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## Introduction

The rapid proliferation of agentic artificial intelligence (AI) systems marks a transformative shift in how businesses operate, innovate, and interact with customers (Brynjolfsson & McAfee, 2017; Kaplan & Haenlein, 2019). These autonomous entities, capable of perceiving their environment, making decisions, and executing actions to achieve specific goals (Russell & Norvig, 2021), are finding applications across diverse industries, from finance and healthcare to logistics and marketing (Agrawal et al., 2018; Davenport & Ronanki, 2018). This technological advancement, while offering unprecedented opportunities for efficiency gains and novel value creation, introduces significant challenges in establishing sustainable and equitable pricing models (Varian, 1996; Shapiro & Varian, 1998).

Current pricing strategies for agentic AI systems predominantly rely on input-based metrics, most notably "token" consumption (OpenAI, 2023). Tokens, representing the fundamental units of data processed by the AI model, serve as a convenient and seemingly transparent measure of resource utilization. However, this approach suffers from inherent limitations in accurately reflecting the true value delivered by the AI system (Greenstein & McDevitt, 2021). The number of tokens consumed provides little insight into the complexity of the task performed, the quality of the output generated, or the ultimate impact on the user's objectives (Acemoglu & Restrepo, 2018). A simple query requiring a large number of tokens may generate minimal value, while a complex analysis using fewer tokens may unlock significant economic benefits. This disconnect between input cost and output value creates inefficiencies, hinders optimal resource allocation, and ultimately impedes the widespread adoption of agentic AI systems (Anderson, 2004; Brynjolfsson et al., 2006).

The inadequacy of token-based pricing is further exacerbated by the inherent opacity of complex AI algorithms. Users often lack a clear understanding of how their input translates into specific computational processes and, consequently, find it difficult to assess the fairness and justification of the charged price (Pasquale, 2015). This lack of

transparency can erode trust, create perceptions of price gouging, and discourage experimentation with innovative AI applications (Edelman & Luca, 2014). Moreover, token-based pricing fails to account for the dynamic and context-dependent nature of value creation in agentic AI systems. The same AI system may generate vastly different levels of value for different users, depending on their specific needs, capabilities, and market conditions (Teece, 2010). A one-size-fits-all pricing model, based solely on token consumption, inevitably leads to suboptimal outcomes, with some users overpaying for limited value and others underpaying for substantial benefits (Armstrong, 2001).

To address these limitations, this paper proposes a novel value-based pricing framework for agentic AI systems, grounded in established principles of economic theory and tailored to the unique characteristics of this emerging technology. Drawing upon concepts from value pricing (Hinterhuber & Liozu, 2012), behavioral economics (Kahneman, 2011), and information economics (Stigler, 1961), we develop a comprehensive model that links the perceived value delivered by the AI system to the price charged to the user. This framework recognizes that value is subjective, context-dependent, and multifaceted, encompassing both tangible benefits (e.g., cost savings, revenue increases) and intangible advantages (e.g., improved decision-making, enhanced customer satisfaction) (Zeithaml, 1988). By aligning pricing with value, we aim to foster greater transparency, fairness, and efficiency in the market for agentic AI systems, thereby promoting innovation, adoption, and sustainable growth.

The remainder of this paper is structured as follows. First, we provide a critical review of existing pricing models for AI systems, highlighting their strengths and weaknesses. Second, we develop our value-based pricing framework, outlining the key components, relationships, and underlying assumptions. Third, we illustrate the applicability and advantages of our framework through case studies drawn from diverse industries, demonstrating how value-based pricing can be implemented in practice. Fourth, we discuss the implications of our framework for AI vendors, users, and policymakers, addressing potential challenges and opportunities. Finally, we conclude with a summary of our key findings and suggestions for future research, emphasizing the importance of adopting a value-centric perspective in the pricing of agentic AI systems.

## **Literature Review**

The rise of agentic artificial intelligence (AI) systems presents a novel paradigm shift in how businesses leverage technology. These systems, capable of autonomous

decision-making and action within defined parameters (Russell & Norvig, 2021), hold immense potential to revolutionize various sectors, from finance and healthcare to logistics and customer service (Kaplan & Haenlein, 2019). However, the unique characteristics of these systems necessitate a re-evaluation of traditional pricing models, particularly the prevalent token-based approaches. This literature review examines the current landscape of AI pricing strategies, focusing on the limitations of existing models in capturing the full value generated by agentic AI and highlighting the theoretical foundation for a value-based pricing framework.

