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THE IMPACT OF PRICING SCHEMES ON CLOUD COMPUTING AND DISTRIBUTED SYSTEMS

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Abstract

This article investigates the economic implications of pricing models in cloud and distributed computing systems, emphasizing their influence on system performance and user cost efficiency. We analyze the efficacy of various pricing structures, including pay-as-you-go and resource-consumption-based models, and their impact on both operational efficiency and financial management. Our findings highlight significant challenges in optimizing cost-efficiency without compromising system effectiveness and call for the development of more sophisticated pricing strategies. By examining the limitations of current economic models and the evolution of dynamic and auction-based pricing mechanisms, the study offers insights into future research directions aimed at enhancing fairness and competitiveness in cloud computing environments.

Keywords: Cloud Computing Pricing; Economic Efficiency; Resource Management;Cost Optimization

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Introduction

In the modern ICT landscape, the challenge of managing the high costs associated with advanced storage and computational systems has driven the adoption of distributed systems. These systems, including grid and cloud computing, provide scalable and cost-effective solutions for handling large data volumes and complex computations [1].. As these technologies evolve, they offer affordable access to powerful resources and services, reshaping traditional system design and optimization paradigms.

Cloud computing, in particular, introduces a new dimension by decoupling users from providers through a pricing scheme based on resource consumption. This shift has transformed how distributed systems are perceived and utilized, moving beyond their conventional roles. Our preliminary research, conducted on Amazon EC2 and a local cloud testbed, highlights a complex interplay between distributed systems and economic factors related to pricing [2]..

This evolving dynamic raises critical questions about pricing models and their impact on system efficiency and user satisfaction.

This paper explores the impact of pricing schemes on cloud and distributed systems. We provide a comparative review of grid and cloud computing economic models, examining how these models address business objectives and economic principles. By analyzing the fundamental changes introduced by cloud computing, we seek to uncover new insights into distributed systems' optimization and economic implications. This exploration will contribute to understanding how pricing mechanisms influence the effectiveness and accessibility of these advanced technologies.

Related Work

Recent cloud providers (e.g., Amazon Web Services, Google Cloud Platform, and Microsoft Azure) have enabled users to perform their computation tasks in a public cloud. These providers use a pricing scheme according to incurred resource consumption[3-4].. For example, Amazon EC2 provides a virtual machine with a single CPU core at $0.095 per hour. This pay-as-you-go model lets users utilize a public cloud at a fraction of the cost of owning a dedicated private one while allowing providers to profit by serving many users. Case studies from these cloud providers indicate that various applications have been deployed in the cloud, such as storage backup, e-commerce and high-performance computing [5].. Defining a uniform pricing scheme for such a diverse set of applications is a non-trivial task for a provider.

This cloud-computing paradigm has transformed a traditional distributed system into a “two-party” computation with pricing as the bridge. A provider designs its infrastructure to maximize profit with respect to the pricing scheme, while a user designs her application according to the incurred cost. This contrasts with a traditional distributed system, where the goal is to optimize for throughput, latency, or other system metrics as a single and the whole system.

Challenges in Economic Models for Grid and Cloud Computing

Grid and cloud computing technologies have rapidly advanced, providing users with powerful, configurable resources and high-speed data transfer at affordable costs [6].. Despite these advancements, widespread adoption is impeded by the absence of effective and affordable economic and pricing models. To be viable, these models must align with legal jurisdictions, tax regulations, and business objectives. However, existing economic models have largely been applied to resource allocation algorithms rather than developing comprehensive pricing structures for commercial use.

Economic models play a critical role in determining pricing and tariff structures to optimize returns on investment, attract customers, and manage resource deployment efficiently. Despite their potential, most economic models have been limited to theoretical studies or simulations rather than practical business implementations [7].. Challenges include creating sustainable tariff structures and reconciling conflicting pricing policies and business objectives. Issues such as dynamic resource loads and varying third-party pricing policies add to the complexity of developing equitable and effective pricing models. Addressing these issues is essential for fostering widespread adoption and operational efficiency in grid and cloud computing environments.

The Interplay Between System Design and Pricing

Pricing in cloud computing is deeply intertwined with system design and optimization. Resource-consumption-based pricing introduces a new dimension to system optimization, making cost an explicit and measurable metric. This shift prompts critical questions about optimising systems for cost efficiency and how these cost metrics relate to traditional performance indicators like throughput [8]..If providers and users optimize based on dollar cost and profit, this could lead to a globally optimal system that achieves the desired outcomes at the lowest cost. However, this relationship between pricing and system design is complex and impacts various aspects of cloud computing.

