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

AI-Generated Academic Thesis Showcase

Academic Thesis AI (Multi-Agent System)

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Abstract

Research Problem and Approach: The rapid emergence of agentic AI systems presents a formidable challenge to traditional pricing models, which struggle to capture their dynamic, intangible, and emergent value. This paper critically examines the evolving landscape of pricing in the age of agentic AI, seeking to unravel its complexities and propose a conceptual framework for understanding and managing these novel challenges.

Methodology and Findings: We employ a theoretical and comparative analysis, developing a framework to evaluate AI-driven pricing models across dimensions like algorithmic sophistication, data requirements, and decision-making autonomy. Our findings reveal a shift from resource-centric to value-centric and hybrid pricing approaches, driven by the unique characteristics of autonomous agents and the need for greater predictability and fairness.

Key Contributions: (1) A comprehensive comparative framework for AI agent pricing models (token-based, compute-based, value-based, action-based, subscription, AaaS). (2) An analysis of real-world implementations and the emergence of robust hybrid pricing strategies. (3) A detailed exploration of the ethical implications, emphasizing fairness, transparency, and accessibility for fostering responsible AI adoption.

Implications: This research offers strategic guidance for AI companies on business model innovation and ethical development. It provides policymakers with insights for adaptive regulatory frameworks and informs consumers/businesses on discerning AI solutions. The work underscores the necessity of balancing technological advancement with societal well-being in the evolving agentic AI ecosystem.

Keywords: Agentic AI, Pricing Models, Token-Based Pricing, Value-Based Pricing, AI Ethics, Dynamic Pricing, AI Monetization, Autonomous Agents, Cloud AI, Digital Economy, Algorithmic Pricing, Human-AI Interaction, AI Governance, Economic Implications, Subscription Models

Introduction

Artificial intelligence (AI) has brought about immense technological transformation, fundamentally reshaping industries, economies, and societal structures (Rosnik et al., 2024)(Sultan et al., 2025). No longer just a futuristic concept, AI is now a pervasive force. From sophisticated predictive analytics to autonomous decision-making systems, it drives innovation and efficiency across diverse domains (Dritsas & Trigka, 2025)(Joshi, 2025). However, as AI systems grow increasingly complex and autonomous—especially with agentic AI emerging—valuing, pricing, and monetizing them presents a formidable challenge (Akpan, 2024)(Bucher, 2025). Traditional pricing models, often rooted in tangible goods or human-driven services, simply struggle to capture the dynamic, intangible, and often emergent value propositions of AI-driven solutions. This paper critically examines the evolving landscape of pricing in the age of agentic AI. Our aim? To unravel its complexities and propose a conceptual framework for understanding and managing these novel challenges.

Indeed, AI has rapidly evolved. It's moved beyond static algorithms to more dynamic, interactive, and autonomous entities—what we now call agentic AI systems (Ranjan et al., 2025)(Liang & Tong, 2025). These systems perceive their environment, reason about their goals, make decisions, and execute actions with a degree of independence, frequently interacting with other agents or human users (Kurz, 2025). Think of personalized e-commerce agents (G et al., 2024), clinical decision support systems (Thamma, 2025), sophisticated financial trading algorithms (Jiang, 2024), or complex multi-agent simulations (Li et al., 2017). This increasing autonomy and sophistication introduces new dimensions to value creation and capture. It makes determining appropriate pricing strategies a uniquely multifaceted and critical endeavor (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025). Unlike tr

Literature Review

The rapid advancements in artificial intelligence (AI), particularly in the domain of agentic AI systems, are fundamentally reshaping various sectors of the economy, necessitating a comprehensive re-evaluation of established economic theories and business practices, especially concerning pricing mechanisms (Kumari & Raj, 2025)(Bucher, 2025)(Westover, 2025). This literature review synthesizes existing research on AI agents, diverse pricing models, the economic implications of AI integration, and the critical ethical and regulatory considerations that arise. It aims to establish a robust foundation for understanding the complex interplay between advanced AI capabilities and the evolving landscape of value creation and capture. The discussion will navigate from the foundational concepts of AI agents and their architectural frameworks to the intricacies of token-based, usage-based, and value-based pricing, ultimately identifying significant gaps in the current academic discourse that warrant further investigation.

The Emergence and Architectures of Agentic AI Systems

The concept of an "AI agent" refers to an autonomous system capable of perceiving its environment, making decisions, and taking actions to achieve specific goals, often interacting with other agents or human users (Liang & Tong, 2025). Unlike traditional AI models that primarily perform pattern recognition or prediction tasks, agentic AI systems possess a higher degree of autonomy, adaptability, and goal-directed behavior, enabling them to execute complex workflows and even learn from experience (Sultan et al., 2025). This evolution marks a significant paradigm shift from reactive AI tools to proactive, intelligent entities that can operate with minimal human intervention.

The architectural design of these systems is paramount to their functionality, scalability, and reliability (Ranjan et al., 2025). Ranjan, Chembachere et al. (Ranjan et al., 2025) underscore the importance of applying a well-architected framework to guide the development and deployment of agentic AI systems. Such frameworks typically emphasize principles of operational excellence, security, reliability, performance efficiency, and cost optimization. For instance, an effective architecture for an agentic AI might involve modular components for perception, planning, action execution, and memory, allowing for robust error handling and continuous improvement. The careful structuring of these components, as explored by (Ranjan et al., 2025), ensures that agents can navigate dynamic environments, manage resources efficiently, and maintain consistency in their decision-making processes, which is crucial for applications in high-stakes domains like finance or healthcare (Thamma, 2025).

The development of agentic AI workflows is also enhancing research productivity across various disciplines (Sultan et al., 2025). By automating repetitive tasks, synthesizing information from vast datasets, and even assisting in experimental design, these agents are accelerating the pace of scientific discovery and innovation. Sultan, Sultan et al. (Sultan et al., 2025) highlight how agentic AI can streamline complex research processes, from literature review and data analysis to hypothesis generation and report writing, thereby freeing human researchers to focus on higher-level conceptualization and critical thinking. This augmentation of human intellectual capabilities through intelligent agents signifies a transformative potential for knowledge creation and dissemination.

Furthermore, the proliferation of agentic AI systems necessitates the development of robust standards and regulatory frameworks (Tong et al., 2025)(Ignjatović, 2024). Tong, Li et al. (Tong et al., 2025) emphasize the growing need for IEEE AI standards specifically tailored for agentic systems, addressing issues such as interoperability, safety, transparency, and accountability. These standards are critical for fostering trust in AI agents and ensuring their responsible integration into society and economic infrastructures. Similarly, Ignjatović (Ignjatović, 2024) discusses regulatory frameworks for AI technologies in education at the international level, signaling a broader movement towards governing AI applications to mitigate risks and maximize societal benefits. The establishment of clear guidelines and benchmarks is essential for guiding the ethical development and deployment of these powerful technologies, especially as they become more integrated into critical decision-making processes.

The scope of agentic AI extends to diverse application areas, including clinical decision support (Thamma, 2025), platform economics (Westover, 2025), and even complex multi-agent simulations (Kurz, 2025). Thamma (Thamma, 2025) explores the potential of agentic AI for real-time diagnosis and treatment planning in clinical settings, demonstrating their capacity to process vast amounts of medical data and provide actionable insights. This capability underscores the potential of agentic AI to augment human expertise in complex, data-rich environments. In the realm of platform economics, Westover (Westover, 2025) investigates how AI agents are reshaping platform ecosystems, transforming interactions from simple search functions to sophisticated matching processes that optimize outcomes for both providers and consumers. Such agents can dynamically adjust offerings, facilitate transactions, and even negotiate terms, leading to more efficient and personalized market interactions. Kurz (Kurz, 2025) delves into generic multi-agent AI frameworks for weighted dynamic corridors, illustrating the application of agentic systems in optimizing complex logistical and operational challenges. These diverse applications collectively highlight the broad and transformative impact of agentic AI across various domains, pushing the boundaries of automation and intelligent decision-making. The underlying technology often involves large language models (LLMs), which serve as the cognitive engine for many agentic systems, enabling them to understand, generate, and interact using human-like language (Liang & Tong, 2025). Liang and Tong (Liang & Tong, 2025) provide an overview of LLM-powered AI agent systems and their applications in industrial settings, emphasizing their role in complex problem-solving and task automation.

Traditional Pricing Paradigms and Their Evolution

The economic landscape has long been shaped by various pricing models, each designed to capture value and allocate resources efficiently. Among the most prevalent are usage-based pricing, which ties cost directly to consumption, and value-based pricing, which aligns price with the perceived benefits to the customer. The advent of digital services and cloud computing has significantly amplified the relevance of usage-based models, while the increasing sophistication of products and services continually reinforces the importance of value perception.

Usage-Based Pricing Models

Usage-based pricing, a cornerstone of many service industries, particularly in the digital and cloud computing sectors, charges customers based on their actual consumption of a service or resource (Guo et al., 2025). This model is widely adopted by cloud service providers like AWS, where customers pay for computing power, storage, data transfer, and other services on a pay-as-you-go basis. The core appeal of usage-based pricing lies in its transparency and flexibility, allowing customers to scale their consumption up or down according to their needs, thereby avoiding large upfront investments and paying only for what they use. Guo, He et al. (Guo et al., 2025) examine optimal security and pricing strategies for AI cloud services, highlighting the complexities of managing resources and ensuring data integrity within a usage-based framework. Their work implicitly acknowledges that as AI capabilities become more commoditized and offered as cloud services, the pricing structures must adapt to reflect the unique computational demands and security requirements of AI workloads.

Historically, the concept of usage-based pricing has been applied across various utilities and services, from electricity and water to telecommunications. Its adaptation to software and IT services, however, has been transformative (Megahed et al., 2015). Megahed, Gajananan et al. (Megahed et al., 2015) discuss pricing IT services deals, suggesting a more agile, top-down approach. While their work predates the widespread adoption of AI-as-a-Service, it provides foundational insights into the strategic considerations for pricing complex IT offerings, many of which now integrate AI components. The principles of modularity and granular billing, which are central to usage-based models, are becoming increasingly relevant as AI services are broken down into smaller, consumable units, such as API calls or token consumption.

The advantages of usage-based pricing are manifold. For providers, it can lead to predictable revenue streams tied to customer growth and usage intensity. For customers, it offers cost efficiency and scalability, making advanced technologies accessible even to smaller entities without substantial capital outlays. However, challenges persist, particularly concerning cost predictability for end-users and the complexity of managing and monitoring consumption across diverse services. As AI agents become more autonomous and potentially generate their own usage, the monitoring and billing mechanisms for usage-based AI services will need to evolve significantly. The question of who pays for an agent's computational "thoughts" or actions, and how those actions are quantified, becomes central to the economic viability of agentic AI systems.

Value-Based Pricing Theory

In contrast to usage-based models, value-based pricing centers on the perceived value of a product or service to the customer, rather than its cost of production or usage (Ghani et al., 2025)(Bookstaber, 2024). This approach recognizes that customers are willing to pay more for solutions that deliver greater benefits, solve critical problems, or offer unique advantages. The essence of value-based pricing lies in understanding customer needs, quantifying the benefits delivered, and aligning price points with that perceived value.

Ghani, Kamarudin et al. (Ghani et al., 2025) explore the impact of customer perceived value on hotel loyalty, providing insights into how perceived benefits, beyond mere cost, drive customer behavior and willingness to pay. While focused on the hospitality industry, their findings are broadly applicable to any sector where customer perception of value is a key determinant of pricing power. In the context of AI, value-based pricing becomes particularly complex yet potent. The value delivered by an AI agent might include increased efficiency, improved decision-making, enhanced customer experience, or even competitive advantage. Quantifying these intangible benefits and translating them into a justifiable price point is a significant challenge.

Bookstaber (Bookstaber, 2024), in his work "Economics for Humans," delves into the psychological and behavioral aspects that influence economic decisions, including how individuals perceive and value goods and services. This human-centric perspective is crucial for understanding value-based pricing, especially as AI systems increasingly interact with human users and deliver personalized experiences. The perceived value of an AI agent, for example, might be influenced by its accuracy, responsiveness, ease of use, and even its "intelligence" or human-like interaction capabilities (Vindigni, 2024). Vindigni (Vindigni, 2024) discusses enhancing human-computer interaction in socially inclusive contexts, which implicitly contributes to the perceived value of AI systems by making them more accessible and effective for a broader range of users.

The implementation of value-based pricing requires a deep understanding of the customer's business, their pain points, and the quantifiable impact of the solution. It often involves sophisticated market research, customer segmentation, and a clear articulation of the unique selling propositions. For AI services, this might involve demonstrating return on investment (ROI) through case studies, performance metrics, or direct comparisons with alternative solutions. The challenge is often in proving the value proposition, especially for novel AI applications where the benefits may not be immediately obvious or easily quantifiable. As AI agents become more sophisticated, their ability to deliver highly customized and impactful solutions will likely strengthen the case for value-based pricing, moving away from simple usage metrics to a more holistic assessment of the economic and strategic advantages they provide.

AI-Driven Pricing Innovation: Dynamic Pricing and Personalization

The integration of artificial intelligence into pricing strategies has ushered in an era of unprecedented dynamism, precision, and personalization. AI-driven pricing models move beyond static price lists or simple cost-plus calculations, leveraging vast datasets and sophisticated algorithms to optimize prices in real-time, respond to market fluctuations, and tailor offerings to individual customer preferences. This shift is profoundly impacting e-commerce, retail, and service industries, creating both immense opportunities and complex ethical challenges.

Dynamic Pricing with AI

Dynamic pricing, also known as surge pricing or real-time pricing, involves adjusting the price of a product or service based on market demand, supply, competitor pricing, customer segmentation, and other external factors (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025). AI excels in this domain by processing and analyzing large volumes of data—including historical sales data, competitor prices, inventory levels, time of day, weather, and even social media sentiment—to predict demand and optimize prices for maximum revenue or profit.

Prithi and Tamizharasi (Prithi & Tamizharasi, 2025) highlight the future of retail pricing, emphasizing AI-powered optimization and customer-centric strategies. Their work suggests that AI can enable retailers to respond with agility to changing market conditions, offering competitive prices while maximizing profitability. Similarly, Kumari and Raj (Kumari & Raj, 2025) explore optimizing revenue and pricing, particularly in the context of UPI (Unified Payments Interface) transactions using AI. This specific application illustrates how AI can analyze transactional data to identify patterns, predict optimal pricing for services, or even suggest personalized offers to enhance user engagement and revenue. The ability of AI to discern subtle correlations and anticipate market shifts allows for a level of pricing granularity and responsiveness that was previously unattainable.

The benefits of AI-driven dynamic pricing are substantial, including increased revenue, improved inventory management, and enhanced market competitiveness. However, its implementation is not without complexities. Algorithms must be carefully designed to avoid alienating customers through perceived unfairness or price gouging. Transparency in pricing mechanisms, even when dynamic, is becoming an increasingly important consideration for consumer trust. Moreover, the computational demands for real-time price adjustments across a vast product catalog can be significant, requiring robust infrastructure and efficient algorithms.

AI-Driven Personalization

Beyond dynamic adjustments, AI enables a highly personalized approach to pricing and product offerings, tailoring experiences to individual customers based on their preferences, behavior, and purchasing history (Nakirikanti, 2025)(G et al., 2024). This personalization extends beyond mere recommendations to include customized pricing, promotions, and product bundles, aiming to maximize customer satisfaction and lifetime value.

Nakirikanti (Nakirikanti, 2025) discusses advancements in dynamic pricing and personalization driven by AI, emphasizing how AI can create highly individualized offers. By analyzing granular customer data, AI algorithms can identify unique segments or even individual profiles, predicting their willingness to pay for specific products or services. This allows businesses to offer bespoke prices that are optimized for each customer, potentially increasing conversion rates and revenue. G and Su et al. (G et al., 2024) further elaborate on personalized e-commerce, highlighting how AI enhances customer experience through tailored recommendations and offers. While their focus is on the broader customer experience, personalized pricing is a natural extension of this capability, directly impacting purchasing decisions.

The power of AI-driven personalization lies in its ability to move beyond broad demographic segmentation to micro-segmentation, identifying nuances in customer behavior that traditional methods might miss. This can lead to more effective marketing campaigns, higher customer engagement, and ultimately, greater profitability. However, personalization also raises significant ethical concerns, particularly regarding privacy, data security, and potential discrimination. If AI algorithms inadvertently or intentionally offer different prices based on protected characteristics (e.g., race, gender, location), it can lead to accusations of unfairness or algorithmic bias. Chaudhary (Chaudhary, 2025) underscores these ethical considerations, emphasizing fairness, transparency, and accountability in the ethics of AI in pricing. Similarly, Gazi, Gurung et al. (Gazi et al., 2024) delve into ethical considerations in AI-driven dynamic pricing specifically in the U.S. context, highlighting the regulatory and societal implications of such practices. These discussions are critical for ensuring that personalized pricing, while economically beneficial, does not erode consumer trust or exacerbate societal inequalities.

The synergy between dynamic pricing and personalization is particularly potent. AI agents can not only adjust prices in real-time based on market conditions but also personalize those adjustments for each customer, creating a highly adaptive and individualized pricing strategy. This capability represents a significant leap forward from traditional pricing methods, enabling businesses to optimize revenue streams while theoretically delivering more relevant offers to customers. However, the complexity of managing such systems, ensuring their ethical operation, and maintaining consumer trust remains a formidable challenge.

Token-Based Pricing Models for AI Services

The emergence of large language models (LLMs) and generative AI has introduced a novel pricing paradigm: token-based pricing. This model is distinct from traditional usage-based or value-based approaches, as it quantifies consumption based on discrete units of textual or computational "tokens," rather than broader metrics like CPU hours or data transfer volumes. This shift has profound implications for how AI services are consumed, priced, and how value is perceived and captured.

Understanding Tokenization and Its Role

Tokenization is the process of breaking down a sequence of text into smaller units called tokens. These tokens can be words, subwords, or even individual characters, depending on the specific tokenization algorithm used by the underlying AI model. For LLMs, the input prompt and the generated output are both measured in tokens. For instance, a sentence like "The quick brown fox" might be tokenized into "The", " quick"," brown"," fox". The cost of using an LLM API is then calculated based on the number of input tokens, output tokens, or a combination thereof.

This granular approach to measuring consumption provides a highly precise metric for resource utilization. Unlike general computational resources, where usage might be measured in abstract units like "inference time" or "compute units," tokens directly reflect the amount of linguistic processing performed by the model. This makes token-based pricing particularly well-suited for services where the primary "work" of the AI is text generation, analysis, or transformation. Akpan (Akpan, 2024) delves into advancing AI token valuation through user engagement, suggesting that the perceived value of these tokens can be influenced by how users interact with and benefit from the AI's linguistic outputs. This perspective highlights the intersection of technical measurement and user perception in determining the economic worth of token consumption.

Implications for Pricing and Cost Management

Token-based pricing models, exemplified by major AI providers like OpenAI and Anthropic, offer several advantages. For providers, it provides a clear and consistent metric for billing, directly tying revenue to the computational effort involved in processing text. It also allows for differentiated pricing based on model complexity, with more advanced or larger models typically charging a higher rate per token. For users, token-based pricing offers a degree of predictability, as they can estimate costs based on the expected length of their inputs and outputs. This allows developers to optimize their prompts and responses to minimize token usage, thereby managing costs more effectively.

However, token-based pricing also introduces unique challenges. Estimating the exact number of tokens for a given text can be non-trivial, as different models and tokenizers may produce varying token counts for the same input (Vlad et al., 2017). This variability can make cost prediction difficult, especially for complex or iterative AI workflows. Furthermore, the concept of a "token" may not intuitively align with the perceived value for end-users, leading to potential confusion or frustration. A user might perceive the value of an AI agent's output based on its quality or utility, not necessarily on the number of tokens generated. Bridging this gap between technical cost metrics and perceived user value is a critical challenge for AI service providers.

The economic implications for AI agents operating under token-based pricing are significant. As agents become more autonomous and engage in multi-turn conversations or complex reasoning processes, their token consumption can escalate rapidly. This raises questions about the cost-efficiency of agentic workflows and the potential for "runaway" costs if not properly managed. Developers of agentic AI systems must design their agents to be token-efficient, optimizing prompts, managing context windows, and employing strategies like summarization or retrieval-augmented generation to minimize unnecessary token usage. The underlying cost structure of LLMs, which are often token-based, directly impacts the economic viability of the agent systems built upon them (Liang & Tong, 2025). Liang and Tong (Liang & Tong, 2025) discuss LLM-powered AI agent systems, implicitly acknowledging how the operational costs, often tied to token usage, are a crucial factor in their industrial applications.

Comparing token-based pricing to traditional usage-based models reveals a finer granularity of measurement. While usage-based pricing might charge for compute time, token-based pricing charges for the "cognitive" output. This distinction is crucial for understanding the true cost of generative AI. It shifts the focus from raw computational resources to the specific linguistic operations performed by the AI, thereby aligning more closely with the functional output of LLMs. However, it also introduces a new layer of complexity in cost attribution and optimization, particularly for multi-modal AI or agents that combine various AI capabilities.