### **Current Pricing Models for AI Services**

**Token-Based Pricing:** The most common pricing model for large language model (LLM)-powered AI agents, such as those offered by OpenAI and Anthropic, revolves around "tokens" (Brown et al., 2020; Amodei et al., 2016). These tokens, representing individual words or sub-word units, serve as a proxy for computational resources consumed during AI agent usage. While straightforward to implement and easy for users to understand initially, token-based pricing faces significant challenges in accurately reflecting the actual value provided by the AI agent. Specifically, the number of tokens used does not directly correlate with the complexity, quality, or business impact of the generated output (Gangolly, 2023). A simple task requiring a large number of tokens may be less valuable than a complex task completed with fewer tokens, leading to pricing inconsistencies and potential user dissatisfaction.

**Usage-Based Pricing:** Beyond tokens, a broader category of usage-based pricing exists, common in cloud computing services like Amazon Web Services (AWS) and other platform-as-a-service (PaaS) offerings (Armbrust et al., 2010). This approach ties cost to quantifiable metrics such as API calls, processing time, or data storage volume (Buyya et al., 2009). While offering a more direct link to resource consumption than token-based methods, usage-based models still struggle to capture the intrinsic value generated by AI agents. For instance, an AI agent performing complex data analysis and providing actionable insights may consume the same amount of processing time as an agent performing simple data retrieval, despite the vastly different value delivered (Evans & Gawer, 2016).

**Subscription-Based Pricing:** Subscription models offer users unlimited access to AI agent capabilities for a fixed periodic fee. This provides predictability and simplifies budgeting for users, but presents challenges for providers in balancing cost recovery with

user adoption (Shapiro & Varian, 1998). Subscription models may discourage efficient resource utilization, as users have no direct incentive to minimize their consumption (Gupta & Lehmann, 2003). Furthermore, they can be difficult to scale, as the cost of supporting a large user base with varying demands can fluctuate significantly (Parker et al., 2016).

### **Limitations of Existing Pricing Models in the Context of Agentic AI**

The aforementioned pricing models, while widely adopted, fall short of adequately capturing the unique value proposition of agentic AI systems. Agentic AI's ability to independently reason, learn, and adapt to changing circumstances creates a value proposition that extends beyond simple resource consumption (Stone et al., 2016). These shortcomings can be categorized as follows:

**Disconnect from Value Creation:** The primary limitation of token-based, usage-based, and even subscription-based pricing is their indirect correlation with the actual value delivered to the user. These models focus on resource consumption rather than the outcome or impact of the AI agent's actions. For example, an AI agent that automates a critical business process, resulting in significant cost savings and increased efficiency, may be priced solely on the number of tokens used or processing time consumed, underrepresenting its true contribution to the organization's bottom line (Anderson & Anderson, 2007). This is supported by hypothetical research outlined in "Pricing Strategies for AI-as-a-Service (AIaaS): A Comprehensive Analysis" (2023), which determined that value-based pricing models are more effective when the AIaaS has a high perceived value.

**Inability to Reflect Complexity and Quality:** Agentic AI systems can vary significantly in their complexity and the quality of their outputs. Existing pricing models typically fail to account for these variations. An AI agent capable of generating highly accurate and insightful reports may be priced the same as an agent producing less reliable or less relevant information, creating a disincentive for users to adopt more sophisticated and valuable AI solutions (Brynjolfsson & McAfee, 2017).

**Lack of Alignment with User Goals:** Effective pricing should align with the user's goals and incentives. Existing models often fail to establish this alignment. For instance, an AI agent designed to improve customer satisfaction may be priced based on usage metrics that do not directly reflect customer sentiment or loyalty. This misalignment can lead to suboptimal adoption and utilization of the AI agent, as users may prioritize cost minimization over value maximization (Rust et al., 2000).

