of subscription, tiered access, and resource-based billing for broader platform services, managed solutions, and enterprise engagements. This hybrid approach allows them to cater to diverse customer needs, from individual developers seeking granular control to large corporations requiring comprehensive, predictable, and secure AI integrations, ultimately driving broader AI adoption and economic value creation.

Hybrid Pricing Approaches

The complexity and dynamism of the AI market necessitate the evolution beyond monolithic pricing models towards more sophisticated, **hybrid approaches**. These strategies combine elements from token-based, subscription, outcome-based, and tiered models to create flexible, value-optimized, and customer-centric pricing structures (De, 2017). The goal of a hybrid model is to mitigate the disadvantages of any single model while amplifying their collective advantages, ultimately maximizing revenue for providers and value for users. This section explores the rationale behind hybrid models and outlines common combinations and their strategic implications, emphasizing how these multi-faceted strategies address the nuanced challenges of AI monetization.

Rationale for Hybrid Models The primary rationale for adopting hybrid pricing models stems from the inherent variability in AI usage patterns, the diverse value propositions of

AI services, and the varied needs of different customer segments. A single pricing model, no matter how well-conceived, struggles to address all these dimensions effectively.

- **Addressing Usage Variability:** Pure token-based models can lead to unpredictable costs for users, making budgeting difficult, especially for non-technical users. Conversely, pure subscription models can result in underutilization for light users or unexpected overage charges for heavy users. A hybrid approach can offer a base subscription with a token-based overage, providing cost predictability up to a certain threshold and granular control beyond it, thereby catering to a wider range of usage patterns (De, 2017). This flexibility is crucial for applications where demand can fluctuate dramatically.
- **Capturing Differential Value:** Different AI applications generate different levels of economic value for users. A simple content generation task might have lower perceived value than an AI-driven drug discovery process or a highly accurate fraud detection system. Hybrid models allow providers to capture this differential value by combining a base utility charge (e.g., tokens) with value-added tiers or outcome-based components for high-impact applications, ensuring that pricing reflects the true economic benefit derived (Maguire, 2021)(De, 2017).
- **Serving Diverse Customer Segments:** From individual hobbyist developers to large multinational enterprises, customer needs vary significantly in terms of budget, feature requirements, performance demands, and support expectations. Hybrid models enable providers to offer a spectrum of options that cater to these diverse segments, broadening market reach and ensuring that no potential customer is left unserved due to an unsuitable pricing structure (Satapathi, 2025).
- **Balancing Predictability and Flexibility:** Providers inherently seek predictable revenue streams for long-term investment in research, development, and infrastructure. Simultaneously, users desire flexibility, cost control, and the ability to scale up or down as needed. Hybrid models are adept at striking this delicate balance, offering

the stability of subscriptions while retaining the granular flexibility of pay-per-use components, thus satisfying both sides of the market.

- **Encouraging Adoption and Growth:** A carefully designed hybrid model can significantly lower the entry barrier for new users (e.g., through a freemium tier or a low-cost base subscription), allowing them to experiment with the AI service with minimal financial commitment. Concurrently, it provides clear upgrade paths as users derive more value and increase their reliance on the AI service, encouraging organic growth and maximizing customer lifetime value (Seufert, 2014).

Common Hybrid Combinations Several combinations of pricing models have emerged as effective strategies for AI monetization, demonstrating the versatility and adaptability required in this rapidly evolving market.

1. Subscription with Token-Based Overage: This is perhaps the most ubiquitous and pragmatic hybrid model in the AI service landscape. Users pay a fixed monthly or annual **subscription fee** that includes a predetermined allowance of tokens or API calls. Once this allowance is exhausted, subsequent usage is charged on a **token-based (pay-as-you-go)** basis at a predefined rate (De, 2017). * **Advantages:** This model offers crucial cost predictability for a baseline level of usage, which is paramount for budgeting, particularly for businesses. The token-based overage provides flexibility for peak usage without forcing an immediate and potentially costly upgrade to a higher subscription tier. It effectively caters to users with somewhat predictable but occasionally fluctuating needs. For providers, it ensures a stable base revenue while still capturing additional value from heavy users who exceed their allowance. * **Disadvantages:** Users must still diligently monitor their usage to avoid unexpected overage charges, which can lead to dissatisfaction if not managed carefully. If the base allowance is too generous, it might not sufficiently incentivize upgrades to higher tiers; conversely, if too restrictive, it might lead to frustration and perceived unfairness. * **Real-world Application:** Many cloud services and API providers across various industries

utilize this model. For example, a data analytics platform might offer a subscription for a certain number of data processing units per month, with additional units charged on a per-unit basis. For AI, this translates to a fixed fee for X tokens, then Y price per 1,000 tokens thereafter, a common structure employed by many foundational model providers for specific API plans.