Our preliminary studies found that optimizing for cost does not necessarily result in the most effective system [9-11]..Users often struggle with optimization due to limited knowledge of the underlying mechanisms deployed by providers. Pricing structures, influenced by system configurations and resource utilization, can lead to significant variations in cost and profitability. Additionally, cloud computing's pay-as-you-go model places the burden of failure costs on users, raising concerns about fairness and responsibility. These insights highlight the need for further exploration into how pricing impacts system design and optimization in cloud computing environments.

Economic Aspects of Pricing: Fairness and Competition

The economic dimensions of cloud computing pricing include key concepts such as fairness and competition, which significantly impact pricing models. Pricing fairness encompasses both personal and social fairness. [12]..Personal fairness addresses individual user expectations, while social fairness ensures that pricing is equitable across all users and does not grant providers excessive profits. For example, socially unfair pricing models are those where some users pay significantly more than others for similar services. This paper examines social fairness within cloud pricing schemes to determine if pricing is uniform and just across all users.

Competition plays a crucial role in shaping cloud pricing strategies. It drives providers to innovate and lower costs to gain a competitive edge 13].Unlike fixed pricing models, competitive markets encourage providers to adopt new technologies and improve cost-efficiency. This dynamic can influence how pricing models evolve and address fairness concerns. Our study highlights the complex interplay between competition and pricing fairness, emphasizing the need for balanced pricing models considering market competitiveness and equitable cost distribution.

Grid and cloud computing architecture

Grid and cloud computing consist of services, protocols, resources and other management functions constituting six layers, as shown in Figure.1 with the following definition: Grid and Cloud System Resources Fabric Layer 1 is the heart of the grid and cloud system architecture. It is the lowest layer, the foundation of all services. Various resources such as processors, storage and networks are accessible in this layer. Communication Connectivity Layer 2 14]. It is responsible for security and communications. It identifies protocols for security functions such as authentication, access control, data integrity, confidentiality and communication. Unified Resources Layer 3: it is responsible for determining protocols for system configuration, accounting, monitoring, control, job initiation, negotiation, and payment of sharing operations on individual resources. Collective and Composite Layer 4: coordinating different resources is the main role of this layer, for example, directory services. Middleware Layer 5: It is a software layer between the operating system and application that enables continuous information sharing between multiple applications. It is also considered a standard for interconnecting components. Middleware employs brokers to act as its virtual service providers to resources in a transparent manner to shield the end-user from complex details.

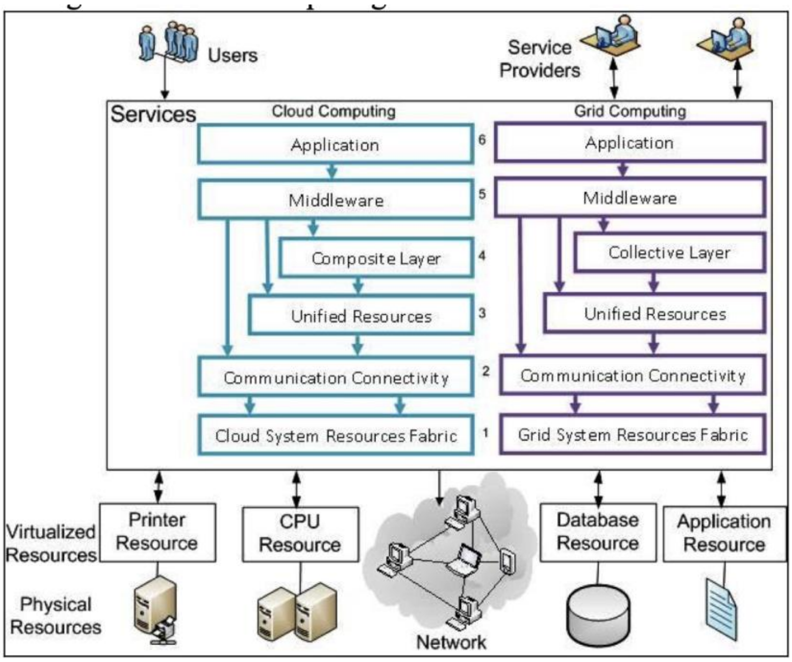

Figure 1. Grid & Cloud Computing Resources, Services & Protocol Architecture

There is no specific categorization for grids. Numerous IT/ICT suppliers, researchers, and scientists have their own classification for grids based on their insight, provision and usage. For example, Mike Ault and Madhu Tumma jointly stated that IBM specified three types of grids [15].:

Computational Grid: Nowadays, even supercomputers are unable to provide computational power. Even if they did, it is not logical from an economic justification point of view. A computational grid is defined as a software and hardware infrastructure providing high computational processing capabilities with consistent, inexpensive, dependable access.