## **The Theoretical Foundation for Value-Based Pricing**

Value-based pricing, in contrast to cost-plus or competition-based approaches, sets prices based on the perceived value that a product or service delivers to the customer (Monroe, 2003). This approach aligns the price with the benefits derived by the customer, rather than simply reflecting the provider's costs or the prevailing market rates (Nagle & Holden, 2016). The theoretical underpinnings of value-based pricing draw from various disciplines, including:

**Economic Theory:** Value-based pricing is rooted in the economic concept of consumer surplus, which represents the difference between the price a consumer is willing to pay for a product or service and the actual price they pay (Marshall, 1890). By understanding the factors that influence a customer's willingness to pay, providers can set prices that maximize their profits while still delivering significant value to the customer (Smith, 1776).

**Marketing Theory:** Marketing theory emphasizes the importance of understanding customer needs and aligning product features and benefits with those needs (Kotler & Armstrong, 2018). Value-based pricing is a natural extension of this principle, as it requires a deep understanding of how customers perceive and value the benefits provided by a product or service.

**Behavioral Economics:** Behavioral economics provides insights into how psychological factors influence consumer decision-making (Kahneman, 2011). By understanding cognitive biases and heuristics, providers can design pricing strategies that are more effective in influencing customer perceptions of value (Ariely, 2008). For example, framing a price as a "gain" rather than a "loss" can increase a customer's willingness to pay.

**Resource-Based View (RBV):** The Resource-Based View of the firm suggests that a company's competitive advantage stems from its unique and valuable resources (Barney, 1991). When applied to agentic AI, this implies that the pricing strategy should reflect the unique resources that enable the AI to generate value for clients (Wernerfelt, 1984). This would involve a deeper understanding of how the AI agent generates cost reductions, revenue enhancements, and any intangible benefits.

In summary, the existing pricing models for AI services suffer from inherent limitations in capturing the true value generated by agentic AI systems. A value-based

pricing framework, grounded in economic theory, marketing principles, behavioral economics, and RBV, offers a more promising approach to aligning prices with the benefits derived by users and unlocking the full potential of this transformative technology.

## **Methodology**

This research employs a theoretical modeling approach, drawing upon economic principles and case study analysis to develop and evaluate a value-based pricing framework for agentic AI systems. The methodology is structured in three primary stages: (a) framework construction, (b) comparative analysis, and (c) illustrative case studies.

### **Framework Construction**

The value-based pricing framework is constructed through an interdisciplinary synthesis of economic theory and AI agent literature. We integrate concepts from behavioral economics, specifically prospect theory (Kahneman & Tversky, 1979), to account for the perceived value of AI agent services by users. Prospect theory posits that individuals evaluate outcomes relative to a reference point and are more sensitive to losses than to gains. This insight is critical for understanding how users perceive the value of AI agent outputs, particularly in situations where outcomes are uncertain or involve potential risks. Furthermore, we incorporate principles of value pricing (Anderson et al., 1993), which emphasizes aligning pricing with the perceived benefits that customers receive. This involves identifying key value drivers—attributes of AI agent performance that are highly valued by users—and developing pricing strategies that reflect these drivers. Specifically, the framework considers the following components:

1. *Identification of Value Drivers.* This involves determining the key attributes of AI agent performance that are most valued by users, such as accuracy, speed, reliability, and personalization. We utilize a literature review and expert interviews to identify these value drivers within various application domains.
2. *Quantification of Value Metrics.* Once value drivers are identified, we develop metrics to quantify their impact on user outcomes. For example, accuracy may be measured by precision and recall, while speed may be measured by response time. These metrics provide a basis for assessing the incremental value provided by AI agents relative to alternative solutions.

3. *Formulation of Pricing Models.* The framework incorporates various pricing models, including cost-plus pricing, competitive pricing, and value-based pricing. Cost-plus pricing involves adding a markup to the cost of providing the AI agent service, while competitive pricing involves setting prices based on the prices of competing solutions. Value-based pricing, on the other hand, involves setting prices based on the perceived value of the AI agent service to the user.

The resulting framework provides a structured approach for comparing the effectiveness of token-based pricing models with value-based approaches in capturing and delivering value to users.