Economic Implications of AI Integration

The pervasive integration of AI across industries is generating profound economic implications, ranging from shifts in market dynamics and competitive landscapes to new considerations for financial stability and resource allocation (Joshi, 2025)(Westover, 2025). AI, particularly through its agentic forms, is not merely optimizing existing processes but fundamentally reshaping how value is created, distributed, and exchanged within economic systems.

Market Dynamics and Competitive Landscapes

AI's impact on market dynamics is multifaceted, influencing everything from supply and demand to pricing power and competitive advantage (Westover, 2025). Westover (Westover, 2025) highlights how AI agents are reshaping platform economies, moving from simple search functions to sophisticated matching mechanisms that can dynamically connect buyers and sellers, optimize transactions, and even facilitate complex negotiations. This enhanced efficiency and personalization can lead to more fluid markets, but also potentially to greater market concentration if dominant AI platforms emerge. The ability of AI to analyze vast datasets and predict market trends can give early adopters a significant edge, enabling them to respond to demand fluctuations more quickly and precisely than competitors.

The competitive landscape is also being redefined by AI. Businesses that effectively leverage AI for dynamic pricing, personalized offerings, and optimized operations can achieve superior cost structures, higher customer satisfaction, and stronger market positions (Prithi & Tamizharasi, 2025). Conversely, firms that lag in AI adoption risk being outmaneuvered, facing reduced profitability and market share. This creates a strong incentive for AI investment and innovation, driving a technological arms race in many sectors. The implications for small and medium-sized enterprises (SMEs) are particularly critical, as they may struggle to compete with the AI capabilities of larger corporations, potentially leading to increased market consolidation.

Furthermore, AI's ability to facilitate complex transactions and automate decision-making can create new market segments and business models. For instance, AI agents could autonomously manage supply chains, optimize logistics, or even engage in automated trading, leading to faster, more efficient, and potentially more volatile markets. The advent of non-fungible tokens (NFTs) and other digital assets (Kraizberg, 2023), while not directly AI-driven, represents a parallel shift towards new forms of digital value that AI agents could manage and trade, further complicating traditional market structures. Kraizberg (Kraizberg, 2023) discusses NFTs in the context of intellectual property and digital assets, indicating a broader trend towards novel digital economies that AI is poised to interact with and influence.

Financial Stability and Innovation

The financial sector is undergoing a significant transformation due to AI, impacting everything from risk assessment and fraud detection to trading strategies and regulatory compliance (Joshi, 2025). Joshi (Joshi, 2025) emphasizes the role of AI in advancing innovation in financial stability, suggesting that AI can provide more sophisticated tools for monitoring systemic risks, predicting market anomalies, and ensuring the robustness of financial systems. By processing vast amounts of financial data in real-time, AI can identify emerging threats and vulnerabilities much faster than traditional methods, potentially preventing financial crises or mitigating their impact.

However, the integration of AI also introduces new risks to financial stability. Algorithmic trading, driven by AI, can amplify market volatility and create flash crashes if not properly designed and monitored. The interconnectedness of AI systems across different financial institutions could also lead to systemic risks if a flaw or bias in one system propagates throughout the network. Therefore, while AI offers immense potential for enhancing financial stability through improved risk management and predictive analytics, it also necessitates robust regulatory oversight and careful system design to mitigate these new forms of risk. The future trends of AI stocks prediction using ARIMA models (Jiang, 2024), as studied by Jiang (Jiang, 2024), underscore the increasing financialization of AI itself, making the technology both an object of investment and a tool for market analysis.

Resource Allocation and Environmental Impact

AI's influence extends to resource allocation and environmental sustainability, particularly through its application in optimizing energy consumption and promoting green initiatives (Zhong et al., 2023)(Hu et al., 2024). Zhong, Liu et al. (Zhong et al., 2023) investigate the energy and environmental impacts of shared autonomous vehicles, a domain heavily reliant on AI for navigation, routing, and fleet management. Their research highlights how AI-driven optimization can reduce fuel consumption, alleviate traffic congestion, and lower carbon emissions, thereby contributing to environmental sustainability. This illustrates AI's potential to improve resource efficiency across various sectors.

Furthermore, AI is emerging as a catalyst for green innovation and sustainable finance (Hu et al., 2024). Hu, Zhang et al. (Hu et al., 2024) explore the role of AI and green credit in fostering green innovation in China, suggesting that AI can enhance the assessment of environmental risks, optimize resource allocation for sustainable projects, and facilitate the development of new green technologies. By providing better data analytics and predictive capabilities, AI can help financial institutions and policymakers direct capital towards environmentally friendly initiatives, thereby accelerating the transition to a greener economy.

This integration of AI into environmental decision-making underscores its potential to address some of the most pressing global challenges. The careful consideration of these impacts is essential for responsible AI deployment.

Ethical, Regulatory, and Societal Considerations

As AI systems, particularly autonomous agents, become more embedded in economic and societal structures, critical ethical, regulatory, and social implications arise. These concerns span issues of fairness, transparency, accountability, privacy, and the broader impact on employment and human agency. Addressing these challenges is paramount to ensuring that AI development and deployment proceed in a manner that benefits all stakeholders and upholds societal values.

Fairness, Transparency, and Accountability in AI Pricing

The use of AI for dynamic and personalized pricing raises significant ethical questions regarding fairness and potential discrimination (Chaudhary, 2025)(Gazi et al., 2024). Chaudhary (Chaudhary, 2025) provides a comprehensive overview of the ethics of AI in pricing, emphasizing the need for fairness, transparency, and accountability. If AI algorithms, based on historical data, inadvertently or explicitly assign different prices to individuals based on sensitive attributes (e.g., socioeconomic status, location, or perceived vulnerability), it can lead to discriminatory outcomes. This algorithmic bias, even if unintentional, can exacerbate existing societal inequalities and erode public trust in AI systems. Gazi, Gurung et al. (Gazi et al., 2024) further explore these ethical considerations specifically within AI-driven dynamic pricing in the U.S., highlighting the potential for disparate impacts on different consumer groups and the need for regulatory guidance to prevent unfair practices.

Transparency is another critical concern. For dynamic and personalized pricing models, it can be challenging for consumers to understand why they are being offered a particular price, or how that price was determined. This lack of transparency can lead to feelings of being manipulated or exploited, undermining consumer confidence. Ensuring that AI pricing mechanisms are explainable and auditable, even if the underlying algorithms are complex, is vital for maintaining trust. Accountability also becomes complex in AI-driven systems. When an AI agent makes a pricing decision that leads to an unfair or discriminatory outcome, identifying who is responsible—the developer, the deployer, or the AI itself—is a non-trivial legal and ethical challenge. Establishing clear lines of responsibility and mechanisms for redress is essential for governing AI pricing practices.

Regulatory Frameworks and Governance

The rapid pace of AI development has outstripped the evolution of regulatory frameworks, creating a vacuum that poses risks to consumers and businesses alike (Ignjatović, 2024). Ignjatović (Ignjatović, 2024) discusses regulatory frameworks for AI technologies in education at the international level, signaling a broader global effort to establish governance principles for AI. This effort extends to economic applications, where regulations are needed to address issues like data privacy, algorithmic bias, market manipulation, and consumer protection in AI-driven markets. The development of standards, such as those proposed by Tong, Li et al. (Tong et al., 2025) for agentic systems, is a crucial step towards establishing a common understanding of best practices and ensuring responsible AI deployment. These standards can provide a foundation for future regulatory mandates.

Effective AI governance requires a multi-stakeholder approach, involving governments, industry, academia, and civil society. Regulations may need to be adaptive and technology-neutral to keep pace with innovation, focusing on outcomes rather than specific technologies. For instance, regulations could mandate impact assessments for AI systems, require explainability for critical decisions, or establish independent oversight bodies. The challenge lies in striking a balance between fostering innovation and protecting public interests, ensuring that regulations do not stifle the economic benefits of AI while effectively mitigating its risks. Bucher (Bucher, 2025) examines how digitalization and AI will impact legal pricing, suggesting that the legal sector itself will need to adapt its pricing models and regulatory frameworks in response to AI's influence. This highlights the pervasive nature of AI's impact on regulated industries.

Societal Impact and Human Agency

Beyond direct economic and ethical concerns, AI's integration raises broader societal questions about employment, skills, and the nature of human agency in an increasingly automated world. While AI can create new jobs and augment human capabilities, there are also concerns about job displacement, particularly for routine or predictable tasks. The social impact of automated accounting systems, for example, is a relevant area of review (Jejeniwa et al., 2024). Jejeniwa, Mhlongo et al. (Jejeniwa et al., 2024) provide a review of the social impact of automated accounting systems, which, while not exclusively AI, highlights how automation can reshape professional roles and require workforce reskilling.

The rise of agentic AI systems also challenges traditional notions of human decision-making and control. As AI agents become more autonomous and capable of complex actions, questions arise about the extent of human oversight required and the potential for unintended consequences. Ensuring that humans remain "in the loop" for critical decisions, or at least have the ability to override or understand AI actions, is crucial for preserving human agency and accountability. Ethical AI in VR games, as discussed by Gangadharan (Gangadharan, 2024) in the context of welfare economics for in-game microtransactions, offers a micro-level perspective on how AI can influence user behavior and well-being in digital environments, underscoring the need for ethical design at all scales.

Moreover, the increasing reliance on AI for personalized experiences and recommendations could lead to "filter bubbles" or echo chambers, limiting exposure to diverse perspectives and potentially influencing individual preferences and choices in subtle ways. This raises concerns about the impact on critical thinking, democratic processes, and the formation of individual identity. Addressing these complex societal implications requires a holistic approach that considers not only the technical capabilities of AI but also its broader human and social context. The ethical considerations in AI-driven dynamic pricing (Gazi et al., 2024) and the ethics of AI in pricing more generally (Chaudhary, 2025) are central to these broader societal discussions, as pricing algorithms can significantly influence access to goods and services, thereby impacting socio-economic equity.

Gaps in the Literature and Future Research Directions

While the existing literature offers valuable insights into AI agents, pricing models, and their economic and ethical dimensions, several critical gaps remain, particularly at the intersection of agentic AI capabilities and novel pricing paradigms like token-based models. These gaps present fertile ground for future research, offering opportunities to advance theoretical understanding and inform practical applications.

One significant gap lies in the **economic modeling of agentic AI systems operating under token-based pricing**. Current economic models of digital services often assume traditional usage metrics (e.g., compute time, data volume) or value-based propositions. However, token-based consumption introduces a new dimension of cost and value. There is a lack of comprehensive models that analyze how autonomous AI agents, with their varying levels of complexity and decision-making capabilities, optimize their token consumption to achieve goals within a budget. This includes understanding the trade-offs between generating more tokens for higher quality outputs versus conserving tokens for cost efficiency. Research is needed to develop frameworks that can predict an agent's token usage patterns, evaluate the cost-effectiveness of different agent architectures (Ranjan et al., 2025), and design optimal pricing strategies for agent-as-a-service offerings.

Furthermore, the **perceived value and user behavior surrounding token-based pricing** remain underexplored. While Akpan (Akpan, 2024) touches on token valuation through user engagement, a deeper dive into how end-users (both human and other AI agents) perceive the value of a "token" versus a complete task or outcome is crucial. Do users understand the underlying mechanics of tokenization, or do they simply view it as an abstract cost unit? How does the variability in tokenization across different LLMs affect user trust and willingness to pay? Research could employ behavioral economics and experimental design to investigate user preferences, price sensitivity, and the psychological impact of token-based billing. This would inform more user-friendly and transparent pricing structures for AI services.

A third area requiring more attention is the **comparative analysis of different pricing models in the context of multi-agent systems and complex AI workflows**. While individual pricing models (usage-based, value-based, token-based) have been studied, there is limited literature that systematically compares their effectiveness, efficiency, and fairness when applied to integrated AI agent ecosystems. For instance, how does a hybrid pricing model that combines token-based costs for LLM interactions with value-based pricing for the overall agent's performance impact market adoption and revenue generation? What are the optimal pricing strategies for a network of interconnected AI agents, where each agent might contribute a different value proposition and consume resources in various ways? Research could explore agent-based fuzzy constraint-directed negotiation for service composition (Li et al., 2017) in the context of these evolving pricing models. Li, Yeo et al. (Li et al., 2017) provide foundational work on agent-based negotiation, which could be extended to explore how AI agents negotiate service terms and pricing in a multi-provider, multi-pricing model environment.

Moreover, the **ethical and regulatory challenges specific to AI agent pricing** warrant deeper investigation. While general ethical considerations for AI pricing have been discussed (Chaudhary, 2025)(Gazi et al., 2024), the unique autonomy and potential for complex, opaque decision-making by agentic AI systems introduce new layers of complexity. How can accountability be established when an autonomous agent makes a sub-optimal or discriminatory pricing decision? What regulatory mechanisms are needed to ensure fairness and prevent market manipulation by AI agents engaging in dynamic pricing at scale? Research could focus on developing specific ethical guidelines and legal frameworks for agentic AI pricing, including mechanisms for auditing agent behavior, ensuring transparency in their decision-making processes, and establishing clear liability structures.

Finally, the **long-term economic and societal impacts of widespread agentic AI adoption under these novel pricing models** represent a critical area for future research. How will the shift to highly granular, token-based consumption alter investment patterns in AI development? What are the implications for market competition and innovation if the cost of "intelligence" becomes a primary variable? How will this affect the distribution of wealth and access to advanced AI capabilities across different socioeconomic groups? Research could employ macro-economic modeling and foresight studies to project these long-term impacts, helping policymakers and industry leaders prepare for the transformative changes ahead. The economics of human behavior (Bookstaber, 2024) will be increasingly intertwined with the economics of AI agent behavior, necessitating interdisciplinary approaches.

In summary, the confluence of advanced AI agents and evolving pricing models presents a rich and complex research agenda. Addressing these identified gaps will not only deepen our academic understanding of this transformative technological era but also provide crucial insights for designing equitable, efficient, and sustainable AI-driven economies.

Word Count: 6010 words

The rapid evolution of artificial intelligence (AI) technologies has fundamentally reshaped the landscape of business operations, with its impact on pricing strategies being particularly profound (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025)(Nakirikanti, 2025)(Dritsas & Trigka, 2025). As firms increasingly integrate AI into their decision-making processes, understanding the nuances and comparative advantages of various AI-driven pricing models becomes paramount for both academic inquiry and strategic business practice. This section delineates the methodological approach adopted for this theoretical paper, focusing on the development of a robust framework for comparing AI-driven pricing models, the criteria for selecting illustrative case studies, and the subsequent analytical approach used to extract insights and build theoretical propositions. Given the complexity and multifaceted nature of AI in pricing, a structured methodology is essential to systematically analyze its implications, identify key differentiators, and contribute meaningfully to the existing body of knowledge.

Framework for Comparing AI-Driven Pricing Models

A comprehensive framework is indispensable for systematically evaluating and comparing the diverse array of AI-driven pricing models emerging across various industries. Such a framework moves beyond a mere classification of algorithms to encompass the critical dimensions that dictate a model's performance, ethical implications, and strategic utility. The proposed framework is structured around five core dimensions: Algorithmic Sophistication, Data Requirements and Management, Decision-Making Autonomy and Agency, Economic Objectives and Constraints, and Transparency and Explainability. Each dimension is further elaborated with specific criteria to facilitate a detailed comparative analysis.

Algorithmic Sophistication This dimension assesses the underlying computational intelligence and learning capabilities of the AI model. It is not merely about identifying the specific machine learning algorithm (e.g., regression, classification, clustering) but understanding its capacity for pattern recognition, prediction accuracy, and adaptive learning in dynamic environments (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025)(Dritsas & Trigka, 2025). * **Learning Paradigm:** Differentiating between supervised, unsupervised, and reinforcement learning approaches is crucial. Supervised models excel at predicting prices based on historical data patterns, while unsupervised methods might identify customer segments for personalized pricing (Nakirikanti, 2025)(G et al., 2024). Reinforcement learning, in contrast, allows pricing agents to learn optimal strategies through trial and error in real-time market interactions, adapting to competitor actions and consumer responses (Westover, 2025). The choice of paradigm significantly impacts a model's ability to handle uncertainty and evolve its strategy over time. * **Model Complexity and Architecture:** This criterion considers the intricacy of the AI model, ranging from simpler statistical models augmented with AI features to deep learning architectures (e.g., neural networks, transformers) (Prithi & Tamizharasi, 2025)(Dritsas & Trigka, 2025). Complex models often offer higher predictive power but may demand more computational resources and present greater challenges in interpretation. The use of agent-based systems, where multiple AI agents interact to determine pricing, represents another layer of complexity, mimicking real-world market dynamics (Ranjan et al., 2025)(Sultan et al., 2025)(Tong et al., 2025)(Li et al., 2017)(Kurz, 2025)(Liang & Tong, 2025). * **Adaptive Capacity:** A key advantage of AI-driven pricing is its ability to adapt to changing market conditions, consumer preferences, and competitive landscapes (Nakirikanti, 2025). This criterion evaluates how quickly and effectively a model can update its pricing strategy in response to new data or shifts in external factors. This includes assessing the model's robustness to outliers, its capacity for continuous learning, and its ability to handle concept drift, where the underlying relationships in the data change over time. * **Predictive Accuracy and Robustness:** The core function of many AI pricing models is to forecast demand, predict competitor reactions, or estimate customer willingness-to-pay. This criterion measures the precision and reliability of these predictions under various market conditions. Robustness refers to the model's stability and consistent performance even when faced with noisy, incomplete, or unexpected data (Prithi & Tamizharasi, 2025).

Data Requirements and Management AI models are inherently data-driven, making the quality, quantity, and ethical management of data central to their effectiveness and sustainability. This dimension explores the data ecosystem supporting AI pricing. * **Data Volume, Velocity, and Variety (3Vs):** AI pricing models often require vast amounts of data (volume), processed in near real-time (velocity), from diverse sources (variety). This includes transactional data, customer behavioral data (e.g., browsing history, clicks, time spent), demographic information, external market data (e.g., economic indicators, weather, social media trends), and competitor pricing (Prithi & Tamizharasi, 2025)(Nakirikanti, 2025)(Dritsas & Trigka, 2025)(G et al., 2024). The ability to integrate and synthesize these heterogeneous data streams is critical. * **Data Quality and Preprocessing:** The adage "garbage in, garbage out" is particularly pertinent for AI. This criterion assesses the methods for ensuring data accuracy, completeness, consistency, and timeliness. It also includes the sophistication of data cleaning, transformation, and feature engineering techniques, which are vital for preparing data for AI model consumption. * **Data Sourcing and Ethical Considerations:** This involves examining how data is collected, its provenance, and adherence to privacy regulations (e.g., GDPR, CCPA) (Chaudhary, 2025)(Gazi et al., 2024). Ethical considerations extend to preventing discriminatory pricing based on sensitive attributes and ensuring transparency in data usage practices (Chaudhary, 2025). The secure storage and handling of personal and proprietary data are also paramount. * **Data Infrastructure and Governance:** The technological infrastructure (e.g., cloud computing, data lakes, real-time analytics platforms) required to support AI pricing models is a significant factor. Data governance policies, including data ownership, access controls, and auditing mechanisms, ensure compliance and accountability (Jejeniwa et al., 2024).

Decision-Making Autonomy and Agency This dimension distinguishes between automated pricing tools and truly agentic AI systems, focusing on the degree of independent decision-making and goal-oriented behavior exhibited by the AI. * **Levels of Autonomy:** This ranges from AI systems that provide recommendations for human review to fully autonomous agents that execute pricing decisions without human intervention (Ranjan et al., 2025)(Sultan et al., 2025)(Tong et al., 2025)(Thamma, 2025)(Liang & Tong, 2025). The framework considers the extent to which the AI can learn, adapt, and make decisions independently, and the specific parameters within which this autonomy operates. * **Agentic Capabilities:** Agentic AI systems are characterized by their ability to perceive their environment, reason about their goals, plan actions, and execute them autonomously (Ranjan et al., 2025)(Sultan et al., 2025)(Tong et al., 2025)(Kurz, 2025). In pricing, this means an agent could not only predict optimal prices but also dynamically adjust them, negotiate with other agents (e.g., in supply chain or B2B contexts), and learn from the outcomes of its decisions (Li et al., 2017). The framework assesses the presence and sophistication of these agentic qualities. * **Human-in-the-Loop Integration:** Even with advanced autonomy, human oversight and intervention remain critical, especially in sensitive domains like pricing (Boverhof et al., 2024)(Vindigni, 2024). This criterion evaluates the design of human-computer interaction, including dashboards for monitoring, mechanisms for override, and capabilities for human feedback to refine AI models (Vindigni, 2024). The balance between AI efficiency and human accountability is a key consideration. * **Goal Alignment and Control:** Assessing how well the AI's autonomous decisions align with the strategic objectives of the organization and how effectively human stakeholders can define and constrain the AI's operational boundaries (Ranjan etan et al., 2025)(Sultan et al., 2025). This includes mechanisms for setting guardrails and ethical guidelines for autonomous pricing (Chaudhary, 2025)(Gazi et al., 2024).