Data Grid: It is a solution for managing, sharing, and controlling large amounts of scattered data. Remote local data is accessible through replica data grids, which offer the most cost-effective solution.3. Scavenging Grid: Jobs are transferred between machines to ensure the smooth operation of the task by cycle- scavengers utilise idling / free/available PCs.

Pay-as-you-go Model

The importance of pricing in economics goes far beyond mere costing and profoundly impacts the use of systems and the allocation of resources. For example, pricing strategies can not only be used to control the congestion of Internet resources but also effectively adjust the demand and supply of computing resources in the cloud computing grid [16-17].The pay-as-you-go model in cloud computing uses pricing as the key connection point between users and service providers, and currently, mainstream cloud service providers such as Amazon have adopted pricing models based on virtual machine hours, such as $0.095 per hour [18].This pricing strategy reflects cloud service providers' dynamic management of computing resources while also driving continued innovation in pricing schemes.

As the cloud services market matures, pricing models are evolving. Amazon now offers a variety of pricing schemes, including auction pricing, designed to meet the needs of different users and optimize resource allocation [19].At the same time, academia and industry have also proposed various innovative pricing schemes to improve the system's behaviour. For example, Singh et al. proposed a dynamic pricing strategy for computing resource bookings, while Jimenez et al. developed a bilateral settlement model to reduce the risk of malicious overcharging [20].These studies not only promote the innovation of the pricing model but also provide new ideas for the fair allocation of cloud computing resources and user cost control.

In addition, research into pay-as-you-go cloud services is receiving increasing attention. Napper et al. and Walker compared Amazon EC2 with private cloud in high-performance computing, analyzing its cost, availability, and performance. These studies have helped to understand the strengths and weaknesses of different cloud service models and have driven the discussion of cloud service pricing optimization [21]. However, this study extends the perspective to the dual cost and profit considerations and deeply explores the interaction between system behaviour and economic efficiency. This comprehensive research can reveal the full impact of pricing strategies on the cloud environment, further pushing the frontiers of cloud service pricing and optimization models.

Methodology

We have assembled a set of workloads to approximate a typical workload in current cloud computing. With these workloads, we use two complementary approaches for evaluations. One is a black-box approach with Amazon EC2 [22]. As other cloud providers, such as Google and Microsoft, use similar pricing schemes, we expect our pricing-related findings to apply to those. Our second approach is to set up a cloud-computing testbed called Spring so that we can perform fully controlled experiments with the full knowledge of how the underlying system works.

Data set

We selected several popular applications to model different application areas, which have been widely used in case studies of cloud service providers.

Postmark: As an I/O intensive benchmark tool, Postmark was used to simulate file transactions in various Web-based applications. In the experiment, the default Settings included a total file size of about 5 GB (1000 files, 5000 KB each); The number of transactions is 1000.

This setup effectively evaluates the performance of file operations and provides real-world data support for I/O-intensive applications.

PARSEC: PARSEC is a benchmarking suite with real-world applications. We selected two applications, Dedup and Black-Scholes, representing storage archiving and high-performance computing in the cloud, respectively. Dedup is used to compress the file by teredo, and its default setting is about 184 MB of input data; Black-Scholes calculates the price of European options, which are set to 10 million by default. [23-26].These two benchmarks can provide insight into the performance of storage and compute tasks.

Hadoop: For large-scale data processing, we used Hadoop 0.20.0 and selected WordCount and StreamSort from the GridMix benchmark. The default input data set for both applications is 16 GB. These tests assess the efficiency and performance of large-scale data processing and reflect Hadoop's ability to handle large amounts of data.

Through these benchmarks, we are able to gain insight into how different types of applications perform in a cloud environment and assess their impact on resource demand and performance.

Amazon EC2

In the Amazon EC2 experiment, our implementation fees were charged according to Amazon's pricing scheme. When considering amortized costs in the long-run scenario, we calculate user expenses as follows:

Costuser=Price×t （1）

Where t is the total running time of the task (in hours)， Price is the cost of virtual machines per hour. To simplify the calculation, we excluded storage and data transfer fees between the client and the cloud, as these accounted for a minuscule percentage of the total cost in our experiment (less than 1%). This processing ensures that our costing is more precise and focuses on the actual running costs of virtual machines, which is critical to evaluating the economics of performing tasks on Amazon EC2. In addition, while storage and data transfer fees typically impact overall costs, within the scope of this experiment, their impact is considered negligible, leading our expense analysis to focus more on the direct use costs of computing resources.

Cost and Profit Estimation in the Spring System

Spring virtualizes physical data centres to provide virtual machines (VMs) to users through two primary modules: the Virtual Machine Monitor (VMM) [27] and the auditor. The VMM handles VM allocation, consolidation, and migration across physical machines, while the auditor calculates user expenses and estimates provider profits, helping to assess the impact of pricing.