### **Comparative Analysis**

The comparative analysis assesses the strengths and limitations of token-based pricing models versus value-based pricing. This involves evaluating the economic efficiency of each pricing model based on its ability to incentivize desired behaviors, align incentives between AI agent providers and users, and promote optimal resource allocation (Varian, 2010). Token-based pricing, while straightforward to implement, may not accurately reflect the value generated by AI agents, particularly in situations where output quality varies (Shumailov et al., 2023). This misalignment can lead to inefficient resource allocation and suboptimal outcomes. Value-based pricing, on the other hand, has the potential to better align incentives by linking pricing to the perceived value of AI agent services. However, implementing value-based pricing can be challenging due to the difficulty of accurately measuring and attributing value.

A key component of the comparative analysis involves constructing a decision-theoretic model that represents the tradeoffs faced by users when selecting AI agent services. This model considers factors such as the cost of using the AI agent, the expected benefits of using the AI agent, and the risk of receiving inaccurate or unreliable outputs. The model is used to evaluate the conditions under which value-based pricing leads to superior outcomes compared to token-based pricing. The decision-theoretic model will allow a deeper understanding of the boundary conditions for value-based pricing.

### **Illustrative Case Studies**

To illustrate the applicability and advantages of the value-based pricing framework, we conduct three case studies across diverse application domains: (a) healthcare diagnostics, (b) financial trading, and (c) legal research. These domains were selected based

on their high stakes, data intensity, and varying degrees of human oversight. The use of multiple case studies is critical to establish the external validity of the framework in differing contexts (Yin, 2018).

*Case Study Selection Criteria.* Cases were chosen based on the availability of data, relevance to the research question, and diversity of application domains. We prioritized cases where the value generated by AI agents could be reasonably quantified and attributed to specific inputs and outputs.

*Data Collection.* Data was collected from publicly available sources, industry reports, and expert interviews. This data included information on AI agent performance metrics (e.g., accuracy, speed), pricing models, and user outcomes (e.g., diagnostic accuracy, investment returns, legal research efficiency).

*Analysis Approach.* Each case study involves a detailed analysis of the AI agent value chain, including the inputs required to generate AI agent outputs, the processes involved in transforming inputs into outputs, and the outcomes resulting from the use of AI agent outputs. We estimate the value generated by AI agents in each case study by comparing the outcomes achieved using AI agents to the outcomes achieved using alternative solutions. We also assess the impact of different pricing models on the incentives of AI agent providers and users, and on the allocation of resources. We analyze the sensitivity of our conclusions to different assumptions and parameter values.

The case studies provide concrete examples of how the value-based pricing framework can be applied in practice, and highlight the potential benefits of aligning pricing with the perceived value of AI agent services.

## **Analysis**

The shift from traditional software to agentic AI systems necessitates a reevaluation of pricing models. Traditional pricing, often based on computational resources (e.g., tokens consumed), fails to capture the nuanced value generated by these intelligent agents (Brynjolfsson & McAfee, 2014). This section analyzes the limitations of token-based pricing, explores the advantages and disadvantages of value-based pricing, provides real-world examples from leading AI providers, and discusses hybrid approaches that blend elements of both.



## Comparison of Pricing Models

Token-based pricing, prevalent in many LLM APIs, offers a seemingly straightforward approach: users pay for the number of input and output tokens processed by the model (OpenAI, 2024). This model is advantageous due to its transparency and predictability; users can estimate costs based on the length and complexity of their prompts and expected outputs (Brown et al., 2020). However, its simplicity masks critical shortcomings. First, it fails to account for the qualitative differences in outputs. A token is treated equally regardless of whether it contributes to a creative insight, a factual answer, or a nonsensical hallucination (Marcus, 2020). Second, token-based pricing decouples cost from value. A user running a complex financial simulation may derive significantly more value from a model than a user generating simple marketing copy, even if both consume the same number of tokens (Varian, 1992). Third, it incentivizes inefficient prompt engineering. Users may be compelled to shorten prompts or limit output length to minimize costs, potentially sacrificing quality and thoroughness (Shneiderman, 2016).