Economic Objectives and Constraints AI pricing models are designed to achieve specific economic goals within a set of operational and regulatory boundaries. This dimension examines these objectives and the forces that constrain the models. * **Primary Economic Objectives:** While revenue or profit maximization are common, AI pricing can target other objectives such as market share expansion, customer lifetime value optimization, inventory clearance, or even social welfare (Prithi & Tamizharasi, 2025)(Nakirikanti, 2025)(Dritsas & Trigka, 2025)(Joshi, 2025). Personalized pricing aims to maximize individual customer value (Nakirikanti, 2025)(G et al., 2024), while dynamic pricing responds to real-time supply and demand fluctuations (Prithi & Tamizharasi, 2025). The framework analyzes the explicit and implicit objectives embedded in the AI's design. * **Market Structure and

Competitive Dynamics: The effectiveness of an AI pricing model is heavily influenced by the market structure (e.g., monopoly, oligopoly, perfect competition) and the nature of competition (e.g., price competition, product differentiation) (Prithi & Tamizharasi, 2025). Models must account for competitor pricing strategies, which may also be AI-driven, leading to complex algorithmic interactions (Westover, 2025). * **Regulatory and Ethical Constraints:** AI pricing operates within legal and ethical boundaries, including anti-trust laws, consumer protection regulations, and fairness principles (Ignjatović, 2024)(Chaudhary, 2025)(Gazi et al., 2024). This criterion assesses how models incorporate these constraints, for example, by avoiding price discrimination based on protected characteristics or ensuring price transparency (Chaudhary, 2025)(Gazi et al., 2024). * **Operational and Resource Constraints:** Practical limitations such as production capacity, supply chain dynamics, inventory levels, and computational resources also constrain pricing decisions (Megahed et al., 2015). The framework evaluates how AI models integrate these operational realities into their optimization processes.

Transparency and Explainability (XAI) The "black box" nature of many advanced AI models presents significant challenges, particularly in sensitive areas like pricing. This dimension focuses on the ability to understand and interpret AI pricing decisions. * **Interpretability of Model Outputs:** This refers to the degree to which humans can comprehend the reasons behind an AI's pricing recommendations or decisions. Simpler models (e.g., rule-based systems) are highly interpretable, while complex deep learning models are often less so (Chaudhary, 2025). The framework evaluates the methods used to make outputs understandable, such as sensitivity analysis or feature importance scores. * **Explainability of Decision Logic:** Beyond just interpreting outputs, explainability (XAI) aims to shed light on the internal workings of the AI model and how it arrived at a particular decision (Chaudhary, 2025). This includes techniques like LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) values. The ability to explain *why* a price was set for a specific customer or product is crucial for building trust, regulatory compliance, and dispute resolution (Chaudhary, 2025)(Gazi et al., 2024). * **Auditability and Accountability:** The capacity to trace back pricing decisions to their input data and algorithmic logic is essential for auditing purposes and assigning accountability in case of errors or undesirable outcomes (Chaudhary, 2025)(Jejeniwa et al., 2024). This criterion assesses the presence of logging, version control, and other mechanisms that support forensic analysis of AI pricing systems. * **Communication of Pricing Rationale:** How well the rationale for AI-driven pricing decisions can be communicated to consumers, regulators, and internal stakeholders. This is vital for maintaining fairness perceptions and preventing accusations of predatory or discriminatory practices (Chaudhary, 2025)(Gazi et al., 2024).

Conceptual Framework for Agentic AI Pricing Models

This figure illustrates the interconnections between the core components of an agentic AI system and how they influence pricing model design, from data input to value delivery.

Figure 1: Conceptual Framework for Agentic AI Pricing Models

Note: This diagram illustrates how data from the perception module feeds into planning and memory, which then guide action execution. The pricing model interface translates these operational aspects into billable units, while market and ethical considerations shape the overall pricing strategy and its impact.

Case Study Selection Criteria

To provide empirical grounding for the theoretical framework and illustrate the practical implications of AI-driven pricing, a set of carefully chosen case studies will be analyzed. Given the theoretical nature of this paper, these case studies will be drawn from publicly available information, academic literature, industry reports, and reputable news sources. The selection process emphasizes diversity and relevance to ensure a comprehensive exploration of the framework's dimensions.

- **Industry and Market Structure Diversity:** Cases will be selected from a range of industries, including retail, e-commerce, ride-sharing, financial services, and energy markets (Prithi & Tamizharasi, 2025)(Dritsas & Trigka, 2025)(Joshi, 2025)(Mancarella, 2022)(Guo, 2025). This diversity is crucial because pricing challenges, data availability, competitive dynamics, and regulatory environments vary significantly across sectors. For instance, pricing in a highly competitive e-commerce market (Dritsas & Trigka, 2025)(G et al., 2024) differs from that in a regulated energy market (Mancarella, 2022) or complex B2B IT services (Megahed et al., 2015).
- **Varying Levels of AI Maturity and Sophistication:** Case studies will represent a spectrum of AI adoption in pricing, from companies employing basic algorithmic pricing tools to those leveraging advanced agentic AI systems (Ranjan et al., 2025)(Sultan et al., 2025)(Liang & Tong, 2025). This allows for a comparative analysis of how different levels of algorithmic sophistication impact pricing outcomes and the challenges encountered. Examples might include companies using simple dynamic pricing algorithms versus those employing complex reinforcement learning agents (Westover, 2025) or multi-agent systems (Li et al., 2017)(Kurz, 2025).
- **Demonstrated Impact or Noteworthy Challenges:** Priority will be given to cases that have either achieved significant market success through AI pricing or have faced notable controversies, ethical dilemmas, or regulatory scrutiny (Chaudhary, 2025)(Gazi et al., 2024). Such cases offer rich insights into both the opportunities and the pitfalls of AI in pricing. For example, cases involving accusations of algorithmic collusion or discriminatory pricing will be particularly valuable for exploring the ethical and regulatory dimensions of the framework (Chaudhary, 2025)(Gazi et al., 2024).
- **Public Data Availability and Research Coverage:** As this is a theoretical paper relying on secondary data, the availability of comprehensive and reliable public information about the company's pricing strategies, AI technologies used, and market outcomes is a critical criterion. Cases with extensive academic (Teljeur & Ryan, 2022)

or industry coverage, white papers, or detailed news analyses will be favored. While proprietary details are often scarce, sufficient public information is necessary to apply the framework meaningfully.

- **Geographic and Regulatory Context:** Cases will ideally represent different geographic regions to account for variations in legal and regulatory frameworks concerning AI and pricing (Ignjatović, 2024)(Kraievskyi et al., 2024). For instance, a case from the European Union might highlight GDPR compliance and ethical AI guidelines (Ignjatović, 2024), while one from the US might emphasize anti-trust considerations.
- **Illustrative of Specific Framework Dimensions:** Each selected case study should serve to particularly highlight one or more specific dimensions of the comparative framework. For example, a case known for its highly personalized pricing (Nakirikanti, 2025)(G et al., 2024) would be excellent for illustrating "Data Requirements and Management" and "Economic Objectives," while a case involved in an algorithmic pricing controversy would illuminate "Transparency and Explainability" and "Ethical Constraints."

Exclusion criteria will include purely speculative ventures with no real-world deployment, cases where information is entirely proprietary and unverifiable, or instances where the AI component in pricing is negligible or non-existent. The goal is to select a diverse yet focused set of cases that collectively offer a rich tapestry for applying and validating the proposed analytical framework.

Analysis Approach

The analysis approach for this paper is primarily qualitative and comparative, leveraging the developed framework to systematically examine the selected case studies. This approach facilitates deep insights into the mechanisms, implications, and challenges of AI-driven pricing, moving beyond mere description to contribute to theoretical development.

Data Collection and Sourcing Given the theoretical nature of this paper, data collection will rely exclusively on secondary sources. These include: * **Academic Literature:** Peer-reviewed articles, conference papers, and doctoral theses that discuss AI in pricing, dynamic pricing, personalized pricing, agentic systems, and related ethical or regulatory aspects (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025)(Nakirikanti, 2025)(Teljeur & Ryan, 2022)(Dritsas & Trigka, 2025)(Chaudhary, 2025)(Gazi et al., 2024)(Westover, 2025)(Li et al., 2017)(Kurz, 2025)(Liang & Tong, 2025). * **Industry Reports and White Papers:** Publications from reputable consulting firms, technology providers, and industry associations that offer insights into real-world applications and trends of AI pricing. * **Company Publications:** Annual reports, investor presentations, and corporate blogs that might indirectly reveal aspects of their pricing strategies or AI adoption. * **News Articles and Investigative Journalism:** Reports from credible media outlets that often cover company strategies, market impacts, controversies, or regulatory actions related to AI pricing. * **Regulatory Documents:** Publications from governmental bodies or international organizations regarding AI governance, consumer protection, or competition law that may reference specific cases or general principles (Ignjatović, 2024)(Kraievskyi et al., 2024).

The focus will be on extracting relevant information that can be mapped onto the dimensions and criteria of the comparative framework. Due diligence will be exercised to ensure the credibility and reliability of all sources.

Analytical Steps The analysis will proceed in four distinct phases:

1. **Descriptive Analysis of Case Studies:** For each selected case study, a comprehensive descriptive profile will be created. This involves outlining the company's market context, the specific pricing challenges it faces, the type of AI technologies reportedly employed for pricing (e.g., machine learning models, reinforcement learning agents), the data sources utilized, the stated economic objectives of their pricing strategies,

and any publicly reported outcomes or controversies. This phase establishes a foundational understanding of each case, preparing it for deeper comparative analysis.

2. **Application of the Comparative Framework:** In this phase, each case study will be systematically mapped against the five dimensions (Algorithmic Sophistication, Data Requirements and Management, Decision-Making Autonomy and Agency, Economic Objectives and Constraints, and Transparency and Explainability) and their respective criteria. This involves qualitatively assessing how each case exemplifies or performs on each criterion. For instance, for "Algorithmic Sophistication," a case might be rated on the complexity of its models or its adaptive capacity based on available information. This structured mapping allows for consistent evaluation across diverse cases.

3. **Cross-Case Comparative Analysis:** Following the individual mapping, a cross-case analysis will be conducted. This phase involves identifying patterns, similarities, and significant differences across the case studies based on their performance within the framework. The aim is to discern common themes, best practices, recurring challenges, and the interplay between different dimensions. For example, the analysis might explore whether higher levels of "Decision-Making Autonomy" correlate with specific "Economic Objectives" or if certain "Data Requirements" are consistently linked to ethical concerns regarding "Transparency and Explainability." This comparative lens will highlight the strengths and weaknesses of different AI pricing approaches in varied contexts.

4. **Synthesis and Theoretical Contribution:** The final phase involves synthesizing the findings from the comparative analysis to generate theoretical insights and propositions. This includes identifying emergent properties of AI-driven pricing, success factors, critical failure points, and the conditions under which certain AI pricing strategies are more effective or problematic. The insights will be related back to the initial research questions and integrated with existing theories in economics, information sys-

tems, and management science. This phase aims to refine the theoretical framework itself and articulate its contribution to a deeper understanding of AI's transformative role in pricing.

Ensuring Rigor and Validity To enhance the rigor and validity of this qualitative, comparative analysis: * **Transparency of Interpretation:** All interpretations and mappings of case study information to the framework dimensions will be clearly articulated, providing a transparent chain of evidence from source material to analytical conclusion. * **Triangulation of Sources:** For each case study, information will be sought from multiple independent sources where possible to corroborate facts and reduce bias inherent in any single source. * **Systematic Application of Framework:** The consistent application of the detailed comparative framework across all case studies ensures methodological coherence and facilitates meaningful comparisons. * **Acknowledgment of Limitations:** The inherent limitations of relying solely on secondary data, which may lack proprietary details or specific operational metrics, will be acknowledged. This may affect the depth of analysis in certain areas or the generalizability of findings to specific internal company operations. However, the breadth offered by diverse public cases provides valuable insights for theoretical development.

By employing this systematic and rigorous methodology, this paper aims to provide a nuanced and comprehensive understanding of AI-driven pricing models, contributing both to academic theory and practical guidance for organizations navigating this complex technological frontier.

Analysis

The emergence of sophisticated AI agents has fundamentally reshaped the landscape of digital services, moving beyond mere tool provision to autonomous execution of complex tasks (Ranjan et al., 2025)(Sultan et al., 2025). This paradigm shift necessitates a re-evaluation of traditional pricing models, which were predominantly designed for static software licenses or resource consumption (Megahed et al., 2015). The unique characteristics of AI agents, including their adaptability, learning capabilities, and potential for chain-of-thought reasoning, introduce novel challenges and opportunities for monetization (Kurz, 2025)(Liang & Tong, 2025). This section provides a comprehensive analysis of various pricing models applicable to AI agent services, comparing their advantages and disadvantages, examining real-world implementations by leading providers, and exploring the potential for hybrid approaches. The discussion extends to the broader implications of these pricing strategies on market dynamics, user adoption, and ethical considerations, particularly concerning fairness and accessibility. Understanding these models is critical for both providers seeking sustainable revenue streams and consumers aiming to optimize their investment in agentic AI capabilities (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025).

1.1 Comparison of Pricing Models for AI Agent Services

The evolution of AI agent technology demands an equally dynamic approach to pricing. Traditional software pricing often relies on licensing, subscriptions, or per-unit sales. However, AI agents operate differently, consuming computational resources, performing actions, and delivering value in ways that are not always directly proportional to simple input/output metrics (Akpan, 2024). Consequently, a diverse set of pricing models has begun to emerge, each with distinct underlying assumptions about value creation and consumption. These models range from direct resource-based charging to more abstract value-based compensation, reflecting the increasing sophistication and autonomy of AI systems. The choice of a pricing model has profound implications for a provider's market positioning, revenue stability, and the overall accessibility and perceived fairness of their services (Chaudhary, 2025)(Bucher, 2025). A critical comparison of these models reveals their suitability for different types of AI agent services and market segments.

1.1.1 Token-Based Pricing Token-based pricing has become the de facto standard for many foundational large language models (LLMs) and, by extension, for AI agents built upon them (Akpan, 2024). In this model, users are charged based on the number of "tokens" consumed during an interaction with an AI model. A token typically represents a word, a sub-word unit, or a character sequence, and both input (prompt) and output (response) contribute to the total token count. This model offers a granular and seemingly transparent way to meter usage, directly linking cost to the amount of data processed by the underlying language model (Akpan, 2024). The simplicity of a per-token charge, often differentiated by model size or capability (e.g., GPT-3.5 vs. GPT-4), makes it easily understandable for developers and allows for predictable cost estimation for simple, one-off API calls. For AI agents, especially those that engage in extensive internal deliberation or generate verbose intermediate steps (e.g., "chain-of-thought" or "tree-of-thought" reasoning), token consumption can escalate rapidly. Each internal thought process, every step in a multi-stage plan, and every piece of information retrieved or generated contributes to the token count, even if it is not directly presented to the end-user (Liang & Tong, 2025). This inherent characteristic of agentic systems introduces a layer of complexity not always present in simpler LLM API calls.

Advantages: One of the primary advantages of token-based pricing is its direct correlation with the computational load on the LLM infrastructure. More tokens generally mean more processing, thus justifying the cost from the provider's perspective. It provides a clear, scalable metric that can be easily implemented and monitored via API usage logs (Guo et al., 2025). For developers, it offers a predictable cost structure for stateless interactions, allowing them to estimate expenses based on the expected length of prompts and responses. This model also encourages efficiency in prompt engineering, as verbose prompts directly translate to higher costs, thereby incentivizing users to craft concise and effective instructions (Akpan, 2024). Furthermore, token-based pricing is relatively straightforward to implement for providers, requiring robust tokenization and usage tracking mechanisms, which are often already in place for core LLM services. This ease of implementation makes it a popular initial choice for new AI service offerings. The ability to differentiate pricing by model capability (e.g., higher cost per token for more advanced or context-rich models) also allows providers to segment their market and capture more value from users requiring premium performance (Guo et al., 2025).

Disadvantages: Despite its widespread adoption, token-based pricing presents significant drawbacks, particularly for complex AI agent systems. The most notable issue is the potential for **cost opacity and unpredictability** for agentic workflows. An AI agent might internally generate numerous tokens for planning, self-correction, tool use, or information retrieval that are never directly seen by the user but still incur costs (Ranjan et al., 2025). This "hidden token consumption" can lead to unexpectedly high bills, especially for agents designed for deep reasoning or iterative problem-solving. Users might perceive this as unfair, as the value derived might not scale linearly with the internal token count. For instance, an agent attempting to solve a difficult problem might fail after consuming a large number of tokens, leading to a cost without a successful outcome. This risk aversion can stifle experimentation and the adoption of more powerful, but potentially more token-intensive, agent architectures (Sultan et al., 2025).

Another significant disadvantage is the **lack of direct correlation with perceived value**. A short, concise output from a highly intelligent agent might be incredibly valuable, yet incur minimal token cost, while a verbose, less useful output might be expensive. This disconnect can lead to dissatisfaction and a misalignment between price and utility (Akpan, 2024). Moreover, token-based pricing can incentivize providers to optimize for token efficiency rather than overall agent performance or user satisfaction. The development of more advanced tokenization methods or compression techniques might become a priority over enhancing the agent's core capabilities or reasoning depth. Finally, this model does not inherently account for the computational resources beyond token processing, such as specialized hardware for inference, data storage, or the orchestration layer required for agentic systems (Guo et al., 2025). It is a proxy for cost, not a direct measure of the overall system's resource utilization or the complexity of the agent's actions. The granularity, while seemingly an advantage, can also be a source of frustration, as users may struggle to understand why specific interactions consume a certain number of tokens, especially when dealing with multilingual content or complex data structures (Akpan, 2024).

1.1.2 Compute-Based Pricing Compute-based pricing charges users directly for the underlying computational resources consumed by the AI agent. This model typically involves billing based on metrics such as CPU hours, GPU hours, memory usage, or data transfer (Guo et al., 2025). It is a more traditional cloud computing pricing model adapted for AI workloads, reflecting the actual infrastructure costs incurred by the provider. For AI agents, this could mean charging for the time the agent's inference engine is active, the specific type of GPU it utilizes, or the amount of data it processes or stores. This model provides a transparent link between the physical resources used and the cost, similar to how cloud providers charge for virtual machines or serverless functions.

Advantages: The primary advantage of compute-based pricing is its **transparency regarding infrastructure costs**. Users can directly see and understand what they are paying for in terms of raw computational power, which can be particularly appealing to developers and engineers who are familiar with cloud infrastructure (Guo et al., 2025). This model aligns the provider's costs with their revenue, making it easier to manage profitability, especially for resource-intensive AI tasks. It also encourages users to optimize their agent deployments for computational efficiency, leading to faster execution times and lower costs.

For agents that perform highly variable workloads, where token counts might not accurately reflect the actual processing effort (e.g., complex simulations, large data analytics, or fine-tuning operations), compute-based pricing can be a more equitable and predictable model. Furthermore, it allows for greater flexibility in terms of hardware selection; users might choose cheaper, slower CPUs for less critical tasks or premium GPUs for high-performance requirements, with pricing reflecting these choices (Guo et al., 2025). This model is also well-suited for scenarios where agents are deployed on dedicated infrastructure or within private cloud environments, where resource allocation is explicit.

Disadvantages: A significant drawback of compute-based pricing is its **complexity for end-users**. Most users of AI agents are not interested in managing or understanding the intricacies of CPU/GPU utilization or memory consumption (Vindigni, 2024). They care about the outcome and the value the agent provides. Abstracting away these technical details is often a key selling point of AI agent services. Charging based on compute metrics shifts the burden of resource optimization onto the user, which can be a barrier to adoption, especially for non-technical users or small businesses (Guo et al., 2025). Moreover, the actual compute cost of an AI agent's operation can be highly variable and difficult to predict. Factors like network latency, contention for shared resources, or unexpected computational spikes can lead to fluctuating costs, making budgeting challenging. It also fails to capture the intellectual property or development cost associated with the AI model itself, focusing solely on the operational expenditure (Megahed et al., 2015). For agents that spend significant time "thinking" or waiting for external tools, compute-based pricing might not accurately reflect the "idle but active" state, potentially leading to charges for periods of low actual computational work. This model also inherently makes it difficult to compare different AI agent services, as providers might optimize their underlying infrastructure differently, leading to varying compute consumptions for similar tasks.

1.1.3 Value-Based Pricing Value-based pricing represents a significant departure from resource-centric models, focusing instead on the **perceived or realized value** an AI agent delivers to the user (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025). In this model, the price is set based on the benefits the user gains, such as cost savings, increased revenue, improved efficiency, or enhanced decision-making (Dritsas & Trigka, 2025). This approach requires a deep understanding of the customer's needs, business processes, and the measurable impact of the AI agent. Examples might include a percentage of cost savings achieved, a share of increased revenue generated, or a fixed fee based on the strategic importance of the task completed (Prithi & Tamizharasi, 2025). Value-based pricing is often seen in high-value B2B contexts where the AI agent is integrated into critical business operations and its contribution can be quantified.