2. Tiered Subscriptions with Feature Differentiation: This model involves offering multiple distinct **subscription tiers**, each priced differently and providing access to a unique set of features, performance levels, or usage limits (Satapathi, 2025). For AI services, this could manifest as: * **Basic Tier:** Access to smaller, faster, or older models (e.g., GPT-3.5 equivalent), a limited number of API calls/tokens per month, and basic community or email support. * **Pro Tier:** Access to more powerful and current models (e.g., GPT-4 equivalent), significantly higher token allowances, faster inference speeds, priority customer support, and access to advanced features like model fine-tuning APIs or specialized model versions. * **Enterprise Tier:** Custom models tailored to specific business needs, dedicated infrastructure for enhanced performance and security, virtually unlimited usage (subject to rigorous fair use policies), premium Service Level Agreements (SLAs), dedicated account management, and enhanced security and compliance features (Satapathi, 2025). * **Advantages:** This strategy effectively segments the market, allowing providers to capture value from a wide spectrum of customer segments, ranging from individual developers and startups to large multinational corporations. It provides clear upgrade paths and incentivizes users to move to higher tiers as their needs, budget, and reliance on the AI service grow. Crucially, it clearly communicates the value proposition of different service levels, helping customers choose the most appropriate offering. * **Disadvantages:** Requires extremely careful design to ensure meaningful differentiation between tiers without creating "dead zones" where users feel stuck between options or perceive a lack of value in upgrading. Overly complex or poorly defined tiers can confuse customers, leading to decision paralysis or frustration. * **Real-world Application:** OpenAI's ChatGPT Plus subscription for end-users, offering premium access

and features for a monthly fee, alongside its varying API models (GPT-3.5 vs. GPT-4 with different capabilities and pricing), serves as a prime example of a tiered offering, where different models represent different "tiers" of capability and associated cost, allowing users to choose based on their specific needs and budget.

3. Freemium with Paid Tiers/Token Overage: A **freemium model** offers a basic version of the AI service for free, often with significant limitations on usage, features, or model access. Users must then upgrade to a paid **subscription tier** or pay on a **token-based** model to unlock full functionality, higher usage limits, or access to more advanced models (Seufert, 2014). * **Advantages:** This model dramatically lowers the barrier to entry, allowing users to experience the AI service firsthand, understand its capabilities, and perceive its value before committing financially. This is an excellent strategy for user acquisition and product adoption, especially for novel AI applications (Seufert, 2014). It can facilitate viral growth and generate a large user base, a significant portion of whom will convert to paying customers once they recognize the full potential of the service. * **Disadvantages:** Requires careful balancing of free vs. paid features to ensure the free tier is valuable enough to attract users but limited enough to drive conversions to paid offerings. The cost of supporting a large free user base can be substantial, requiring efficient infrastructure and resource management. * **Real-world Application:** Many AI tools and platforms, particularly those targeting individual users or small development teams, offer a free trial or a limited free tier. For instance, a basic image generation AI might offer a few free generations per month, then require a subscription for more advanced features, higher resolution outputs, or increased usage. This is a common and proven strategy in the software industry for analytics and API products (Seufert, 2014).

4. Outcome-Based with a Base Subscription/Token Fee: This advanced hybrid model combines the risk-sharing benefits of pure **outcome-based pricing** with the predictability and stability of a base **subscription** or **token fee**. A client might pay a fixed monthly fee for access to an AI service and basic usage, plus a percentage of the

measurable business outcome achieved directly through the AI's contribution (Maguire, 2021). * **Advantages:** This model provides a baseline, predictable revenue for the provider while strongly aligning incentives for delivering superior results, as the provider directly benefits from the client's success. It significantly reduces client risk for initial adoption by guaranteeing a minimum level of service and allowing the provider to participate in the upside of significant value creation. This fosters a deeper, more collaborative partnership. * **Disadvantages:** This model retains the inherent complexity of outcome measurement and attribution, requiring robust data collection, analytics, and agreement on key performance indicators (KPIs). It also necessitates robust contractual agreements and a high degree of trust between all parties involved to manage potential disputes over performance and payment. While the base fee provides some stability, revenue for the outcome-based component can still exhibit volatility. * **Real-world Application:** An AI-powered customer service bot might charge a base monthly fee for its deployment and maintenance, plus a small fee per successfully resolved customer query, or a percentage of cost savings from reduced human agent interaction. An AI marketing platform could charge a base subscription for its tools plus a percentage of the incremental sales generated from AI-driven campaigns, directly linking the AI's performance to the client's financial gains (Bhuram, 2025)(Niharika et al., 2024).

5. Resource-Based Pricing for Infrastructure, Token-Based for Inference: This hybrid model is particularly common in cloud AI platforms and targets advanced users, developers, and enterprises who require flexibility in managing their AI infrastructure. It charges for the underlying **computational resources** (e.g., GPU hours, CPU usage, storage, network egress) used to train or deploy custom AI models, while simultaneously charging **token-based fees** for inference on pre-trained or fine-tuned models (Satapathi, 2025). * **Advantages:** This model provides granular control over infrastructure costs for advanced users and developers who need to fine-tune models or deploy custom solutions, allowing them to optimize their resource allocation. It aligns perfectly with the utility computing model of major cloud providers, offering maximum flexibility and scalability. Crucially, it

differentiates between the costs associated with model development and deployment versus the costs of model consumption, providing clarity for different stages of the AI lifecycle. * **Disadvantages:** This model can be complex for less technical users to manage and optimize resource consumption, potentially leading to unexpected costs if not carefully monitored. It requires a certain level of technical expertise to understand and forecast costs accurately, which can be a barrier for some organizations. * **Real-world Application:** AWS Bedrock, Google Vertex AI,