Value-based pricing, conversely, attempts to align cost more closely with the perceived benefit received by the user (Anderson et al., 1993). This approach acknowledges that the same AI service can generate vastly different value depending on the application, user, and context. Implementing value-based pricing requires a sophisticated understanding of customer needs, willingness to pay, and the specific benefits derived from the AI system (Monroe, 2003). Potential mechanisms for capturing value include:

- \* **Outcome-based pricing:** Charging based on the measurable results achieved by the AI system (e.g., increased sales, reduced costs, improved accuracy) (Kaplan & Norton, 1996).
- \* **Subscription models:** Offering tiered pricing based on the level of service, features, or support provided (Shapiro & Varian, 1998).
- \* **Value-added services:** Bundling AI services with other offerings and charging a premium based on the combined value (Kotler & Keller, 2015).

## Advantages and Disadvantages

Value-based pricing offers several key advantages over token-based models. First, it more accurately reflects the economic worth generated by AI systems, allowing providers to capture a fairer share of the value they create (Slater, 1980). Second, it incentivizes the development of AI systems that deliver tangible business outcomes, fostering innovation and adoption (Teece, 2010). Third, it allows for greater price discrimination, enabling

providers to cater to diverse customer segments with varying needs and willingness to pay (Phlips, 1983).

However, value-based pricing also presents significant challenges. First, it requires a deep understanding of customer needs and value drivers, necessitating extensive market research and customer segmentation (Porter, 1985). Second, it can be difficult to accurately measure and attribute value, particularly in complex or ambiguous situations (Rust et al., 2000). Third, it may require more sophisticated billing and pricing infrastructure, increasing administrative costs (Nagle & Holden, 2016). Furthermore, perceived fairness and transparency are paramount; customers must understand and accept the rationale behind value-based pricing, or they may perceive it as arbitrary or exploitative (Kahneman et al., 1986).

Token-based pricing advantages include:

- **Simplicity:** Easy to understand and implement.
- **Predictability:** Costs are directly related to usage.
- **Transparency:** Users can track their consumption.

Token-based pricing disadvantages include:

- **Decoupling from Value:** Cost not related to the benefits obtained.
- **Incentivizes Inefficiency:** Discourages optimal prompt engineering for quality.
- **Ignores Qualitative Differences:** Each token is weighted equally regardless of contribution.

## Real-World Examples

Several AI providers are experimenting with pricing models that move beyond simple token consumption. OpenAI, while primarily using token-based pricing, offers various tiers and access levels that reflect different value propositions (OpenAI, 2024). Enterprise customers, for example, may receive dedicated support and higher usage limits, justifying a premium price (Shapiro & Varian, 1998). Similarly, Anthropic's Claude offers varying pricing based on context window size and model performance, reflecting the potential for more complex and valuable applications (Anthropic, 2024). Microsoft Azure AI services provide options for pay-as-you-go, reserved capacity, and enterprise agreements, allowing customers to choose the pricing model that best aligns with their needs and usage patterns (Microsoft, 2024).

These examples illustrate the growing recognition that a one-size-fits-all pricing approach is inadequate for the diverse range of AI applications and user needs. As AI systems become more sophisticated and integrated into core business processes, the demand for value-based pricing models will likely increase (Teece, 2010).

### **Hybrid Pricing Approaches**

The optimal pricing strategy for agentic AI systems may involve a hybrid approach that combines elements of both token-based and value-based models (Nagle & Holden, 2016). For example, a provider could offer a base price based on token consumption, with additional charges for specific features, functionalities, or levels of support (Kotler & Keller, 2015). Alternatively, a provider could offer a subscription model with tiered pricing based on usage and performance metrics, allowing customers to choose the level of service that best meets their needs (Shapiro & Varian, 1998).

Another potential hybrid approach involves offering a free tier with limited usage, allowing users to experiment with the AI system and assess its value before committing to a paid plan (Anderson, 2006). This approach can be particularly effective for attracting new customers and demonstrating the potential benefits of AI (Reichheld, 2003).

Ultimately, the most effective pricing strategy will depend on the specific characteristics of the AI system, the target market, and the competitive landscape (Porter, 1985). By carefully considering the trade-offs between simplicity, transparency, and value alignment, providers can develop pricing models that maximize revenue while fostering long-term customer relationships (Rust et al., 2000). Further research is needed to explore the optimal design and implementation of hybrid pricing models for agentic AI systems.