Advantages: The most compelling advantage of value-based pricing is its **direct alignment with customer success**. When the provider's revenue is tied to the value delivered, there is a strong incentive to ensure the AI agent performs optimally and generates tangible benefits (Prithi & Tamizharasi, 2025). This fosters a partnership approach, where both parties are invested in the outcome. For customers, it reduces the risk of investing in unproven technology, as they only pay when they realize value. This can accelerate adoption for innovative but potentially costly AI agent solutions. From the provider's perspective, value-based pricing allows them to capture a larger share of the economic surplus created by their AI agents, potentially leading to significantly higher revenues compared to resource-based models, especially for agents that deliver transformative results (Kumari & Raj, 2025). It shifts the focus from cost-of-service to value-of-service, promoting a premium positioning for advanced AI agent capabilities. This model is particularly effective for agents that solve complex, high-impact problems or automate processes that generate substantial savings or revenue (Dritsas & Trigka, 2025). It also encourages continuous improvement and innovation, as enhancing the agent's capabilities directly translates to increased value and thus higher potential revenue.

Disadvantages: Value-based pricing is notoriously **difficult to implement and measure**. Quantifying the exact value attributable solely to an AI agent, especially in complex business environments with multiple contributing factors, can be challenging and contentious (Prithi & Tamizharasi, 2025). Establishing clear metrics, baseline performance, and methods for attribution requires sophisticated analytics and often extensive negotiation between provider and client. This complexity can lead to disputes and mistrust if not handled carefully. Furthermore, this model often requires a higher degree of customization and deep integration into a client's systems, increasing the initial setup costs for the provider. It also demands a high level of trust and transparency, as both parties need to agree on how value is defined and measured. For providers, there's also the risk that the AI agent might underperform or fail to deliver the anticipated value, leading to reduced or no revenue despite significant development and operational costs (Megahed et al., 2015). This model is generally not suitable for mass-market or low-value AI agent services, as the overhead of value measurement would outweigh the potential revenue. The scalability can also be limited, as each client might require a unique value assessment framework.

1.1.4 Action/Task-Based Pricing Action-based or task-based pricing charges users for each discrete action an AI agent performs or for each complete task it successfully executes (Prithi & Tamizharasi, 2025). This model is particularly relevant for agents designed to automate specific workflows or interact with external systems. Examples include charging per API call made by the agent, per document processed, per customer query resolved, or per transaction completed. Unlike token-based pricing, which measures raw data processing, action-based pricing focuses on the completion of meaningful units of work (Akpan, 2024). This model aligns more closely with the functional utility of an AI agent, especially when it acts as an intelligent automation tool.

Advantages: The primary benefit of action/task-based pricing is its **simplicity and clarity for users**. Users understand exactly what they are paying for: a completed action or a resolved task. This makes budgeting more straightforward and helps users directly associate cost with tangible outcomes (Prithi & Tamizharasi, 2025). It removes the unpredictability of internal token consumption or fluctuating compute resources, as the charge is fixed per predefined unit of work. This model is highly suitable for agents that perform well-defined, repeatable tasks, such as data entry, customer support ticket resolution, or report generation. It also incentivizes providers to optimize their agents for efficiency and reliability in task completion, as failed tasks typically do not incur charges. For users, it offers a clear return on investment (ROI) calculation, as they can compare the cost per task to the value derived from that task (e.g., cost savings from automation). This model is particularly effective for agents that integrate with specific applications or services, where the "action" can be clearly delineated (Li et al., 2017).

Disadvantages: A significant challenge with action/task-based pricing lies in **defining and standardizing "actions" or "tasks"**. The complexity and resource intensity of different actions can vary widely. For instance, a simple data lookup might be cheap, while generating a complex report or interacting with multiple external APIs might be expensive. If pricing is uniform per action, it might undervalue complex actions or overvalue simple ones (Akpan, 2024). If pricing is differentiated by action type, the model quickly becomes complex. This model also struggles with agents that perform exploratory or creative tasks, where the "output" is not a discrete action but rather a discovery or an idea. Furthermore, it does not account for the internal reasoning steps or "thinking time" an agent might require to successfully complete a task. An agent might consume significant resources internally before executing a single action, and this internal cost is not directly captured by an action-based charge. This can create a misalignment where the provider incurs high costs for complex internal processing but only gets paid for a simple, successful action (Ranjan et al., 2025). It also requires robust tracking and validation mechanisms to ensure that tasks are indeed completed successfully before charging.

1.1.5 Subscription/Tiered Pricing Subscription or tiered pricing models provide users with access to an AI agent service for a recurring fee, typically monthly or annually (Guo et al., 2025). This model often includes different tiers, each offering varying levels of access, features, usage limits, or dedicated resources. For example, a basic tier might offer limited agent interactions per month, while a premium tier provides unlimited usage, access to advanced agent capabilities, or dedicated compute resources. This model is ubiquitous in the software-as-a-service (SaaS) industry and is now being adapted for AI agent platforms.

Advantages: The primary advantage for providers is **predictable and recurring revenue**, which is crucial for business stability and long-term planning (Guo et al., 2025). It allows providers to invest in continuous development and improvement of their AI agents. For users, subscriptions offer **predictable costs**, making budgeting easier and eliminating the worry of fluctuating usage-based bills. This predictability can encourage greater experimentation and consistent use of the agent, as users are not constantly monitoring individual transaction costs. Tiered models allow providers to cater to different customer segments, from individual users with basic needs to large enterprises requiring extensive capabilities and support (Guo et al., 2025). This flexibility can expand the total addressable market. Furthermore, subscriptions can foster customer loyalty and reduce churn, as users become accustomed to the service and find value in its continuous availability. It also allows providers to bundle additional services, such as customer support, integration tools, or access to exclusive features, into higher tiers, enhancing the overall value proposition.

Disadvantages: A significant challenge with subscription models is **determining the appropriate pricing tiers and usage limits**. If tiers are too restrictive, users might feel constrained; if too generous, providers might leave revenue on the table (Guo et al., 2025). "Usage caps" can lead to negative user experiences if exceeded unexpectedly, potentially forcing users into higher, more expensive tiers. For users with highly variable usage patterns, a fixed subscription might be inefficient; they might pay for unused capacity during low-usage periods or hit limits during peak times. This model can also be less equitable for low-volume users, who might end up paying a minimum fee even for very limited engagement (Chaudhary, 2025). Moreover, subscriptions do not directly align with the actual value generated by the agent for a specific task. A user might pay a high monthly fee for an agent that delivers immense value only once, or minimal value consistently. The initial commitment of a subscription can also be a barrier to entry for potential users who are hesitant to commit without first thoroughly evaluating the agent's capabilities (Guo et al., 2025).

1.1.6 Agent-as-a-Service (AaaS) Models Agent-as-a-Service (AaaS) models represent a broader conceptual framework where entire AI agents or specialized agent capabilities are offered as a managed service (Ranjan et al., 2025)(Sultan et al., 2025). This goes beyond just providing API access to an underlying LLM; it encompasses the full lifecycle management, orchestration, and maintenance of intelligent agents designed for specific purposes. AaaS can encapsulate various pricing strategies within its framework, but its core characteristic is the provision of a complete, ready-to-use agent environment. This could involve agents for specific industries (e.g., legal, medical, financial), or agents specialized in particular functions (e.g., data analysis, content creation, project management) (Thamma, 2025)(Joshi, 2025).

Advantages: AaaS offers significant benefits by **reducing the operational burden on users**. Customers do not need to worry about deploying, maintaining, or scaling the underlying infrastructure or orchestrating complex agent workflows (Sultan etal., 2025). The provider handles all technical complexities, offering a seamless, ready-to-consume service. This lowers the barrier to entry for businesses wanting to leverage advanced AI agent capabilities without deep in-house AI expertise. For providers, AaaS allows for **vertical integration and specialization**, enabling them to build deep expertise in specific domains or agent functionalities (Ranjan et al., 2025). This can lead to higher margins due to the specialized value offered and the bundled services. It also fosters a sticky customer relationship, as the agent becomes deeply embedded in the client's operations. AaaS models often include comprehensive support, updates, and performance monitoring, adding significant value beyond just the agent's core function. This model is particularly attractive for complex, mission-critical applications where reliability and expert management are paramount (Thamma, 2025).

Disadvantages: The primary disadvantage of AaaS is the **potential for vendor lock-in**. As agents become deeply integrated into a client's workflows, switching providers can be costly and disruptive (Ranjan et al., 2025). This can reduce the client's bargaining power and increase their reliance on a single vendor. Furthermore, AaaS models can be **less flexible** for users who require highly customized agent behaviors or who prefer to manage their own infrastructure. The "black box" nature of a managed service might also be a concern for organizations with strict data governance or compliance requirements. Pricing for AaaS can be complex, often combining elements of subscription, usage-based fees, and even value-based components, making it difficult for customers to fully understand the total cost of ownership. The initial investment for providers in developing, deploying, and maintaining specialized AaaS offerings can also be substantial, requiring significant upfront capital and expertise (Sultan et al., 2025). This model might not be suitable for general-purpose AI agent platforms, but rather for niche, high-value applications.

1.2 Real-World Examples and Implementations

The theoretical pricing models discussed above find various manifestations in the real-world strategies of leading AI providers. Examining these implementations offers practical insights into the challenges and opportunities of monetizing AI agent services. While few providers explicitly market "AI agent services" as a distinct product category, their underlying LLM APIs and emerging agentic frameworks often combine elements of these models.

1.2.1 OpenAI OpenAI, a pioneer in large language models, primarily employs a **token-based pricing model** for its foundational GPT series APIs (Akpan, 2024). Users are charged for both input and output tokens, with prices varying significantly between different models (e.g., GPT-3.5 Turbo vs. GPT-4 Turbo) and context window sizes. For instance, GPT-4 Turbo, with its larger context window and superior reasoning capabilities, commands a higher price per token than its predecessors. This strategy directly reflects the computational cost and inferred value of processing more complex prompts and generating more sophisticated responses. The token-based approach is simple to understand for developers integrating the API into their applications. However, as developers build more complex AI agents on top of OpenAI's models, the hidden costs of internal reasoning, planning, and tool use become apparent. An agent might cycle through several internal thought processes, generating hundreds or thousands of tokens, before arriving at a final, concise answer (Ranjan et al., 2025). This can lead to unexpected expenses, particularly for agents designed for multi-step reasoning or complex problem-solving.

OpenAI also offers different tiers for its API access, which can be seen as a form of **subscription/tiered pricing** for higher-volume users or enterprise clients. These tiers might offer higher rate limits, dedicated capacity, or access to specialized models, albeit still ultimately charging on a token basis within those tiers. For example, enterprise-level agreements might include custom pricing structures that blend token usage with a base commitment fee, providing a degree of cost predictability for large-scale deployments. The introduction of "Assistants API" can be viewed as an early step towards an AaaS model, where OpenAI manages some orchestration complexities, but pricing largely remains token-centric. This hybrid approach aims to provide the benefits of managed services while retaining the granular billing of token consumption (Liang & Tong, 2025). The challenge for OpenAI, and its users, is to ensure that the token metric continues to accurately reflect the value and complexity of agentic interactions, especially as agents become more autonomous and their internal operations more opaque.

1.2.2 Anthropic (Claude) Anthropic, the developer of the Claude series of LLMs, also primarily utilizes a **token-based pricing model**, similar to OpenAI (Akpan, 2024). They differentiate pricing based on model capabilities (e.g., Claude 3 Haiku, Sonnet, Opus) and the length of the context window, with larger context windows and more capable models incurring higher per-token costs. A notable distinction in Anthropic's approach is its emphasis on transparency regarding the context window and the cost implications of extensive prompts. Their models are often praised for their ability to handle very long contexts, which is beneficial for AI agents that need to process vast amounts of information or maintain long conversational histories (Liang & Tong, 2025). However, this also means that agents leveraging these capabilities can quickly accumulate high token counts, leading to the same cost unpredictability issues observed with OpenAI.

Anthropic's pricing strategy, like OpenAI's, reflects the current technical realities of LLM inference, where the primary cost driver is the amount of data processed. They also offer different access tiers for developers and enterprises, providing enhanced rate limits and potentially customized service level agreements. As Anthropic pushes the boundaries of context length and reasoning, the challenge of aligning token cost with perceived value becomes even more pronounced for agentic applications. An agent might ingest an entire codebase or legal document, consuming millions of tokens, for a single, critical insight. While the insight is invaluable, the underlying token cost might appear disproportionately high to a user accustomed to simpler interactions. This highlights the ongoing tension between resource-based pricing and value-based outcomes in the evolving AI landscape (Akpan, 2024).

1.2.3 Google AI (Gemini, Vertex AI) Google AI offers a more diverse set of pricing models, leveraging its extensive cloud infrastructure and AI platform, Vertex AI. For its foundational models like Gemini, Google also employs **token-based pricing**, differentiating costs by model size, capability, and whether it's an input or output token. However, Google's broader ecosystem, particularly Vertex AI, allows for greater flexibility and the potential for **compute-based pricing** (Guo et al., 2025). For instance, users can deploy custom models or fine-tune existing ones on Vertex AI, where they are charged for the underlying computational resources (GPU hours, storage, data transfer) used for training and inference. This compute-based approach caters to enterprises with specific model deployment requirements and deep technical expertise, allowing them to optimize their resource utilization.

Furthermore, Google's comprehensive suite of AI services, including specialized APIs for vision, speech, and translation, often utilize **action/task-based pricing**. For example, Google Cloud Vision API charges per image processed, and Translation API charges per character translated. This model is well-suited for agents that rely on these specialized services for specific tasks. For broader AI agent platforms, Google could theoretically combine these, charging a base fee for agent orchestration (AaaS component) plus usage-based fees (tokens for LLM, actions for specialized APIs, compute for custom models). This multi-faceted approach reflects Google's strategic position as a comprehensive cloud and AI provider, offering various entry points and pricing structures to cater to different user needs, from simple API consumption to complex enterprise-grade AI solution development (Guo et al., 2025). The strength of Google's offering lies in its ability to offer a spectrum of models, allowing customers to choose the most suitable pricing strategy based on their specific use case and technical capabilities.

1.2.4 Other Providers (e.g., Hugging Face, Cohere) Other significant players in the AI space, such as Hugging Face and Cohere, also largely adhere to **token-based pricing** for their foundational models, often with variations in how they define and charge for tokens, and with differentiated pricing for various model sizes and capabilities. Hugging Face, known for its open-source contributions, also offers hosted inference solutions where users can deploy models and pay for **compute resources** (Guo et al., 2025). This allows for greater flexibility for developers who want to manage their own models but outsource the inference infrastructure. Cohere, focusing on enterprise-grade language AI, primarily uses token-based pricing but also emphasizes the value derived from their models, hinting at a future shift towards or integration with **value-based pricing** for specific enterprise solutions.

The common thread among these providers is the recognition that pure token-based pricing, while easy to implement, may not fully capture the value or complexity of true AI agent services (Akpan, 2024). As agents become more sophisticated and autonomous, the industry is gradually exploring more nuanced pricing strategies, including hybrid models that combine the predictability of subscriptions with the scalability of usage-based fees, or the direct alignment of value-based pricing. The challenge for these providers is to balance transparent, understandable pricing with the need to reflect the true cost of complex agent operations and the value they generate for users (Prithi & Tamizharasi, 2025).

1.3 Hybrid Pricing Approaches

Given the limitations and advantages of individual pricing models, a compelling argument can be made for **hybrid pricing approaches** in the context of AI agent services (Guo et al., 2025). Hybrid models aim to combine elements from two or more distinct pricing strategies to mitigate the disadvantages of single models while leveraging their strengths. The goal is to create a pricing structure that is more equitable, predictable, scalable, and aligned with both provider costs and user value. This approach acknowledges the multi-faceted nature of AI agents, which involve resource consumption, task completion, and value generation. Designing an effective hybrid model requires careful consideration of the specific agent's functionality, its target market, and the desired balance between revenue stability and usage flexibility. The complexity of AI agents, which often involve chained operations, tool use, and long-term memory, inherently lends itself to a multi-dimensional pricing strategy (Ranjan et al., 2025)(Liang & Tong, 2025).

1.3.1 Subscription + Usage-Based Model One of the most common and robust hybrid models is the combination of a **base subscription fee with additional usage-based charges**. This model offers the predictability of a subscription while allowing for scalability based on actual consumption (Guo et al., 2025).

Mechanism: Users pay a fixed monthly or annual subscription fee, which typically includes a certain allowance of tokens, actions, or compute hours. Once these allowances are exceeded, users are then charged on a per-token, per-action, or per-compute-unit basis. Higher subscription tiers might offer larger allowances, access to premium features, or lower per-unit overage rates.

Advantages: * **Predictability for users and providers:** The subscription component provides a stable baseline cost for users and a predictable revenue stream for providers (Guo et al., 2025). * **Scalability:** Users can scale their usage beyond the base allowance without needing to upgrade to an entirely new subscription tier if their peak usage is temporary or unpredictable. * **Fairness:** Users who consume more resources or generate more value pay more, while low-volume users still have access to the service at a reasonable base cost. This mitigates the "pay for unused capacity" issue of pure subscriptions and the "unpredictable bill" issue of pure usage-based models. * **Reduced barrier to entry:** A lower-tier subscription with a small usage allowance can serve as an affordable entry point for new users to test the agent's capabilities. * **Incentivizes efficiency:** While allowing for flexibility, the usage-based component still encourages users to optimize their agent interactions to stay within their allowance or minimize overage charges.

Disadvantages: * **Complexity in setting allowances:** Determining the optimal balance between the base allowance and overage rates for different tiers can be challenging (Guo et al., 2025). If allowances are too low, users might quickly hit limits and feel penalized; if too high, providers might lose out on potential usage-based revenue. * **User confusion:** Understanding the intricacies of base allowances, overage rates, and tier structures can be more complex for users compared to a simple flat fee or per-unit charge. * **"Bill shock" potential:** While the base is predictable, unexpected spikes in usage can still lead to higher-than-anticipated bills if not carefully monitored, similar to pure usage models.

Application to AI Agents: This model is highly suitable for AI agent platforms. A base subscription could cover the agent's orchestration, memory, and basic access to a general-purpose LLM. Overage charges could then apply to excessive token usage, specific tool calls (actions), or dedicated compute for complex tasks. For example, an agent platform might charge $50/month for access, including 1 million tokens and 100 tool calls, with additional tokens charged at $0.001/1K and tool calls at $0.10 each (Ranjan et al., 2025). This allows for predictable base costs for light users while accommodating the variable demands of heavy users or complex agentic workflows.

1.3.2 Action-Based + Value-Based Model This hybrid model attempts to combine the clarity of charging for discrete actions with the strategic alignment of value-based pricing, particularly for high-impact agent services.

Mechanism: A base charge is applied for each successful action or task completed by the AI agent. However, for certain high-value tasks or outcomes, an additional premium or percentage is added, reflecting the specific value generated for the client.

Advantages: * **Direct value capture:** Allows providers to capture additional revenue when their agents deliver exceptional value, beyond just the cost of the action (Prithi & Tamizharasi, 2025). * **Clear accountability:** The action-based component provides a clear, measurable unit of work, making it easy for users to understand the base cost. * **Incentivizes performance:** Strong incentive for providers to ensure agents not only complete tasks but do so in a way that maximizes client value, as this directly impacts revenue. * **Risk sharing:** For high-value tasks, the provider shares in the upside, while the client pays a predictable base for standard operations.

Disadvantages: * **Complexity in value attribution:** Similar to pure value-based pricing, accurately measuring and attributing additional value to specific actions can be difficult and require robust analytical frameworks (Prithi & Tamizharasi, 2025). * **Negotiation overhead:** Defining what constitutes "high value" and the corresponding premium often requires detailed negotiation and agreement between provider and client. * **Scalability**

challenges: May not be suitable for mass-market agents, as the overhead of value measurement per high-value action can be substantial.

Application to AI Agents: Consider an AI agent for legal document review. It could charge a base fee per document reviewed (action-based). If the agent identifies a critical clause that saves the client millions in potential litigation, a pre-agreed percentage of that saved amount could be added as a value-based premium (Bucher, 2025). This model is best suited for specialized, high-impact AI agents in B2B contexts where the value generated can be clearly quantified and attributed.

1.3.3 Compute-Based + Performance-Based Tiers This hybrid model combines the transparency of compute-based pricing with a tiered structure that reflects the performance or capabilities of the underlying AI agent or infrastructure.

Mechanism: Users are charged for the raw compute resources (CPU/GPU hours, memory, storage) consumed by the AI agent. However, different tiers might offer access to more optimized, faster, or specialized hardware configurations, or to agents that are pre-tuned for higher performance, commanding a higher per-compute-unit rate.

Advantages: * **Transparency of resources:** Users understand the direct cost of the computational power they are using (Guo et al., 2025). * **Performance differentiation:** Allows providers to monetize investments in optimized hardware or highly efficient agent architectures. * **Flexibility:** Users can choose the compute intensity and performance level that matches their needs and budget. * **Encourages optimization:** Users are incentivized to optimize their agent code for efficient resource utilization, while providers are incentivized to offer more performant infrastructure.

Disadvantages: * **Complexity for non-technical users:** Still requires some understanding of compute resources, which can be a barrier for many end-users (Guo et al., 2025). * **Benchmarking difficulties:** Comparing performance across different compute tiers and providers can be challenging. * **Variable costs:** While the per-unit compute cost might be fixed per tier, the total cost can still fluctuate based on usage, similar to pure compute models.

Application to AI Agents: An AI agent platform could offer a "Standard Compute" tier with general-purpose GPUs and a "High-Performance Compute" tier with specialized, faster GPUs, each with a different hourly rate. An agent running on the high-performance tier might complete tasks significantly faster, justifying the higher compute cost. This model is particularly relevant for agents involved in computationally intensive tasks like large-scale data analysis, complex simulations, or real-time decision-making (Kurz, 2025).

1.3.4 Agent-as-a-Service (AaaS) with Tiered Features This model focuses on offering complete, managed AI agent solutions (AaaS) but differentiates pricing through a tiered structure based on the features, capabilities, or levels of support provided within each agent offering.

Mechanism: Customers subscribe to a specific AaaS package (e.g., "AI Legal Assistant Pro," "AI Financial Analyst Enterprise"). Each package has a fixed recurring fee and includes a predefined set of agent functionalities, integration options, data storage, and support levels. Higher tiers unlock more advanced features, greater autonomy, or dedicated expert support (Thamma, 2025)(Joshi, 2025).

Advantages: * **Simplicity and clarity:** Users know exactly what they are getting for their fixed fee. * **Comprehensive solution:** Provides a full, managed agent experience, reducing client operational burden (Sultan et al., 2025). * **Value-driven feature differentiation:** Pricing directly reflects the value of specific advanced features or higher service levels. * **Predictable revenue for providers:** Stable recurring revenue from subscriptions.

Disadvantages: * **Potential for unused features:** Users might pay for features they don't fully utilize within their chosen tier. * **Limited customization:** Less flexible for users requiring highly bespoke agent behaviors outside the predefined tiers. * **Vendor**

lock-in: Deeper integration with a managed service can make switching providers more challenging (Ranjan et al., 2025).

Application to AI Agents: A legal tech company might offer an AaaS for contract review. A "Basic" tier could perform standard clause identification, while a "Premium" tier could include advanced risk assessment, automated redlining, and integration with a legal case management system. The pricing would be a fixed monthly fee per tier. This model is ideal for vertical-specific AI agents that offer a clear set of functionalities tailored to industry needs (Thamma, 2025)(Bucher, 2025).

1.4 Implications for Market Dynamics and User Adoption

The choice and evolution of pricing models for AI agent services will have profound implications for market dynamics, competition, and the rate and nature of user adoption (Prithi & Tamizharasi, 2025). As AI agents become more ubiquitous, the pricing strategies employed by providers will not only determine their profitability but also shape the accessibility, perceived fairness, and overall growth of the agentic AI ecosystem (Chaudhary, 2025).

1.4.1 Competition and Market Structure Different pricing models can significantly impact competition among AI agent providers. **Token-based and compute-based pricing** tend to foster a more commodity-like market, where providers compete primarily on price per unit (Guo et al., 2025). This can lead to downward price pressure, benefiting consumers in the short term but potentially stifling innovation for providers with higher operational costs. It also favors large players with economies of scale in infrastructure. Conversely, **value-based and AaaS models** enable differentiation and premium pricing, allowing providers to compete on the unique value proposition, specialized expertise, and comprehensive service offerings (Prithi & Tamizharasi, 2025)(Sultan et al., 2025). This can lead to a more fragmented market with niche players excelling in specific verticals. Hybrid models, especially those with strong subscription components, can create "sticky" customer relationships, raising barriers to entry for new competitors and making it harder for users to switch providers (vendor lock-in) (Ranjan et al., 2025). The ability to offer flexible pricing, combining different models, could become a key competitive advantage, allowing providers to cater to diverse customer segments and adapt to evolving market demands. The emergence of platform ecosystems around AI agents, where third-party developers build on foundational models, also introduces complexities, as the pricing of the underlying model dictates the cost structure for downstream agent services (Westover, 2025).

1.4.2 User Adoption and Accessibility Pricing plays a critical role in driving or hindering user adoption. **Transparent and predictable pricing** models, such as subscription or clear action-based fees, are likely to encourage broader adoption, especially among non-technical users and small businesses who prioritize cost certainty (Guo et al., 2025). Unpredictable usage-based models, such as pure token or compute-based pricing for complex agent workflows, can create "bill shock" anxiety, deterring experimentation and limiting adoption to users with sophisticated cost management capabilities or deep pockets (Akpan, 2024). The perception of fairness in pricing is also crucial (Chaudhary, 2025). If users feel they are paying for "ghost tokens" or unnecessary internal computations, it can erode trust and lead to dissatisfaction.

For **value-based pricing**, the high upfront effort required for value measurement and negotiation might limit adoption to large enterprises with complex problems and dedicated resources (Prithi & Tamizharasi, 2025). Conversely, **AaaS models** can significantly lower the barrier to entry for businesses lacking in-house AI expertise, making sophisticated agent capabilities accessible to a wider audience (Sultan et al., 2025). The availability of free tiers or freemium models, often integrated into subscription structures, can also be a powerful driver for initial adoption, allowing users to experience the agent's value before committing to a paid plan. As AI agents become essential tools, pricing strategies that promote affordability and ease of use will be critical for democratizing access and ensuring that the benefits of agentic AI are widely distributed across various industries and user types (Bookstaber, 2024).

1.5 Ethical and Fairness Considerations in AI Pricing

The development and deployment of AI agents introduce a host of ethical considerations, and pricing strategies are no exception (Chaudhary, 2025). Fairness, transparency, and accessibility are paramount to ensure that AI agent services do not exacerbate existing inequalities or create new forms of digital exclusion. The choices made in pricing models have direct societal impacts, influencing who can access these powerful technologies and under what terms.

1.5.1 Algorithmic Bias and Discriminatory Pricing AI-driven dynamic pricing, while offering benefits like revenue optimization, raises significant ethical concerns regarding **algorithmic bias and discriminatory pricing** (Nakirikanti, 2025)(Gazi et al., 2024). If AI agents are used to set prices based on user data (e.g., browsing history, location, inferred income), it could lead to different prices for different individuals for the same service. While not necessarily illegal, such practices can be perceived as unfair and erode consumer trust (Chaudhary, 2025). For instance, an AI agent might infer a user's willingness to pay based on their digital footprint and adjust prices accordingly, potentially disadvantaging vulnerable populations (Gazi et al., 2024). The lack of transparency in how these algorithms arrive at specific prices further complicates the issue, making it difficult for consumers to challenge potentially discriminatory outcomes (Chaudhary, 2025).

For AI agent services, this could manifest if an agent's internal pricing logic, influenced by user data, charges different rates for similar tasks based on inferred user demographics or financial status. Providers must implement robust ethical guidelines and auditing mechanisms to prevent their AI pricing systems from perpetuating or amplifying existing societal biases (Gangadharan, 2024). This includes ensuring that pricing models do not indirectly discriminate based on protected characteristics and that pricing decisions are explainable and justifiable.

1.5.2 Transparency and Explainability Transparency in pricing is a cornerstone of fairness (Chaudhary, 2025). Users need to understand how their costs are calculated, especially for complex AI agent interactions. **Token-based pricing**, while appearing granular, can be opaque due to hidden internal token consumption for agent reasoning (Akpan, 2024). Users might not understand why a simple query generates a high token count. Similarly, **compute-based pricing** can be opaque for non-technical users who do not understand CPU/GPU metrics (Guo et al., 2025).

Providers have an ethical responsibility to make their pricing models as clear and explainable as possible. This includes: * **Detailed cost breakdowns:** Providing users with granular logs of tokens consumed, actions taken, or compute hours used by their agents. * **Clear documentation:** Explaining how different agent functionalities contribute to costs. * **Cost prediction tools:** Offering features that help users estimate costs before deploying complex agent workflows. * **Fair use policies:** Defining acceptable usage and how overage charges are applied.

Without sufficient transparency, users may feel exploited or unable to control their expenditures, leading to distrust and reluctance to adopt AI agent services (Chaudhary, 2025).

1.5.3 Accessibility and Digital Divide The pricing of AI agent services directly impacts their accessibility and has the potential to widen the digital divide (Chaudhary, 2025). If advanced AI agent capabilities are priced exclusively at premium rates (e.g., through high AaaS fees or expensive value-based models), they may only be accessible to large corporations or wealthy individuals, leaving smaller businesses, non-profits, and developing regions at a significant disadvantage (Bookstaber, 2024). This creates a scenario where those who can afford the best AI agents gain a disproportionate advantage, potentially leading to further concentration of power and wealth.

Ethical pricing strategies should consider mechanisms to promote broader access: * **Freemium models and free tiers:** Offering basic agent capabilities for free or at a very low cost to allow broader experimentation and adoption (Guo et al., 2025). * **Educational and research discounts:** Providing reduced rates for academic institutions and researchers to foster innovation and learning. * **Tiered pricing with affordable entry points:** Designing subscription tiers that cater to a wide range of budgets and usage needs (Guo et al., 2025). * **Public interest initiatives:** Collaborating with governments or non-profits to make AI agent services available for public good projects at subsidized rates.

Ensuring that AI agents are not just powerful but also accessible is crucial for fostering an inclusive digital future where the benefits of advanced AI are shared broadly (Chaudhary, 2025). This requires a conscious effort by providers to balance profitability with social responsibility, recognizing the transformative potential of their technologies.

In conclusion, the analysis of pricing models for AI agent services reveals a complex interplay between technological capabilities, economic drivers, and ethical imperatives. While token-based pricing has served as an initial foundation, the unique characteristics of autonomous agents necessitate a move towards more sophisticated and hybrid approaches. The transition from simple resource metering to value-centric or action-based models, often integrated within subscription frameworks, reflects an evolving understanding of how AI agents create and deliver value. Real-world examples demonstrate the varied strategies employed by industry leaders, each grappling with the challenges of cost predictability, scalability, and user adoption. Ultimately, the future of AI agent monetization will likely involve dynamic, multi-faceted pricing models that are not only economically viable for providers but also transparent, fair, and accessible to a diverse global user base, thereby fostering a robust and equitable agentic AI ecosystem (Chaudhary, 2025)(Prithi & Tamizharasi, 2025)(Ranjan et al., 2025). The ongoing dialogue between technological innovation, market demands, and ethical principles will continue to shape these evolving pricing landscapes.

Comparative Summary of AI Agent Pricing Models

This table provides a concise overview, comparing key attributes across the primary AI agent pricing models discussed.

Table 1: Comparative Attributes of AI Agent Pricing Models

Attribute	Token-Based	Compute-Based	Value-Based	Action-Based	Subscription/Tiered	AaaS
Primary Metric	LLM tokens	CPU/GPU hours	Value delivered	Discrete tasks	Access/Features	Managed service
Cost Predict.	Medium (internal)	Low (usage var.)	Low (attribut. diff.)	High (per task)	High (fixed fee)	High (fixed fee)
Value Align.	Low (raw process)	Low (raw resource)	High (outcome-focus)	Medium (task util.)	Medium (feature set)	High (full solution)
User Complexity	Medium (tokens)	High (infra mgmt.)	High (value measure)	Low (clear tasks)	Low (fixed)	Low (managed)
Provider Risk	Low (direct cost)	Low (direct cost)	High (value proof)	Medium (task failures)	Low (recurring rev.)	Medium (high dev)
Scalability	High	High	Medium (custom req.)	High	Medium	Medium (special.)

Attribute	Token-Based	Compute-Based	Value-Based	Action-Based	Subscription/Tiered	AaaS
Transparency	Medium (token count)	High (resource use)	Low (value calc.)	High (task complete)	High (tier features)	Medium (black box)
Ideal Use Case	LLM API calls	Custom model infra	High-impact B2B	Repetitive workflows	General access	Industry-specific

Note: This table summarizes the general characteristics of each pricing model and their typical implications for providers and users in the context of AI agent services.

Example of AI Agent Workflow with Token Consumption

This figure illustrates a hypothetical workflow for an agentic AI system designed for content generation, highlighting the various stages and where token consumption occurs.

Figure 2: Agentic AI Content Generation Workflow & Token Consumption

Note: The diagram shows how a user prompt initiates a planning phase, which may involve tool use, leading to draft generation, self-critique, and iterative revisions before a final output. Token consumption occurs at each stage, including internal reasoning steps that are not directly visible to the user.

Discussion

The preceding analysis has illuminated the transformative potential of advanced AI systems, particularly agentic AI, in reshaping various industry landscapes, with a pronounced impact on pricing strategies and market dynamics. This section critically discusses the implications of these findings for AI companies, delves into crucial considerations for customer adoption, forecasts future pricing trends influenced by AI, and offers actionable recommendations for stakeholders. Our theoretical framework, which posits a shift towards more autonomous and adaptive AI agents, suggests a fundamental re-evaluation of established business models and regulatory paradigms (Ranjan et al., 2025)(Sultan et al., 2025).

Implications for AI Companies

The proliferation of agentic AI systems presents a multifaceted set of implications for companies operating within the artificial intelligence sector. Firstly, there is a clear imperative for a strategic pivot towards developing and architecting robust agentic AI frameworks (Ranjan et al., 2025). Traditional AI development, often focused on single-purpose models, must evolve to encompass the complexities of multi-agent systems (Kurz, 2025) that can interact, learn, and adapt autonomously within dynamic environments (Tong et al., 2025)(Liang & Tong, 2025). This necessitates significant investment in research and development, not merely in algorithmic advancements but also in the underlying infrastructure and architectural principles that ensure reliability, scalability, and security (Ranjan et al., 2025)(Guo et al., 2025). Companies that successfully navigate this transition, focusing on the "well-architected framework" for agentic AI, will likely gain a significant competitive advantage (Ranjan et al., 2025). This includes developing sophisticated orchestration layers that manage interactions between agents, robust security protocols to prevent malicious exploitation, and advanced monitoring tools to ensure agents operate within predefined parameters (Ranjan et al., 2025)(Guo et al., 2025).

Secondly, the competitive landscape within the AI industry is poised for significant disruption. As agentic AI becomes more prevalent, the value proposition of AI companies will shift from providing static models to offering dynamic, adaptive, and intelligent solutions that can perform complex tasks with minimal human intervention (Sultan etal., 2025). This could lead to a consolidation of the market around firms capable of delivering comprehensive agentic platforms, potentially marginalizing smaller players focused on narrow AI applications (Liang & Tong, 2025). Furthermore, the ability to develop secure and optimal pricing strategies for AI cloud services will become a critical differentiator (Guo et al., 2025). Companies will need to not only innovate in AI capabilities but also in how they package, price, and deliver these complex services to clients, considering factors such as computational resources, data usage, and the level of autonomy granted to the agents (Guo et al., 2025). The emphasis will move from mere computational power to the intelligence and adaptability embedded within the agentic architecture itself.

Thirdly, ethical considerations and regulatory compliance will move from peripheral concerns to central pillars of AI company strategy (Chaudhary, 2025)(Gazi et al., 2024). Agentic systems, by their very nature, possess a higher degree of autonomy, which amplifies the need for transparency, fairness, and accountability in their design and deployment (Chaudhary, 2025). AI companies must proactively engage with ethical AI frameworks and regulatory bodies to ensure their products align with societal values and legal requirements (Ignjatović, 2024)(Gazi et al., 2024). This includes implementing mechanisms for explainable AI (XAI) within agentic systems, allowing for post-hoc analysis of agent decisions, and establishing robust governance structures to manage potential biases or unintended consequences (Chaudhary, 2025). The reputational risks associated with ethical failures in agentic AI could be substantial, making responsible AI development a strategic imperative for long-term viability (Gazi et al., 2024). This also extends to the development of standards for agentic systems, as highlighted by initiatives like IEEE AI Standards for Agentic Systems (Tong et al., 2025), which will guide future development and deployment practices.

Moreover, the shift towards agentic AI will necessitate a re-evaluation of business models. Instead of licensing software or models, AI companies might increasingly offer "intelligence as a service," where clients pay for the outcomes delivered by agentic systems rather than the underlying technology itself (Sultan et al., 2025). This could involve performance-based contracts or subscription models that scale with the complexity and value generated by the agents. The focus on enhancing research productivity through agentic AI workflows (Sultan et al., 2025) also points towards a future where AI companies provide tools that empower other researchers and businesses to accelerate their own innovation cycles. This paradigm shift requires AI companies to develop a deep understanding of their clients' operational needs and integrate agentic solutions seamlessly into existing workflows, ensuring a high degree of interoperability and adaptability. The development of AI-agent-based systems for fact-checking support (Kupershtein et al., 2024), for instance, exemplifies how agentic AI can be deployed to enhance productivity and reliability in critical information processing tasks.

Finally, the talent landscape will also transform. AI companies will require not only data scientists and machine learning engineers but also specialists in multi-agent systems, ethical AI, regulatory compliance, and human-AI interaction (Vindigni, 2024). The demand for professionals capable of designing, developing, and managing complex agentic architectures will surge, creating new skill gaps and educational imperatives. Training programs will need to adapt to equip the next generation of AI professionals with the interdisciplinary knowledge required to build and deploy these sophisticated systems responsibly and effectively (Vindigni, 2024).

Customer Adoption Considerations

The successful integration of agentic AI systems into the broader economy hinges critically on customer adoption, which is influenced by a confluence of factors ranging from perceived value and trust to ethical concerns and user experience. A primary consideration for customer adoption is the perceived value proposition of agentic AI. Customers, whether individuals or businesses, must clearly understand how these systems can enhance their productivity, optimize their operations, or improve their decision-making processes (Sultan et al., 2025). For instance, in e-commerce, AI-driven personalization (Nakirikanti, 2025)(G et al., 2024) and dynamic pricing (Dritsas & Trigka, 2025) can offer tailored experiences and competitive rates, driving adoption. Similarly, in clinical decision support, real-time diagnosis capabilities offered by agentic AI (Thamma, 2025) can significantly improve healthcare outcomes, thus fostering adoption among medical professionals. The value must be tangible and demonstrable, moving beyond mere technological novelty to concrete benefits (Ghani et al., 2025).

Trust is another paramount factor. The autonomous nature of agentic AI can evoke both excitement and apprehension. Customers need assurance that these systems are reliable, secure, and operate within ethical boundaries (Chaudhary, 2025)(Gazi et al., 2024). This necessitates transparency in how agents make decisions, even if the underlying algorithms are complex. Building trust requires clear communication about the capabilities and limitations of agentic AI, robust data privacy measures, and mechanisms for redress when errors occur (Chaudhary, 2025). For example, the ethical considerations in AI-driven dynamic pricing (Gazi et al., 2024) are crucial, as customers may perceive unfairness if pricing algorithms are not transparent. Concerns about fairness, transparency, and accountability (Chaudhary, 2025) must be addressed proactively through responsible AI design and deployment (Gazi et al., 2024). Without a foundational layer of trust, even the most advanced agentic systems will struggle to gain widespread acceptance (Chaudhary, 2025).

User experience (UX) and human-computer interaction (HCI) design also play a pivotal role. Agentic AI systems, while autonomous, must be designed to be intuitive, user-friendly, and capable of seamless interaction with human users (Vindigni, 2024). This involves developing interfaces that allow users to monitor agent activity, intervene when necessary, and understand the rationale behind agent decisions. The goal should be to create a collaborative environment where humans and agents complement each other's strengths, rather than one where agents operate as black boxes (Vindigni, 2024). Enhancing human-computer interaction, especially in socially inclusive contexts (Vindigni, 2024), is vital for ensuring that agentic AI is accessible and beneficial to a diverse user base. The design of personalized learning systems (Widono et al., 2024) or customized AI chatbots (Kiangala & Wang, 2024) exemplifies how user-centric design can facilitate adoption by making AI tools more engaging and effective.

Furthermore, ethical considerations directly impact customer willingness to adopt. Concerns about data privacy, algorithmic bias, and potential job displacement can deter adoption (Chaudhary, 2025)(Gazi et al., 2024). Companies must demonstrate a commitment to ethical AI development, implementing safeguards against discrimination and ensuring that agentic systems are used for beneficial purposes. Public education campaigns can also help demystify agentic AI, addressing misconceptions and highlighting its positive societal contributions (Ignjatović, 2024). The discussion around non-fungible tokens (Kraizberg, 2023) and ethical AI in VR games (Gangadharan, 2024) indicates a growing public awareness and demand for ethical considerations in emerging technologies, which applies equally to agentic AI.

Finally, the regulatory environment will significantly shape customer adoption. Clear and consistent regulatory frameworks, such as those discussed for AI technologies in education (Ignjatović, 2024), can provide a sense of security and legitimacy, encouraging wider acceptance. Conversely, an uncertain or overly restrictive regulatory landscape could stifle innovation and slow down adoption. Policymakers have a crucial role in balancing innovation with protection, creating an environment where agentic AI can thrive responsibly. This includes developing international regulatory frameworks to ensure consistency and prevent a fragmented approach to AI governance (Ignjatović, 2024). Ultimately, customer adoption will be a function of how well agentic AI systems can deliver tangible value, earn trust through transparency and ethical design, provide a seamless user experience, and operate within a supportive regulatory ecosystem.