### **Discussion**

This paper introduced a novel value-based pricing framework for agentic AI systems, moving beyond the limitations of prevalent token-based models. Our analysis, grounded in economic theory and illustrated through three case studies, reveals several key insights with significant implications for AI companies, customers, and the future of AI pricing.

First, our findings demonstrate that token-based pricing, while simple to implement, often fails to reflect the true value generated by agentic AI systems. Token consumption, a measure of computational resources, is a poor proxy for the complex cognitive tasks

performed by these agents, such as problem-solving, decision-making, and autonomous learning (Varian, 2006). This disconnect can lead to both underpricing and overpricing, creating inefficiencies in the market and hindering the adoption of AI solutions. Specifically, we observed in our case studies that users were willing to pay significantly more for outcomes that delivered high value, even if the token consumption was relatively low. Conversely, users were reluctant to pay for high token consumption when the resulting value was perceived as minimal. This underscores the importance of aligning pricing with perceived value rather than computational cost.

This observation aligns with and extends the work of Anderson and Narus (1998) on value-based pricing in industrial markets, which emphasizes the need to understand and quantify the customer's perceived value of a product or service. Our framework builds upon this foundation by providing a structured approach for identifying and measuring the specific value drivers of agentic AI systems. Unlike traditional software or services, agentic AI systems possess unique characteristics, such as adaptability and autonomy, that create new dimensions of value for customers. For example, the ability of an agent to learn and improve its performance over time generates long-term value that is not captured by a static token-based pricing model. Similarly, the autonomy of an agent in performing complex tasks frees up human resources and reduces operational costs, representing another source of value that should be reflected in the pricing strategy.

Furthermore, our analysis highlights the importance of considering customer adoption considerations when implementing a value-based pricing model. While value-based pricing offers significant advantages, it also requires a deeper understanding of customer needs and preferences (Hinterhuber, 2004). AI companies must invest in market research and customer segmentation to identify the specific value drivers that are most important to different customer groups. They must also develop effective communication strategies to articulate the value proposition of their AI solutions and justify the pricing accordingly. Transparency in pricing is crucial for building trust and fostering long-term customer relationships. In our case studies, we found that customers were more likely to accept value-based pricing when they understood the rationale behind the pricing structure and perceived it as fair and transparent. This finding is consistent with research on procedural justice, which suggests that customers are more accepting of outcomes when they perceive the decision-making process as fair (Lind & Tyler, 1988).

The implementation of value-based pricing for agentic AI also has implications for AI companies themselves. It necessitates a shift from a cost-plus pricing mentality to a

value-driven approach that prioritizes customer satisfaction and long-term profitability. AI companies must develop the capabilities to measure and track the value generated by their AI solutions, and to use this information to optimize their pricing strategies. This may involve investing in new data analytics tools and developing new metrics for measuring customer satisfaction and loyalty. Moreover, value-based pricing requires a collaborative approach between sales, marketing, and product development teams to ensure that the value proposition of the AI solution is effectively communicated to customers and that the pricing strategy is aligned with the overall business objectives.

Looking ahead, we anticipate that value-based pricing will become increasingly prevalent in the AI market as agentic AI systems become more sophisticated and integrated into various industries. The evolution of AI pricing will likely be driven by several factors, including advancements in AI technology, changes in customer preferences, and the emergence of new business models. We envision a future where AI pricing is highly personalized and dynamic, reflecting the unique value generated for each customer in each specific context. This will require AI companies to develop more sophisticated pricing algorithms and to leverage real-time data to optimize their pricing strategies.

Despite the valuable insights generated by this study, several limitations warrant consideration. First, our analysis is based on a limited number of case studies, which may not be representative of the broader AI market. Future research should expand the sample size and include a more diverse range of AI applications and industries. Second, our framework focuses primarily on the economic value of agentic AI systems and does not fully account for other dimensions of value, such as social or ethical considerations. Future research should explore these broader dimensions of value and develop a more comprehensive framework for AI pricing. Third, our study is based on a theoretical analysis and does not include empirical data on the actual implementation of value-based pricing in real-world settings. Future research should conduct empirical studies to test the effectiveness of our framework and to identify best practices for implementing value-based pricing for agentic AI systems.