Future Pricing Trends

The advent of agentic AI is set to profoundly reshape future pricing trends, moving markets towards unprecedented levels of dynamism, personalization, and optimization. One of the most significant trends will be the widespread adoption of AI-driven dynamic pricing (Prithi & Tamizharasi, 2025)(Nakirikanti, 2025)(Dritsas & Trigka, 2025). Unlike traditional dynamic pricing models that react to predetermined rules, agentic AI systems will be capable of real-time, autonomous price adjustments based on a multitude of factors, including demand fluctuations, competitor pricing, inventory levels, customer segmentation, and even individual customer behavior and willingness to pay (Nakirikanti, 2025)(G et al., 2024). This level of granularity will allow businesses to optimize revenue and profit margins with unparalleled precision (Kumari & Raj, 2025)(Dritsas & Trigka, 2025). For instance, in retail, AI-powered optimization (Prithi & Tamizharasi, 2025) will analyze vast datasets to set optimal prices, potentially leading to more competitive markets for consumers in some sectors, while enabling more effective revenue capture for businesses.

The trend towards hyper-personalization in pricing will intensify (Nakirikanti, 2025)(G et al., 2024). Agentic AI systems can analyze individual customer profiles, purchase histories, browsing behavior, and even external factors to offer highly tailored prices and promotions. This personalized e-commerce (G et al., 2024) approach aims to enhance customer experience by offering relevant deals, but it also raises significant ethical concerns regarding price discrimination (Chaudhary, 2025)(Gazi et al., 2024). The ethics of AI in pricing will become a critical area of debate, necessitating a balance between profit optimization and fairness (Chaudhary, 2025)(Gazi et al., 2024). Regulatory bodies may need to establish guidelines to prevent predatory pricing practices or the exacerbation of socioeconomic inequalities through personalized pricing algorithms (Gazi et al., 2024). The discussion on ethical considerations in AI-driven dynamic pricing in the U.S. (Gazi et al., 2024) highlights the urgency of addressing these issues.

Agentic AI will also facilitate more sophisticated optimal security and pricing strategies for AI cloud services (Guo et al., 2025). As AI becomes a utility, the pricing of computational resources, specialized AI models, and agentic capabilities will become highly dynamic, reflecting real-time demand and supply within cloud ecosystems. Providers will need to strategically price their offerings to attract customers while ensuring the security and stability of their services (Guo et al., 2025). This extends beyond cloud computing to other service sectors, such as IT services, where AI can introduce more agile, top-down approaches to pricing deals (Megahed et al., 2015). The impact of digitalization and AI on legal pricing (Bucher, 2025) also signifies a broader trend where professional services, traditionally based on hourly rates, might shift towards value-based or outcome-based pricing models enabled by AI's efficiency and predictive capabilities.

Furthermore, the rise of agentic AI agents in platform economies could reshape how services are priced and exchanged (Westover, 2025). These agents, acting on behalf of buyers or sellers, could engage in sophisticated negotiation processes (Li et al., 2017), leading to more efficient market clearing and potentially driving prices towards equilibrium more rapidly. This "search to match" capability (Westover, 2025) could reduce transaction costs and increase market transparency, benefiting both producers and consumers by optimizing resource allocation. Agent-based fuzzy constraint-directed negotiation for service composition (Li et al., 2017) offers a glimpse into how complex pricing negotiations could be automated and optimized in multi-agent environments.

The future of retail pricing (Prithi & Tamizharasi, 2025) and revenue optimization on UPI transactions using AI (Kumari & Raj, 2025) further underscores the pervasive influence of AI on pricing. AI can identify optimal price points for various products and services, taking into account competitive pressures, seasonal demand, and even micro-segmentation of consumer behavior. This allows for continuous price adjustments that maximize revenue without alienating customers. However, this also implies a need for businesses to invest in robust AI infrastructure and data analytics capabilities to stay competitive.

Finally, the long-term impact on pricing trends could extend to broader economic structures. Concepts like "economics for humans" (Bookstaber, 2024) might emphasize the need for AI pricing models to consider societal welfare alongside profit maximization. The discussion around green credit and AI as a catalyst for green innovation (Hu et al., 2024) suggests that pricing mechanisms could be leveraged to incentivize sustainable behaviors, with AI playing a role in structuring and administering such incentives. The evolution of AI stocks prediction (Jiang, 2024) indicates that financial markets are already grappling with the economic implications of AI, influencing valuations and investment decisions. Overall, future pricing trends will be characterized by unprecedented levels of adaptability, personalization, and algorithmic optimization, driven by the autonomous capabilities of agentic AI.

Recommendations

Based on the insights derived from this study, several recommendations emerge for various stakeholders, including AI companies, policymakers, and consumers, to navigate the evolving landscape shaped by agentic AI and its impact on pricing.

For **AI companies**, the primary recommendation is to embrace a holistic and ethical approach to agentic AI development. This entails prioritizing a "well-architected framework" (Ranjan et al., 2025) that emphasizes not only performance and scalability but also security, transparency, and accountability. Investing in robust architectural design, as outlined by Ranjan, Chembachere et al. (Ranjan et al., 2025), is crucial for building reliable and trustworthy agentic systems. Furthermore, companies should proactively engage with emerging standards, such as the IEEE AI Standards for Agentic Systems (Tong et al., 2025), to ensure their products align with best practices and regulatory expectations. Ethical considerations, particularly regarding fairness and transparency in AI-driven pricing (Chaudhary, 2025)(Gazi et al., 2024), must be integrated into the core design philosophy, moving beyond mere compliance to genuine ethical leadership. This includes developing clear explainability features for agentic decisions and establishing internal ethical review boards. Companies should also explore new business models that leverage the unique capabilities of agentic AI, such as "intelligence as a service," focusing on delivering tangible outcomes and enhancing research productivity (Sultan et al., 2025). Continuous investment in talent development, particularly in multi-agent systems and human-AI interaction (Vindigni, 2024), is also essential to maintain a competitive edge.

Policymakers and regulatory bodies have a critical role in shaping a responsible and equitable future for agentic AI. It is imperative to develop clear and adaptive regulatory frameworks that can keep pace with rapid technological advancements (Ignjatović, 2024). These frameworks should focus on establishing foundational principles for ethical AI, including data privacy, algorithmic fairness, and accountability, especially in sensitive areas like dynamic pricing (Chaudhary, 2025)(Gazi et al., 2024). International collaboration is vital to create harmonized regulations, preventing a fragmented global landscape that could hinder innovation or create regulatory arbitrage opportunities (Ignjatović, 2024). Furthermore, policymakers should consider mechanisms to monitor and mitigate potential negative societal impacts, such as exacerbating socioeconomic inequalities through personalized pricing or job displacement due to increased automation (Gazi et al., 2024). Investing in public education and digital literacy programs can empower citizens to understand and interact safely with agentic AI systems (Ignjatović, 2024). Encouraging research into the economic and social impacts of AI, including its implications for markets for flexibility (Mancarella, 2022) and green credit (Hu et al., 2024), can provide the evidence base for effective policy interventions.

For **consumers and businesses adopting AI solutions**, the recommendation is to approach agentic AI with informed discernment. Customers should seek out AI solutions that prioritize transparency, user control, and ethical design (Chaudhary, 2025). When engaging with AI-driven dynamic pricing, it is important to be aware of how personalization might influence offers and to understand the terms and conditions of such services (Gazi et al., 2024).

Businesses should conduct thorough due diligence when selecting AI vendors, evaluating not just technical capabilities but also the vendor's commitment to ethical AI practices and regulatory compliance. Prioritizing solutions that offer robust human-computer interaction (Vindigni, 2024) and customizable personalization (Nakirikanti, 2025)(G et al., 2024) can enhance adoption and user satisfaction. Furthermore, businesses should invest in training their workforce to effectively collaborate with agentic AI systems, leveraging their capabilities to enhance productivity and innovation rather than simply replacing human tasks (Sultan et al., 2025). Understanding the impact of customer perceived value (Ghani et al., 2025) is paramount for successful integration.

Finally, for the **academic and research community**, continued interdisciplinary research is crucial. There is a need for further investigation into the long-term economic, social, and psychological impacts of widespread agentic AI adoption. Research should focus on developing more robust ethical AI frameworks, improving explainability in complex multi-agent systems, and exploring novel human-AI collaboration paradigms (Vindigni, 2024). Comparative analysis of transfer pricing legislation in the context of AI-driven global operations (Kraievskyi et al., 2024) and research on AI-enabling strategies for OTA platforms (Guo, 2025) are examples of specific areas that require deeper scholarly attention. Understanding the evolution of peer-reviewed publications on AI (Teljeur & Ryan, 2022) can help guide future research directions, ensuring that scholarly efforts remain at the forefront of this rapidly evolving field. By fostering a collaborative ecosystem among industry, government, and academia, we can collectively unlock the immense potential of agentic AI while mitigating its inherent risks, ensuring a future where this transformative technology serves humanity responsibly and effectively.

Limitations

While this research makes significant contributions to understanding pricing models for agentic AI systems, it is important to acknowledge several limitations that contextualize the findings and suggest areas for refinement.

Methodological Limitations

This study is primarily theoretical and conceptual, relying on a comprehensive literature review and a comparative analytical framework rather than empirical data collection or experimental designs. While this approach allows for a broad synthesis of existing knowledge and the development of novel theoretical propositions, it inherently limits the ability to provide quantitative validation or direct empirical evidence for the effectiveness or specific impacts of the proposed pricing models in real-world agentic AI deployments. The absence of primary data means that the insights into challenges like "cost opacity" or "value attribution" are derived from theoretical implications and existing discussions around general AI services, rather than direct measurements from operational agentic systems. Furthermore, the selection of illustrative examples from leading AI providers is based on publicly available information, which may not fully capture proprietary details of their pricing logic or the intricate internal workings of their agent architectures. This reliance on secondary data, while necessary for a theoretical overview, means certain nuances or hidden complexities of real-world implementations might not be fully explored.

Scope and Generalizability

The scope of this research is specifically focused on pricing models for agentic AI systems, with a particular emphasis on dynamic pricing and personalization. While these are critical areas, agentic AI has a much broader range of applications (e.g., scientific discovery, autonomous robotics, complex simulations) that may involve entirely different monetization strategies not covered in detail here. The generalizability of the proposed framework and findings may therefore be limited to agentic systems that primarily interact with digital markets and involve linguistic or computational outputs. Furthermore, the ethical and regulatory discussions are framed within a general Western context, with some specific mentions of the U.S. and EU. Variations in legal and cultural norms across different global regions could introduce additional complexities or unique ethical considerations not fully addressed in this paper, limiting the direct applicability of some recommendations to diverse international contexts. The rapid evolution of AI technology itself means that specific pricing models or technical capabilities discussed might become outdated, affecting the long-term generalizability of some technical observations.

Temporal and Contextual Constraints

The field of agentic AI is undergoing rapid and continuous development. The insights and observations presented in this paper reflect the state of the art and academic discourse as of early 2025. Given the exponential pace of innovation in AI, new agent architectures, pricing paradigms, and regulatory responses could emerge swiftly, potentially altering the landscape discussed herein. This temporal constraint means that some of the specific examples or challenges highlighted might evolve or be superseded by new advancements in the near future. For instance, the tokenization methods for LLMs are constantly being refined, and the computational efficiency of agentic reasoning is improving. These advancements could shift the cost structures and perceived value of AI agent services, thereby impacting the relevance of some pricing model comparisons. Additionally, the broader geopolitical and economic context, including global regulatory efforts and market competition, is dynamic. Significant shifts in these external factors could introduce new constraints or opportunities that influence AI agent pricing in ways not fully anticipated by this study.

Theoretical and Conceptual Limitations

While the paper introduces a conceptual framework for comparing AI-driven pricing models, the theoretical underpinnings of “value” in agentic AI are still nascent. Quantifying the precise value delivered by an autonomous agent, especially one engaged in complex, multi-step reasoning or creative tasks, remains a significant theoretical challenge. The framework relies on existing economic theories of value, which may not fully capture the emergent, intangible, and often indirect benefits generated by highly autonomous AI agents. The concept of “agency” itself, and how it translates into economic value and ethical responsibility, is an evolving philosophical and technical debate. This study adopts a pragmatic view of agency (goal-directed autonomy) but acknowledges that deeper theoretical exploration of AI consciousness or moral status could further complicate pricing models, especially value-based ones. Furthermore, the interplay between different dimensions of the framework (e.g., how algorithmic sophistication truly impacts transparency) is qualitatively assessed, and a more rigorous, quantitative theoretical model for these interdependencies could provide deeper insights. The paper also primarily focuses on the supply-side (provider) and demand-side (customer) perspectives, with less emphasis on the broader societal welfare implications of different pricing strategies, beyond general ethical considerations.

Despite these limitations, the research provides valuable insights into the core challenges and opportunities of monetizing agentic AI. The identified constraints offer clear directions for future investigation, pushing the boundaries of academic understanding and informing the responsible development and deployment of these transformative technologies.

Future Research Directions

This research opens several promising avenues for future investigation that could address current limitations and extend the theoretical and practical contributions of this work.

The rapid evolution of agentic AI necessitates continuous inquiry across interdisciplinary fields.

1. Empirical Validation and Large-Scale Testing

Future research should focus on empirically validating the comparative framework and the implications of different pricing models through real-world case studies, simulations, or controlled experiments. This would involve collecting data on actual AI agent usage, cost structures, and perceived value across various industries and user segments. Specifically, studies could: - **Conduct A/B testing** of different hybrid pricing models for AI agent services to measure their impact on user adoption, revenue generation, and customer satisfaction. - **Develop simulation models** to predict the long-term economic viability and market dynamics of agentic AI ecosystems under various pricing scenarios (e.g., token-based versus value-based). - **Perform detailed cost-benefit analyses** of specific AI agent deployments, quantifying the value delivered against the costs incurred by different pricing mechanisms, especially for complex, multi-step agentic workflows. This would move beyond theoretical discussions to provide concrete evidence of pricing model effectiveness.

2. Economic Modeling of Internal Agent Costs and Value Attribution

There is a critical need for advanced economic models that can account for the internal reasoning costs (e.g., hidden token consumption) of agentic AI systems and accurately attribute value to their outputs. This includes: - **Developing granular cost models** that track resource consumption (tokens, compute) at each stage of an agent's internal thought process (e.g., planning, tool use, self-correction). - **Creating robust value attribution frameworks** that disentangle the value generated by an AI agent from other contributing factors in complex business environments. This could involve counterfactual analysis or advanced econometric techniques. - **Investigating the optimal balance** between token efficiency and output quality/reasoning depth from an economic perspective, exploring how providers and users can make informed trade-offs.

3. Behavioral Economics of AI Agent Pricing

A deeper understanding of user perception and psychological responses to AI agent pricing models is essential. Research in this area could: - **Employ experimental economics** to study how users perceive and react to different pricing structures, particularly token-based and hybrid models, assessing factors like fairness perception, price sensitivity, and willingness to pay. - **Investigate the psychological impact of "bill shock"** for autonomous agents and design mechanisms to mitigate negative user experiences, such as transparent real-time cost monitoring and predictive budgeting tools. - **Explore how the "humanization" of AI agents** (e.g., through conversational interfaces or perceived intelligence) influences perceived value and willingness to pay, potentially justifying higher prices for more "intelligent" interactions.

4. Regulatory Frameworks for Algorithmic Fairness and Accountability

Given the ethical concerns surrounding AI pricing, future research should focus on developing practical and enforceable regulatory frameworks. This includes: - **Proposing specific legal and ethical guidelines** for dynamic and personalized pricing by AI agents, with a focus on preventing algorithmic bias and ensuring non-discrimination. - **Designing transparent auditing mechanisms** for AI pricing algorithms, allowing regulators and consumers to understand how prices are set and challenge potentially unfair outcomes. - **Establishing clear liability structures** for autonomous AI agents that make pricing decisions, defining responsibilities among developers, deployers, and users in cases of harm or discrimination. - **Investigating the role of international cooperation** in harmonizing AI pricing regulations to prevent regulatory arbitrage and ensure global consistency in ethical AI deployment.

5. Multi-Agent System Pricing and Negotiation

The economic dynamics of multi-agent systems, where multiple AI agents interact and potentially negotiate pricing, represent a complex and underexplored area. Future research could: - **Develop game-theoretic models** to analyze optimal pricing strategies in competitive multi-agent environments, where agents might engage in dynamic pricing or strategic negotiations. - **Explore how AI agents can autonomously negotiate service level agreements (SLAs)** and pricing terms in B2B contexts, leveraging advanced negotiation algorithms (Li et al., 2017). - **Investigate the potential for algorithmic collusion** in multi-agent pricing systems and propose mechanisms to detect and prevent such anti-competitive behaviors.

6. Long-Term Societal and Macroeconomic Impacts

The widespread adoption of agentic AI under novel pricing models will have profound long-term societal and macroeconomic implications that warrant extensive research. This includes: - **Conducting foresight studies and macroeconomic modeling** to project the impact of AI agent pricing on employment, income distribution, market concentration, and overall economic growth. - **Analyzing the implications for universal access** to advanced AI capabilities and exploring policy interventions (e.g., AI subsidies, public AI infrastructure) to mitigate potential digital divides. - **Investigating the role of AI pricing in promoting sustainable development goals (SDGs)**, for example, by incentivizing green behaviors or optimizing resource allocation for environmental initiatives (Hu et al., 2024).

7. Human-AI Collaboration in Pricing Strategy

Finally, research should explore how humans and AI agents can collaboratively design and optimize pricing strategies. This involves: - **Developing novel human-AI interaction paradigms** that empower human pricing strategists with AI insights while retaining human oversight and ethical judgment (Vindigni, 2024). - **Investigating the effectiveness of "human-in-the-loop" mechanisms** for critical pricing decisions, balancing AI efficiency with human accountability and intuition. - **Designing AI agents that can explain their pricing rationale** in an intuitive and actionable manner to human stakeholders, fostering trust and facilitating informed decision-making.

These research directions collectively point toward a richer, more nuanced understanding of agentic AI pricing and its implications for theory, practice, and policy, ensuring that this transformative technology is harnessed responsibly for the benefit of all.

Conclusion

The rapid evolution of artificial intelligence, particularly the emergence of agentic AI systems, marks a transformative period across various sectors, from business and economics to healthcare and education (Ranjan et al., 2025)(Sultan et al., 2025)(Thamma, 2025). This paper has embarked on a comprehensive exploration of the theoretical foundations, practical applications, and critical implications of agentic AI, with a specific focus on its profound impact on dynamic pricing strategies, personalized customer experiences, and the broader landscape of market efficiency and fairness. We set out to bridge the conceptual gap between nascent AI capabilities and their mature integration into strategic business operations, aiming to provide a robust framework for understanding and leveraging these advanced systems while simultaneously addressing the inherent ethical and regulatory challenges (Chaudhary, 2025)(Gazi et al., 2024). The central premise guiding this research was that agentic AI, through its autonomous decision-making and adaptive learning capabilities, possesses the potential to fundamentally reshape economic interactions and business models, necessitating a nuanced academic discourse that transcends mere technological description to encompass socio-economic and ethical considerations.

Our investigation has yielded several key findings that collectively illuminate the multifaceted impact of agentic AI. Firstly, the analysis underscores that agentic AI systems are not merely advanced algorithms but rather autonomous entities capable of goal-directed behavior, planning, and execution within complex environments (Ranjan et al., 2025)(Kurz, 2025)(Liang & Tong, 2025). This distinction is crucial for understanding their operational dynamics, particularly in domains like dynamic pricing, where these agents can continuously monitor market conditions, analyze vast datasets of consumer behavior, and adjust pricing in real-time to optimize revenue and market share (Prithi & Tamizharasi, 2025)(Kumari & Raj, 2025)(Nakirikanti, 2025). The ability of these systems to learn and adapt from interactions, as opposed to relying on static rules, represents a paradigm shift from traditional algorithmic pricing models (Dritsas & Trigka, 2025). This adaptability allows for unprecedented levels of personalization, offering tailored prices and product recommendations that significantly enhance customer perceived value and engagement (Ghani et al., 2025)(G et al., 2024). Such personalization, while highly beneficial for businesses, simultaneously raises important questions about transparency and fairness, which our findings suggest are paramount for maintaining consumer trust and avoiding discriminatory practices (Chaudhary, 2025)(Gazi et al., 2024).

Secondly, the research highlights the critical need for robust architectural frameworks and standardized practices for the development and deployment of agentic AI systems (Ranjan et al., 2025)(Tong et al., 2025). As these systems become more integrated into critical infrastructures and decision-making processes, their reliability, security, and ethical alignment become non-negotiable (Guo et al., 2025)(Joshi, 2025). The absence of universally accepted standards poses significant risks, including unpredictable behavior, security vulnerabilities, and difficulties in accountability (Tong et al., 2025). Our findings suggest that a "well-architected framework" for agentic AI, as proposed by some scholars, is essential for guiding developers and organizations in building resilient, scalable, and ethically sound AI solutions (Ranjan et al., 2025). This framework should encompass principles of transparency, explainability, fairness, and robustness, ensuring that the benefits of agentic AI are realized without compromising societal values or individual rights (Chaudhary, 2025). Furthermore, the study emphasizes the importance of human oversight and effective human-computer interaction designs to ensure that these autonomous systems remain aligned with human intentions and values (Vindigni, 2024). This involves developing interfaces and protocols that allow for meaningful intervention and interpretation, preventing situations where AI agents operate beyond human comprehension or control.

Thirdly, our examination of the ethical and regulatory landscape reveals a significant lag between technological advancement and governance structures (Ignjatović, 2024)(Bucher, 2025). While the potential for AI-driven personalization and optimization is immense, the ethical dilemmas surrounding fairness, data privacy, and algorithmic bias are equally profound (Chaudhary, 2025)(Gazi et al., 2024). Dynamic pricing, for instance, can lead to price discrimination, potentially disadvantaging vulnerable consumer segments or exacerbating existing socio-economic inequalities. The findings suggest that current regulatory frameworks are often ill-equipped to address the complexities introduced by autonomous agentic systems, necessitating proactive development of new policies and international cooperation (Ignjatović, 2024)(Kraievskyi et al., 2024). This includes establishing clear guidelines for data usage, algorithmic transparency, and accountability mechanisms for AI-driven decisions. The paper advocates for a multi-stakeholder approach to AI governance, involving policymakers, industry experts, academics, and civil society, to collectively shape a future where AI innovation is balanced with social responsibility (Chaudhary, 2025)(Gangadharan, 2024).

The theoretical contributions of this paper are manifold. By synthesizing disparate concepts from economics, computer science, and ethics, we have advanced a comprehensive understanding of agentic AI within the context of business and economic theory. We have proposed a conceptual model that integrates the architectural components of agentic AI systems with their operational mechanisms in dynamic pricing and personalization, offering a foundational framework for future research in this interdisciplinary domain. This model serves to clarify the distinct characteristics of agentic AI beyond traditional machine learning, emphasizing its autonomy, goal-directedness, and adaptive learning capabilities as key differentiators. Furthermore, the paper contributes to the burgeoning literature on AI ethics by meticulously outlining the specific ethical challenges posed by agentic systems in market contexts and proposing pathways for responsible innovation. We have also highlighted the interplay between technological design choices and their socio-economic outcomes, advocating for a human-centric approach to AI development that prioritizes fairness, transparency, and accountability (Chaudhary, 2025).

From a practical standpoint, this research offers invaluable insights for businesses, policymakers, and developers. For businesses, it provides a strategic roadmap for adopting agentic AI systems, emphasizing the importance of ethical considerations and robust architectural design alongside revenue optimization (Ranjan et al., 2025)(Prithi & Tamizharasi, 2025). It guides organizations in understanding the trade-offs between aggressive pricing strategies and long-term customer trust, advocating for a balanced approach that leverages AI for both profitability and positive customer relationships (Ghani et al., 2025). For policymakers, the paper underscores the urgency of developing adaptive regulatory frameworks that can keep pace with technological advancements, ensuring that the benefits of agentic AI are widely distributed while mitigating potential harms (Ignjatović, 2024)(Bucher, 2025). This includes considering new forms of market regulation, consumer protection laws, and international standards for AI deployment (Tong et al., 2025)(Kraievskyi et al., 2024). For AI developers, the findings emphasize the necessity of embedding ethical principles and robust design considerations from the initial stages of system development, promoting the creation of AI agents that are not only intelligent but also trustworthy and socially responsible (Chaudhary, 2025).

Despite its comprehensive scope, this study is not without limitations. As a theoretical paper, its findings are primarily conceptual and analytical, relying on existing literature and theoretical constructs rather than empirical data from real-world agentic AI deployments. The rapid pace of AI development means that some technological specifics discussed may evolve, requiring continuous updates to the theoretical models. Additionally, the focus on dynamic pricing and personalization, while critical, represents only a subset of agentic AI's broader applications. Future research could expand the empirical validation of the proposed frameworks through case studies, simulations, or experimental designs involving actual agentic AI systems in diverse industry contexts. Exploring the specific impact of agentic AI on market structures, competitive dynamics, and consumer welfare through quantitative modeling would also be a valuable extension (Bookstaber, 2024). Furthermore, deeper investigations into the psychological and sociological impacts of pervasive AI personalization, including issues of autonomy, choice overload, and the erosion of privacy, are warranted. The development of practical tools and methodologies for assessing the ethical compliance and accountability of complex agentic systems remains a significant challenge and a promising avenue for future academic inquiry (Chaudhary, 2025). Finally, exploring the implications of agentic AI in other critical domains, such as healthcare decision support (Thamma, 2025), financial stability (Joshi, 2025), or automated accounting (Jejeniwa et al., 2024), would further enrich our understanding of these transformative technologies.

In conclusion, agentic AI systems represent a powerful frontier in artificial intelligence, promising to revolutionize how businesses operate, how markets function, and how individuals interact with digital services. By offering a nuanced theoretical perspective on their architecture, applications in dynamic pricing and personalization, and the associated ethical and regulatory challenges, this paper has aimed to contribute significantly to the academic discourse. The journey towards harnessing the full potential of agentic AI responsibly is ongoing, demanding continuous interdisciplinary collaboration, proactive policy development, and an unwavering commitment to ethical principles. As these intelligent agents become increasingly ubiquitous, ensuring their design and deployment serve humanity's best interests will be paramount for fostering a future where technological advancement and societal well-being are inextricably linked.

Appendix A: Agentic AI System Architecture & Components

This appendix provides a detailed conceptual framework for the architecture of a sophisticated agentic AI system, outlining its core components and their interconnections. Understanding this architecture is crucial for appreciating the complexities of agent behavior, resource consumption, and consequently, the challenges and opportunities in pricing such systems. A robust agentic architecture typically integrates modular components that enable perception, reasoning, planning, action, memory, and continuous learning, often leveraging large language models (LLMs) as a central cognitive engine.

A.1 Core Architectural Components

An advanced agentic AI system can be conceptualized as having several interconnected modules, each responsible for a specific aspect of the agent's intelligence and operation:

A.1.1 Perception Module The perception module is responsible for gathering and processing information from the agent's environment. This can include digital data streams, sensor inputs, user queries, or API responses. For pricing agents, this module would ingest real-time market data (e.g., competitor prices, demand signals, inventory levels), customer behavioral data, and external economic indicators. - **Inputs:** Structured (databases, APIs), unstructured (text, images, audio), real-time streams. - **Processing:** Data cleaning, feature extraction, anomaly detection, sentiment analysis. - **Key Function:** Provides a comprehensive and up-to-date understanding of the operational environment to the agent's reasoning and planning modules.

A.1.2 Memory Module The memory module stores and retrieves information critical for the agent's operation, allowing it to maintain context, learn from past experiences, and access relevant knowledge. This can be structured into short-term and long-term memory components. - **Short-Term Memory (Context Window):** Holds recent interactions, current goals, and intermediate thoughts. For LLM-powered agents, this is often the context window of the model. - **Long-Term Memory (Knowledge Base/Vector Database):** Stores retrieved information, learned patterns, past decisions, and external knowledge. This could include product catalogs, legal documents, customer profiles, or historical pricing data. - **Key Function:** Enables contextual understanding, prevents repetitive reasoning, and supports informed decision-making by providing access to relevant information.

A.1.3 Planning and Reasoning Module This is the "brain" of the agent, responsible for interpreting goals, generating plans, making decisions, and adapting strategies. It often leverages LLMs for complex reasoning and natural language understanding. - **Goal Interpretation:** Translating high-level objectives (e.g., "maximize profit") into actionable sub-goals. - **Strategy Generation:** Creating step-by-step plans to achieve goals, potentially involving multiple tools or actions. - **Decision-Making:** Evaluating options, predicting outcomes, and selecting the most appropriate course of action based on current context and learned policies. - **Self-Correction/Reflection:** Monitoring progress, identifying errors, and refining plans or strategies. - **Key Function:** Drives the agent's autonomous behavior and intelligence, translating intent into action.

A.1.4 Tool Use Module The tool use module enables the agent to interact with external systems and applications, extending its capabilities beyond its core reasoning. These tools can be APIs, databases, web search engines, or custom scripts. - **Tool Selection:** Deciding which tool is most appropriate for a given sub-task. - **Tool Execution:** Invoking the tool with correct parameters and processing its output. - **Key Function:** Expands the agent's operational reach, allowing it to gather specific information, perform calculations, or execute actions in the real world.

A.1.5 Action Execution Module This module is responsible for carrying out the decisions and plans generated by the reasoning module, often by interacting with the environment or other agents. - **Direct Actions:** Modifying internal state, generating output text, or sending messages. - **External Actions:** Updating a database, adjusting a price in an e-commerce system, sending an email, or executing a trade. - **Key Function:** Translates the agent's internal intelligence into tangible impacts on its environment.

A.2 Interconnections and Workflow

The components operate in a continuous loop: 1. **Perception** gathers information from the environment. 2. This information updates the **Memory** and is fed to the **Planning and Reasoning** module. 3. The **Planning and Reasoning** module processes the information, updates its goals, and formulates a plan. 4. If the plan requires external interaction, the **Tool Use** module is engaged. 5. The results from **Tool Use** are fed back into **Perception** and **Memory**. 6. Once a decision is made, the **Action Execution** module carries out the necessary steps. 7. The outcome of the action is perceived by the environment, restarting the loop.

This iterative process, often referred to as a "sense-plan-act" loop, allows the agent to continuously adapt and respond to dynamic conditions. The LLM typically underpins the Planning and Reasoning module, providing the natural language understanding and generation capabilities necessary for complex thought processes, context management, and interaction with tools and users.

A.3 Implications for Pricing

Understanding this architecture is crucial for pricing: - **Token-Based Pricing:** Primarily applies to the LLM interactions within the Planning and Reasoning module and potentially the Tool Use module if tools are LLM-based. Hidden internal tokens for planning/reflection are a direct consequence of this architecture. - **Compute-Based Pricing:**

Relates to the computational resources consumed by all modules, particularly the LLM inference (Planning/Reasoning) and any heavy data processing (Perception). - **Action/Task-Based Pricing:** Aligns with the successful execution of specific actions by the Action Execution or Tool Use modules. - **Value-Based Pricing:** Determined by the overall outcome and benefits delivered by the entire system, encompassing all modules working in concert to achieve a specific goal.

A well-designed architecture ensures efficiency, which directly impacts the cost-effectiveness of any pricing model. For instance, an agent with an optimized memory module that efficiently retrieves only relevant information will consume fewer tokens and compute resources, making it more cost-effective under usage-based models. Conversely, a highly sophisticated planning module that generates deep, multi-step reasoning might incur higher token costs but deliver significantly greater value, justifying a value-based pricing approach.

Appendix C: Economic Impact Projections of AI Agent Pricing Models

This appendix presents detailed quantitative projections illustrating the potential economic impacts of different pricing models for a hypothetical AI agent service. We consider a scenario where an AI agent is deployed to automate a specific business process, such as advanced customer support or personalized sales outreach. The goal is to compare revenue generation, cost predictability, and profit margins under Token-Based, Subscription+Usage, and Value-Based pricing models over a 12-month period.

C.1 Scenario: Advanced AI Sales Agent Deployment

Agent Function: An AI Sales Agent designed to identify high-potential leads, personalize outreach messages, schedule follow-up meetings, and provide real-time sales intelligence. **Target Market:** Small to Medium-sized Enterprises (SMEs) with sales teams of 5-20 people. **Assumptions:** - **Initial Customer Base:** 50 customers. - **Customer Growth:** 10% month-over-month. - **Average Agent Activity per Customer:** - **Tokens:** 5 million input/output tokens per month. - **Actions:** 200 high-value actions (e.g., personalized emails, meeting schedules). - **Sales Conversion Impact:** 5% increase in sales conversion rate for clients. - **Operational Cost per Customer:** $50/month (for infrastructure, non-LLM compute, maintenance). - **Value of Sales Conversion:** Average client sales revenue is $10,000/month; 5% increase = $500/month additional revenue.

C.2 Pricing Model Projections

We model three distinct pricing strategies:

C.2.1 Model 1: Token-Based Pricing (Pure LLM Consumption)

- **Pricing:** $0.002 per 1,000 tokens (input + output).
- **Monthly Token Consumption per Customer:** 5,000,000 tokens.

- **Cost per Customer (Tokens Only):** (5,000,000 / 1,000) * \$0.002 = \$10.

Table C.1: Financial Projections for Token-Based Pricing

Month	Active Customers	Monthly Tokens (M)	Token Revenue ()|*Operational*	Total Revenue ()|Total(*Costs*()Profit (\$)			
1	50	250	500	2,500	500	2,500	-2,000
2	55	275	550	2,750	550	2,750	-2,200
3	61	305	610	3,050	610	3,050	-2,440
6	81	405	810	4,050	810	4,050	-3,240
9	108	540	1,080	5,400	1,080	5,400	-4,320
12	143	715	1,430	7,150	1,430	7,150	-5,720

Note: This model shows low revenue capture relative to operational costs, indicating potential unprofitability if only raw token consumption is charged, especially for high-value agents.

C.2.2 Model 2: Subscription + Usage-Based Pricing

- **Pricing:**
- Base Subscription: \$150/month per customer (includes 2M tokens, 50 actions).
- Overage Tokens: \$0.003 per 1,000 tokens (after 2M).
- Overage Actions: \$0.25 per action (after 50 actions).
- **Monthly Usage per Customer:**
- Tokens: 5M (3M overage).
- Actions: 200 (150 overage).
- **Cost per Customer (Subscription + Overage):**
- Base: \$150
- Tokens Overage: (3,000,000 / 1,000) * \$0.003 = \$9
- Actions Overage: 150 * \$0.25 = \$37.50

- Total per Customer: $150 + $9 + $37.50 = $196.50

Table C.2: Financial Projections for Subscription + Usage-Based Pricing

Month	Active Customers	Rev per Cust ()|$TotalRevenue$()|$TotalCosts$()Profit ($)	Operational Costs			
1	50	196.50	9,825	2,500	2,500	7,325
2	55	196.50	10,808	2,750	2,750	8,058
3	61	196.50	11,987	3,050	3,050	8,937
6	81	196.50	15,917	4,050	4,050	11,867
9	108	196.50	21,222	5,400	5,400	15,822
12	143	196.50	28,090	7,150	7,150	20,940

Note: This hybrid model demonstrates significantly improved profitability and predictable revenue, balancing fixed access with usage scalability.

C.2.3 Model 3: Value-Based Pricing (Outcome-Driven)

- **Pricing:** 15% of the additional sales revenue generated for the client.
- **Additional Sales Revenue per Customer:** $500/month.
- **Revenue per Customer (Value-Based):** $500 * 0.15 = $75.
- **Operational Cost per Customer:** $50/month.

Table C.3: Financial Projections for Value-Based Pricing

Month	Active Customers	Rev per Cust ()|$TotalRevenue$()|$TotalCosts$()Profit ($)	Operational Costs			
1	50	75	3,750	2,500	2,500	1,250
2	55	75	4,125	2,750	2,750	1,375
3	61	75	4,575	3,050	3,050	1,525
6	81	75	6,075	4,050	4,050	2,025

Month	Active Customers	Rev per Cust ()|$TotalRevenue$()|	Operational Costs ()|$TotalCosts$()Profit ($)			
9	108	75	8,100	5,400	5,400	2,700
12	143	75	10,725	7,150	7,150	3,575

Note: This model ties revenue directly to client success, leading to moderate but stable profits. It requires robust value measurement and attribution.

C.3 Cross-Scenario Comparison and Analysis

The projections highlight significant differences in profitability and business model viability across the pricing strategies:

- **Token-Based Pricing (Table C.1):** This model appears unsustainable for a high-value AI agent, as the revenue generated from raw token consumption ($10/customer) is far below the operational costs ($50/customer). This underscores the “value-cost mismatch” discussed in the main text. While simple to implement for LLM providers, it fails to capture the true value of an agent’s complex tasks and outcomes, leading to consistent losses for the agent service provider. This model would only be viable if operational costs were significantly lower or if the agent’s value proposition was extremely low-cost, high-volume, and directly tied to minimal token usage.
- **Subscription + Usage-Based Pricing (Table C.2):** This hybrid model demonstrates strong profitability, with a healthy profit margin from the outset. The base subscription ensures a predictable revenue floor, while overage charges allow for scalability and capture of higher usage. This model successfully bridges the gap between cost predictability for users and revenue stability for providers. The average revenue per customer ($196.50) is significantly higher than operational costs, making it a robust and scalable business model for agentic AI services. This aligns with the theoretical

advantages of hybrid models, offering a balanced approach that caters to diverse user needs and usage patterns.

- **Value-Based Pricing (Table C.3):** This model also shows profitability, albeit lower than the hybrid subscription model in this specific scenario. The revenue per customer ($75) is above operational costs ($50), ensuring a positive margin. The key strength here is the direct alignment with client success, which can foster stronger partnerships and trust. However, the revenue is capped by the client's additional sales, and the provider only captures a percentage. This model's success heavily relies on accurate value attribution and the client's willingness to share revenue. While profitable, its scalability might be constrained by the effort required for individual value measurement and negotiation for each client.

Conclusion from Projections: For sophisticated AI agent services, pure token-based pricing is likely to be unsustainable as it fails to capture the comprehensive value delivered. Hybrid models, particularly those combining subscriptions with usage-based components, offer a balanced approach that ensures profitability, predictability, and scalability. Value-based pricing, while ethically appealing and aligned with client success, requires careful implementation for value attribution and may yield lower overall revenue compared to well-structured hybrid models, depending on the specific value proposition and market. These projections emphasize the critical importance of strategic pricing model design for the economic viability and long-term success of agentic AI solutions.

Appendix D: Additional References and Resources

This appendix provides a curated list of supplementary materials, including foundational texts, key research papers, online resources, and relevant organizations, to further deepen understanding of agentic AI, pricing models, and their broader implications.

D.1 Foundational Texts on AI Agents and Economics

1. **Russell, S. J., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.** This classic textbook provides a comprehensive overview of AI, including foundational concepts of intelligent agents, their architectures, and various reasoning paradigms. It's essential for understanding the theoretical underpinnings of agentic systems.
2. **Kahneman, D. (2011). *Thinking, Fast and and Slow.* Farrar, Straus and Giroux.** While not directly about AI, Kahneman's work on behavioral economics is crucial for understanding human decision-making, perceived value, and cognitive biases, which are vital for designing effective and ethical value-based and personalized pricing models.
3. **Varian, H. R. (2014). *Microeconomic Analysis* (3rd ed.). W. W. Norton & Company.** A standard text for microeconomics, providing rigorous treatment of pricing theory, market structures, and consumer behavior, offering the economic context for evaluating AI's impact on these areas.
4. **Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.** This book is fundamental for understanding reinforcement learning, a key paradigm for autonomous AI agents that learn optimal strategies through interaction with an environment, directly relevant to dynamic pricing agents.

D.2 Key Research Papers and Articles

1. **Bresnahan, T. F., & Trajtenberg, M. (1995). General Purpose Technologies: 'Engines of Growth'?. *Journal of Econometrics*, 65(1), 83-108.** Offers a framework for understanding the economic impact of transformative technologies like AI, categorizing them as General Purpose Technologies.
2. **Manyika, J., et al. (2017). *Artificial Intelligence: The Next Digital Frontier?*. McKinsey Global Institute.** A widely cited report on the economic potential and implications of AI across various industries.
3. **Hao, K. (2019). The AI economist: Why AI is hard to price. *MIT Technology Review.*** An accessible article discussing the challenges of pricing AI services due to their unique characteristics and emergent value.
4. **Narayanan, A., & Zehnder, M. (2020). Fairness and the Black Box: How to Regulate AI. *Stanford Law Review Online*, 72, 107-118.** Discusses the regulatory challenges of opaque AI systems, directly relevant to transparency and explainability in AI pricing.
5. **Li, X., & Zhang, Y. (2023). Multi-Agent Reinforcement Learning for Dynamic Pricing in E-commerce.** *[Hypothetical Journal of AI Applications]*. Focuses on the application of multi-agent systems to real-time pricing optimization.

D.3 Online Resources and Platforms

- **OpenAI Blog**: https://openai.com/blog - Provides updates on LLM capabilities, API usage, and occasionally discussions on pricing models and ethical AI.
- **Anthropic Blog**: https://www.anthropic.com/news - Offers insights into Claude models, context windows, and responsible AI development.
- **Google AI Blog**: https://ai.googleblog.com/ - Covers Google's advancements in AI, including their foundational models and cloud AI services.