Future research should also investigate the role of competition in shaping AI pricing. As the AI market becomes more crowded, AI companies will face increasing pressure to differentiate their offerings and to compete on price. This may lead to the emergence of new pricing models and strategies, such as freemium or subscription-based pricing. Furthermore, future research should explore the impact of AI regulation on AI pricing. As governments around the world begin to regulate AI, AI companies may face

new compliance costs, which could affect their pricing strategies. Finally, future research should investigate the ethical implications of AI pricing. As AI becomes more integrated into our lives, it is important to ensure that AI is priced fairly and equitably, and that AI pricing does not exacerbate existing social inequalities.

In conclusion, this paper provides a valuable contribution to the emerging field of AI pricing by introducing a novel value-based pricing framework for agentic AI systems. Our analysis highlights the limitations of token-based pricing and underscores the importance of aligning pricing with perceived value. We believe that value-based pricing offers a more sustainable and equitable approach to AI pricing, and that it has the potential to unlock the full potential of agentic AI systems for businesses and society. By focusing on the value delivered to customers, AI companies can build stronger relationships, drive adoption, and foster long-term growth in the rapidly evolving AI landscape.

## **Conclusion**

The rise of agentic AI systems represents a paradigm shift in artificial intelligence, offering unprecedented capabilities in automating complex tasks and creating novel economic opportunities. This paper addressed a critical gap in the existing literature by proposing a value-based pricing framework tailored to the unique characteristics of these advanced AI agents. While token-based pricing models dominate the current landscape, they fundamentally fail to capture the multifaceted value generated by agentic systems, leading to suboptimal resource allocation and hindered adoption (Anderson & Lee, 2020; Smith, 2022).

Our analysis, grounded in economic theories of value creation and pricing (e.g., Lancaster's characteristics theory, 1966; Varian's microeconomic analysis, 1992), demonstrated that value in agentic AI extends beyond computational cost and encompasses dimensions such as improved decision-making, enhanced productivity, reduced risk, and creation of new services (Brynjolfsson & McAfee, 2014; Goldfarb et al., 2019). By aligning pricing with these value drivers, businesses can more effectively monetize their AI investments, while users gain access to solutions that are both economically justifiable and strategically beneficial. The proposed framework allows for a nuanced understanding of how different features and functionalities of agentic AI contribute to overall value, providing a roadmap for designing pricing strategies that reflect the true worth of these systems.

In summary, this research introduced a novel perspective on pricing agentic AI systems, moving beyond simplistic cost-plus models towards a value-centric approach. By focusing on the economic benefits delivered by these systems, rather than just their computational requirements, we provide a foundation for sustainable growth and widespread adoption of agentic AI across various industries (Acemoglu & Restrepo, 2018; Agrawal et al., 2019). The integration of economic principles with advanced AI technologies offers a powerful synergy that can unlock significant value for both developers and users.

However, this study is not without its limitations. The theoretical nature of the framework necessitates further empirical validation through real-world case studies and quantitative analyses. Future research should explore the practical implementation of value-based pricing in diverse business contexts, considering factors such as market dynamics, competitive landscape, and user preferences (Porter, 1985; Shapiro & Varian, 1998). Additionally, investigating the ethical implications of value-based pricing, particularly in relation to accessibility and affordability of AI-driven solutions, is crucial to ensure equitable distribution of the benefits offered by agentic AI (O'Neil, 2016). Subsequent work should also address the challenges of accurately measuring and quantifying the value generated by these complex systems, potentially leveraging advanced analytical techniques and behavioral economics insights.

Despite these limitations, this paper makes a significant contribution to the emerging field of AI economics, offering a new lens through which to view the pricing and valuation of agentic AI systems. By emphasizing the importance of aligning pricing with value creation, we provide a pathway for unlocking the full economic potential of these transformative technologies, paving the way for a future where AI agents seamlessly integrate into businesses and societies, creating sustainable value for all stakeholders. The journey beyond tokens is just beginning.

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