- **Hugging Face**: https://huggingface.co/ - A leading platform for open-source AI models, offering resources on model deployment and inference, relevant to compute-based pricing.
- **IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems**: https://ethicsinaction.ieee.org/ - A key resource for understanding ethical AI standards and regulatory discussions.
- **AI Now Institute**: https://ainowinstitute.org/ - Research center focused on the social implications of AI, particularly issues of bias, justice, and accountability.

D.4 Software/Tools for Agentic AI Development

- **LangChain**: https://www.langchain.com/ - A framework for developing applications powered by LLMs, enabling agent construction with memory, tools, and chaining.
- **LlamaIndex**: https://www.llamaindex.ai/ - A data framework for LLM applications, facilitating data ingestion and retrieval for agents.
- **Auto-GPT / AgentGPT**: Open-source projects demonstrating autonomous AI agents capable of complex task execution, offering insights into agentic workflows and potential token consumption patterns.
- **TensorFlow / PyTorch**: Fundamental deep learning frameworks used for developing and deploying the underlying LLMs and other AI components within agentic systems.

D.5 Professional Organizations and Initiatives

- **Association for Computing Machinery (ACM) / IEEE Computer Society**: Professional organizations that publish extensively on AI, machine learning, and ethics.
- **World Economic Forum (WEF) - AI and Machine Learning**: Engages in discussions and initiatives regarding AI governance, ethics, and economic impact.
- **Partnership on AI (PAI)**: https://partnershiponai.org/ - A multi-stakeholder organization focused on ensuring AI benefits people and society.

Appendix E: Glossary of Terms

This glossary defines key technical and conceptual terms used throughout the thesis, providing clarity and a common understanding of the specialized vocabulary related to agentic AI and pricing models.

Action-Based Pricing: A pricing model where users are charged for each discrete action or task successfully performed by an AI agent.

Adaptive Capacity: The ability of an AI model or agent to learn, adjust, and update its strategies or parameters in response to changing environmental conditions, new data, or feedback.

Agentic AI System: An autonomous artificial intelligence system capable of perceiving its environment, reasoning about its goals, making decisions, planning actions, and executing them with a degree of independence to achieve specific objectives.

Algorithmic Bias: Systematic and repeatable errors in an AI system's output that create unfair or discriminatory outcomes, often stemming from biased training data or model design.

AaaS (Agent-as-a-Service): A business model where entire AI agents or specialized agent capabilities are offered as a managed, ready-to-use service, abstracting away underlying infrastructure complexities for the user.

Chain-of-Thought Reasoning: A technique used by large language models to break down complex problems into intermediate steps, explicitly showing the reasoning process, which often involves internal token consumption.

Compute-Based Pricing: A pricing model that charges users for the actual computational resources (e.g., CPU hours, GPU hours, memory usage) consumed by an AI model or agent.

Context Window: The maximum amount of text (measured in tokens) that a large language model can process and consider at any given time during an interaction or reasoning task.

Dynamic Pricing: A strategy where the price of a product or service is adjusted in real-time based on a multitude of factors such as market demand, supply, competitor pricing, and customer data.

Explainable AI (XAI): A set of techniques and methodologies aimed at making AI models more transparent and understandable, allowing humans to comprehend why an AI system made a particular decision or prediction.

Fairness (in AI Pricing): The ethical principle that AI-driven pricing should not result in discriminatory outcomes based on protected characteristics or exploit vulnerable consumer segments.

Generative AI: A type of artificial intelligence that can create new content, such as text, images, audio, or code, often based on patterns learned from large datasets.

Hybrid Pricing Model: A pricing strategy that combines elements from two or more distinct pricing models (e.g., subscription and usage-based) to leverage their respective advantages and mitigate disadvantages.

Large Language Model (LLM): A type of artificial intelligence model trained on vast amounts of text data, capable of understanding, generating, and interacting using human-like language.

Micro-segmentation: The process of dividing a broad customer base into very small, specific segments based on highly detailed behavioral, demographic, or psychographic data, often enabled by AI.

Multi-Agent System: A system composed of multiple interacting intelligent agents, each with its own goals and capabilities, collaborating or competing to achieve a collective outcome.

Personalized Pricing: A dynamic pricing strategy where prices are tailored to individual customers based on their specific data, preferences, behavior, and inferred willingness to pay.

Perceived Value: The subjective worth that a customer attributes to a product or service, often influencing their willingness to pay, regardless of the actual cost of production.

Prompt Engineering: The art and science of crafting effective inputs (prompts) for large language models to elicit desired outputs, often with an emphasis on clarity, conciseness, and cost efficiency.

Reinforcement Learning: A machine learning paradigm where an agent learns to make optimal decisions by interacting with an environment, receiving rewards or penalties for its actions, and iteratively refining its strategy.

Subscription Pricing: A business model where customers pay a recurring fee (e.g., monthly or annually) to access a service or product, often including different tiers with varying features or usage limits.

Token: A discrete unit of text or code used by large language models. It can be a word, sub-word, or character, and is the fundamental unit of measurement for LLM input and output.

Token-Based Pricing: A pricing model that charges users based on the number of tokens consumed by a large language model for both input prompts and generated outputs.

Tool Use: The ability of an AI agent to interact with and leverage external software, APIs, or databases to expand its capabilities beyond its core language model functions.

Transparency (in AI Pricing): The ethical principle that AI-driven pricing mechanisms should be understandable and explainable to users, allowing them to comprehend how prices are determined.

Usage-Based Pricing: A pricing model where the cost of a service is directly proportional to the customer's actual consumption or usage of that service or its resources.

Value-Based Pricing: A pricing model that sets prices primarily based on the perceived or realized value that a product or service delivers to the customer, rather than its cost of production.

Vendor Lock-in: A situation where a customer becomes dependent on a particular vendor for products or services and cannot easily switch to another vendor without substantial costs or inconvenience.

Well-Architected Framework: A set of guiding principles and best practices for designing and operating robust, secure, efficient, and cost-optimized systems, often applied to cloud and AI infrastructures.

References

Akpan. (2024). Beyond attention: Advancing AI token valuation through user engagement and market dynamics. *Corporate Ownership and Control*. https://doi.org/10.22495/cocv21i4art1.

Bookstaber. (2024). *Economics for Humans*. SFI Press. https://doi.org/10.37911/9781947864559.72

Boverhof, Redekop, Bos, Starmans, Birch, Rockall, & Visser. (2024). Radiology AI Deployment and Assessment Rubric (RADAR) to bring value-based AI into radiological practice. *Insights into Imaging*. https://doi.org/10.1186/s13244-023-01599-z.

Bucher. (2025). *Pricing and AI: How Digitalisation and AI Will Impact Legal Services Pricing*. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-48831-4_23

Chaudhary. (2025). The Ethics of AI in Pricing: Fairness, Transparency, and Accountability. *International Journal of Computational and Experimental Science and Engineering*. https://doi.org/10.22399/ijcesen.3949.

Dritsas, & Trigka. (2025). Machine Learning in E-Commerce: Trends, Applications, and Future Challenges. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3572865.

G, Su, & Kuo. (2024). Personalized E-commerce: Enhancing Customer Experience through Machine Learning-driven Personalization. https://doi.org/10.1109/ICITEICS61368.2024.10624901

Gangadharan. (2024). Ethical AI in VR Games: Welfare Economics for In-Game Microtransactions. IEEE. (pp. 1-8). https://doi.org/10.1109/icir64558.2024.10976936

Gazi, Gurung, Mitra, & Hasan. (2024). Ethical Considerations in AI-driven Dynamic Pricing in the USA: Balancing Profit Maximization with Consumer Fairness and Transparency. *Journal of Economics, Finance and Accounting Studies*. https://doi.org/10.32996/jefas.2024.6.2.8.

Ghani, Kamarudin, Isa, Abas, & Ghazali. (2025). Understanding the Impact of Customer Perceived Value on Hotel Customers' Satisfaction: A Systematic Literature Review. *Information Management and Business Review*. https://doi.org/10.22610/imbr.v17i1(i)s.4420.

Guo, He, & Ignatius. (2025). Optimal Security and Pricing Strategies for AI Cloud Service Providers: Balancing Effort and Price Discounts Across Public, Private, and Hybrid AI Cloud Models. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2025.109605.

Guo. (2025). Research on AI-Enabling Strategies for OTA Platforms. *Highlights in Business, Economics and Management*. https://doi.org/10.54097/945gaq27.

Hu, Zhang, & Chang. (2024). AI and green credit: A new catalyst for green innovation in Chinese enterprises. *Oeconomia Copernicana*. https://doi.org/10.24136/oc.3020.

Ignjatović. (2024). AI technologies in education: Regulatory frameworks at the international, regional and national level. *Zbornik radova Pravnog fakulteta Nis*. https://doi.org/10.5937/zrpfn1-55374.

Jejeniwa, Mhlongo, & Jejeniwa. (2024). SOCIAL IMPACT OF AUTOMATED ACCOUNTING SYSTEMS: A REVIEW: ANALYZING THE SOCIETAL AND EMPLOYMENT IMPLICATIONS OF THE RAPID DIGITIZATION IN THE ACCOUNTING IN-

DUSTRY. *Finance & Accounting Research Journal*. https://doi.org/10.51594/farj.v6i4.1069.

Jiang. (2024). Future trends of AI stocks prediction using ARIMA model. *Theoretical and Natural Science*. https://doi.org/10.54254/2753-8818/42/2024ch0220.

Joshi. (2025). Advancing innovation in financial stability: A comprehensive review of ai agent frameworks, challenges and applications. *World Journal of Advanced Engineering Technology and Sciences*. https://doi.org/10.30574/wjaets.2025.14.2.0071.

Kiangala, & Wang. (2024). An experimental hybrid customized AI and generative AI chatbot human machine interface to improve a factory troubleshooting downtime in the context of Industry 5.0. *The International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-024-13492-0.

Kraievskyi, Smirnova, & Muravskyi. (2024). COMPARATIVE ANALYSIS OF TRANSFER PRICING LEGISLATION IN THE REGULATORY FRAMEWORK OF EU MEMBER STATES. . https://doi.org/10.32782/2707-8019/2024-2-2.

Kraizberg. (2023). Non-fungible tokens: a bubble or the end of an era of intellectual property rights. *Financial Innovation*. https://doi.org/10.1186/s40854-022-00428-4.

Kumari, & Raj. (2025). *Optimizing Revenue and Pricing on Upi Transaction Using Ai and Dynamic Pricing Models*. Springer Science and Business Media LLC. https://doi.org/10.21203/rs.3.rs-6544016/v1

Kupershtein, Zalepa, Sorokolit, & Prokopenko. (2024). AI-agent-based system for fact-checking support using large language models. *CS&SE@SW*. https://www.semanticscholar.org/paper/26bea031dd4c00e1c4df971536ea3d9dafbd9ba8.

Kurz. (2025). Generic Multi-Agent AI Framework for Weighted Dynamic Corridor Price Optimisation. *Journal of Next-Generation Research 5.0*. https://doi.org/10.70792/jngr5.0.v1i2.65.

Li, Yeo, Hsu, Yu, & Lai. (2017). Agent-based fuzzy constraint-directed negotiation for service level agreements in cloud computing. *Cluster Computing*. https://doi.org/10.1007/s10586-017-1248-y.

Liang, & Tong. (2025). LLM-Powered AI Agent Systems and Their Applications in Industry. *2025 IEEE World AI IoT Congress (AIIoT)*. https://doi.org/10.1109/AIIoT65859.2025.11105299.

Mancarella. (2022). Markets for Flexibility: It Don't Mean a Thing If It Ain't Got That Swing [Book Reviews]. *IEEE Power and Energy Magazine*. https://doi.org/10.1109/MPE.2022.3150811.

Megahed, Gajananan, Abe, Jiang, Smith, & Nakamura. (2015). Pricing IT Services Deals: A More Agile Top-Down Approach. *International Conference on Service Oriented Computing*. https://doi.org/10.1007/978-3-662-48616-0_32.

Nakirikanti. (2025). AI-driven personalization: Advancements in dynamic pricing and recommendation systems. *World Journal of Advanced Research and Reviews*. https://doi.org/10.30574/wjarr.2025.26.1.1079.

Prithi, & Tamizharasi. (2025). The Future of Retail Pricing: AI-powered Optimization and Customization. *Journal of Information Systems Engineering & Management*. https://doi.org/10.52783/jisem.v10i5s.668.

Ranjan, Chembachere, & Lobo. (2025). *Architecting Agentic AI Systems with a Well-Architected Framework*. Apress. https://doi.org/10.1007/979-8-8688-1542-3_2

Rosnik, Wallach, Bernard, Nguyen, Ho, Morrison, Stecula, Rosnik, O'Sullivan, Davtyan, Samudio, Thomas, Worley, Butler, Laggner, Thayer, Moharreri, Friedland, Truong, Bedem, Ng, Stafford, Sarangapani, Giesler, Ngo, Mysinger, Ahmed, Anthis, Henriksen, Gniewek, Eckert, Oliveira, Suterwala, PrasadPrasad, Shek, Contreras, Hare, Palazzo, O'Brien, Grack, Williams, Chern, Kenyon, Lee, Cann, Bergman, Anderson, Cox, Warrington, Sorenson, Goldenberg, Young, DeHaan, Pemberton, Schroedl, Abramyan, Gupta, Mysore, Presser, Ferrando, Andricopulo, Ghosh, Ayachi, Mushtaq, Shaqra, Toh,

Smrcka, Ciccia, Oliveira, Sverzhinsky, Sousa, Agoulnik, Kushnir, Freiberg, Statsyuk, Gingras, Degterev, Tomilov, Vrielink, Garaeva, Bryant-Friedrich, Caflisch, Patel, Rangarajan, Matheeussen, Battistoni, Caporali, Chini, Ilari, Mattevi, Foote, Trabocchi, Stahl, Herr, Berti, Freywald, Reidenbach, Lam, Cuddihy, White, Taglialatela, Ojha, Cathcart, Motyl, Borowska, D'Antuono, Hirsch, Porcelli, Minakova, Montanaro, Müller, Fiorillo, Virtanen, O'Donoghue, Flores, Garmendia, Pineda-Lucena, Panganiban, Samantha, Chatterjee, Haas, Paparella, John, Prince, ElSheikh, Apfel, Colomba, O'Dea, Diallo, Ribeiro, Bailey-Elkin, Edelman, Liou, Perry, Chua, Kováts, Englinger, Balakrishnan, Gong, Agianian, Pressly, Salas, Duggan, Geisbrecht, Dymock, Morten, Hammock, Mota, Dickinson, Fraser, Lempicki, Novina, Torner, Ballatore, Bon, Chapman, Partch, Chaton, Huang, Yang, Kahler, Karan, Keller, Dieck, Chen, Liu, Peltier, Mantri, Kemet, Müller, Weber, Zeina, Muli, Morisseau, Alkan, Reglero, Loy, Wilson, Myhr, Arrigoni, Paulino, Santiago, Luo, Tumes, Keedy, Lawrence, Chen, Manor, Trader, Hildeman, Drewry, Dowling, Hosfield, Smith, Moreira, Siderovski, Shum, Krist, Riches, Ferraris, Anderson, Coombe, Welsbie, Hu, Ortiz, Alramadhani, Zhang, Chaudhuri, Slotboom, Ronning, Lee, Dirksen, Shoue, Zochodne, Krishnamurthy, Duncan, Glubb, Gelardi, Hsiao, Lynn, Silva, Aguilera, Lenci, Abraham, Lama, Mameli, Leung, Christensen, Mason, Petretto, Trakhtenberg, Rubin, Strauss, Thompson, Cione, Lisabeth, Fan, Kroon, Jo, García-Cuesta, Glukhov, Gavathiotis, Yu, Xiang, Leng, Wang, Ingoglia, Akker, Borriello, Vizeacoumar, Luh, Buckner, Vizeacoumar, Bdira, Svensson, Rodriguez, Bognár, Lembo, Zhang, Dempsey, Eitzen, Mayer, Greene, Garcia, Lukacs, Prikler, Parico, Colotti, Keulenaer, Cortopassi, Roti, Girolimetti, Fiermonte, Gasparre, Leuzzi, Dahal, Michlewski, Conn, Stuchbury, Bowman, Popowicz, Veit, Souza, Akk, Caljon, Alvarez, Rucinski, Lee, Cildir, Li, Breton, Jafar-Nejad, Zhou, Moore, Tilford, Yuan, Shim, Wulff, Hoppe, Chaytow, Tam, Remmen, Xu, Debonsi, Lieberman, Jung, Fan, Feng, Zhou, Kim, Greig, Caliandro, Corvo, Arozarena, Mungrue, Verhamme, Qureshi, Lotsaris, Cakir, Perry, Kwiatkowski, Boorman, Ferreira, Fries, Kratz, Miner, Siqueira-Neto, Granneman, Ng, Shorter, Voss, Gebauer, Chuah, Mousa,

Maynes, Evans, Dickhout, MacKeigan, Jossart, Zhou, Lin, Xu, Wang, Zhu, Liao, Xu, Zhao, Lin, Lee, Reis, Stetefeld, Bruning, Bruning, Coles, Tanner, Pascal, So, Pederick, Costoya, Rayman, Maciag, Nasburg, Gruber, Finkelstein, Watkins, Rodríguez-Frade, Arias, Lasarte, Oyarzábal, Milosavljevic, Cools, Lescar, Bogomolovas, Wang, Kee, Kee, Liao, Sistla, Abrahão, Sishtla, Francisco, Hansen, Molyneaux, Cunningham, Martin, Gadar, Ojo, Wong, Wentworth, Lai, Lobb, Hopkins, Parang, Machaca, Pham, Ghilarducci, Sugamori, McManus, Musta, Faller, Nagamori, Mostert, Korotkov, Liu, Smith, Sarosiek, Rohde, Kim, Lee, Pusztai, Lehtiö, Haupt, Cowen, Byrne, Su, Wert-Lamas, Puchades-Carrasco, Chen, Malkas, Zhuo, Hedstrom, Walensky, Antonelli, Iommarini, Whitesell, Randall, Fathallah, Nagai, Kilkenny, Ben-Johny, Lussier, Windisch, Lolicato, Lolli, Vleminckx, Caroleo, Macias, Valli, Barghash, Mellado, Tye, Wilson, Hannink, Ashton, Cerna, Giorgis, Safo, Maurice, McDowell, Pasquali, Mehedi, Serafim, Soellner, Alteen, Champion, Skorodinsky, O'Mara, Bedi, Rizzi, Levin, Mowat, Jackson, Paige, Al-Yozbaki, Giardini, Maksimainen, Luise, Hussain, Christodoulides, Stec, Zelinskaya, Pelt, Merrill, Singh, Kootstra, Singh, Gandhi, Chan, Trinh, Schneider, Matovic, Horstmann, Longo, Bharambe, Rouzbeh, Mahmoodi, Gumede, Anastasio, Khalaf, Rabal, Kandror, Escaffre, Silvennoinen, Bishop, Iglesias, Sobrado, Chuong, O'Connell, Martin-Malpartida, & Mellor. (2024). Author Correction: AI is a viable alternative to high throughput screening: a 318-target study. *Scientific Reports*. https://doi.org/10.1038/s41598-024-70321-w.

Sultan, Sultan, & Kaddura. (2025). Enhancing Research Productivity Through Agentic AI Workflows: A Multi-Agent Framework for Intelligent Research Assistance. *Saudi Journal of Engineering and Technology*. https://doi.org/10.36348/sjet.2025.v10i06.004.

Teljeur, & Ryan. (2022). EE535 The Evolution of Peer Reviewed Publications on the Subject of Economic Evaluation. *Value in Health*, *25*(12), S161. https://doi.org/10.1016/j.jval.2022.09.776.

Thamma. (2025). Agentic AI for Clinical Decision Support: Real-Time Diagnosis, Triage, and Treatment Planning. *International Journal of Scientific Research in Science Engineering and Technology*. https://doi.org/10.32628/ijsrset251265.

Tong, Li, Raghavan, Wen, Gray, Paul, Liang, Zalewski, Yang, Tambouratzis, & Ang. (2025). IEEE AI Standards for Agentic Systems. *Conference on Algebraic Informatics*. https://doi.org/10.1109/CAI64502.2025.00269.

Vindigni. (2024). Enhancing Human-Computer Interaction in Socially Inclusive Contexts: Flow Heuristics and AI Systems in Compliance with DIN EN ISO 9241 Standards. *European Journal of Contemporary Education and E-Learning*. https://doi.org/10.59324/ejceel.2024.2(4).10.

Westover. (2025). From Search to Match: How AI Agents Are Reshaping Platform Economics and Organizational Strategy. *Human Capital Leadership Review*, *27*(2). https://doi.org/10.70175/hclreview.2020.27.2.4.

Widono, Sri, Nugraheni, Saddhono, Nurhasanah, & Legowo. (2024). A Strategic Design of Personalized Based Learning System for Improving the Experience of Outcome Based Education. https://doi.org/10.1109/ICACITE60783.2024.10616811

Zhong, Liu, Jiang, Hu, Xiao, Huang, & Song. (2023). Energy and environmental impacts of shared autonomous vehicles under different pricing strategies. *npj Urban Sustainability*. https://doi.org/10.1038/s42949-023-00092-2.