We subtract the total provider cost from the expected user payments derived from the incurred virtual machine hours to estimate provider profit. The total provider cost includes the amortized cost of operating the data centre and the cost of fully burdened power consumption, as estimated by Hamilton. Full burdened power consumption is calculated using:

Costfull=p×Praw×PUE(2)

where pp is the electricity price (dollars per kWh), PrawPraw is the total energy consumption of IT equipment (kWh), and \text{PUE} is the Power Usage Effectiveness metric[28]..

The total provider cost is given by:

$Cost_{provider}=(Cost_{full}+Cost_{amortized}) \times Scale$ (3)

$Cost_{amortized}$ is the amortized cost of servers. Scale adjusts the total cost based on the ratio of estimated total cost to the sum of fully burdened power consumption and amortized server cost.

To estimate Costamortized$_{Costamortized}$, we use:

$Cost_{amortized}=C_{amortizedUnit} \times t_{server}$ (4)

$C_{amortizedUnit}$is is the amortized cost per server per hour, and t_{server} is the server usage time in hours.

Power consumption is modelled for servers and routers. For servers, energy consumption is estimated with a linear regression model based on resource utilization:

$P_{server}=P_{idle}+u_{cpu} \times c_0+u_{io} \times c_1$ (5)

where $u_{cpu}$and u_{io} are CPU utilization and I/O bandwidth, respectively, and c_0 and c_1 are the model coefficients. Router power consumption follows a model from previous research.

Table 1: The configurations and prices on different VM types on Amazon (Linux, California, America, Jan- 2010)

Instance Type	CPU (#virtual core)	RAM (GB)	Storage (GB)	Price ($/h)
Small	1	1.7	160	0.095
Medium	2	1.7	350	0.19

Experimental Setup and Configuration

To investigate the interaction between pricing mechanisms and system performance, we conducted experiments on both Amazon EC2 and Spring [29].The experimental setup was designed to ensure comparability across platforms.

Amazon EC2 Configuration: We utilized the default on-demand virtual machine types offered by EC2: small and medium instances. These instances, running Fedora Linux, were deployed in California, USA. The specific configurations and pricing details for these instances are outlined in Table 1. This setup allowed us to evaluate the performance and cost efficiency of various instance types in a cloud environment.

Spring Configuration: For our experiments on Spring, we employed VirtualBox [24]. to create and manage virtual machines. VirtualBox provided the flexibility to simulate the configurations and pricing of different instances akin to those on Amazon EC2. The host operating system was Windows Server 2003, and the guest OS was Fedora 10. We used an eight-core machine for single-machine benchmarks and a cluster of 32 four-core machines for evaluating Hadoop. Each VM was allocated a dedicated CPU core to mimic virtual core allocation in EC2.[30]. For instance, we consolidated up to four medium instances on an eight-core machine. We also utilized a power meter to measure and validate power consumption, ensuring that our power consumption model accurately reflected real-world measurements.

Table 2: Hardware configuration of machines in Spring

	Eight-core machine	Four-core machine
CPU	Intel Xeon E5335 8-way 2.00GHz	Intel Xeon X3360 Quad 2.83GHz
RAM (GB)	32	8
Disk	RAID 5 (SCSI disks)	RAID 0 (SATA disks)
Network	1 Gigabit	1 Gigabit
Power model	$P_{idle} = 299$, $c_0 = 0.46$, $c_1 = 0.16$	$P_{idle} = 250$, $c_0 = 0.4$, $c_1 = 0.14$

Table 3: Elapsed time and costs of single-machine benchmarks on small and medium instances on EC2

	On a small instance		On a medium instance	
	Elapsed time (sec)	Cost ($)	Elapsed time (sec)	Cost ($)
Postmark	204.0	0.0054	203.2	0.0106
Dedup	45	0.0012	14	0.0008
BlackScholes	934	0.0246	215	0.0113

The current price of the SSD is around $350, and the price of a SATA hard drive (500GB) is around $50. We adjust the amortized cost of the machine with an SSD to $0.09 per hour. SSDs also offer a power efficiency advantage compared to hard disks, and we adjust power consumption accordingly.

We study Spring's system throughput in terms of the number of tasks finished per hour, user costs, and provider profits.

Optimizing for Cost

We study the difference between optimizations for cost and optimizations for performance on users and providers separately. We first present the results of user optimizations on EC2, since the results on Spring are similar to those on EC2 [31]. Next, we present the results of provider optimizations, including consolidation and dif- ferent workload scheduling algorithms on Spring.

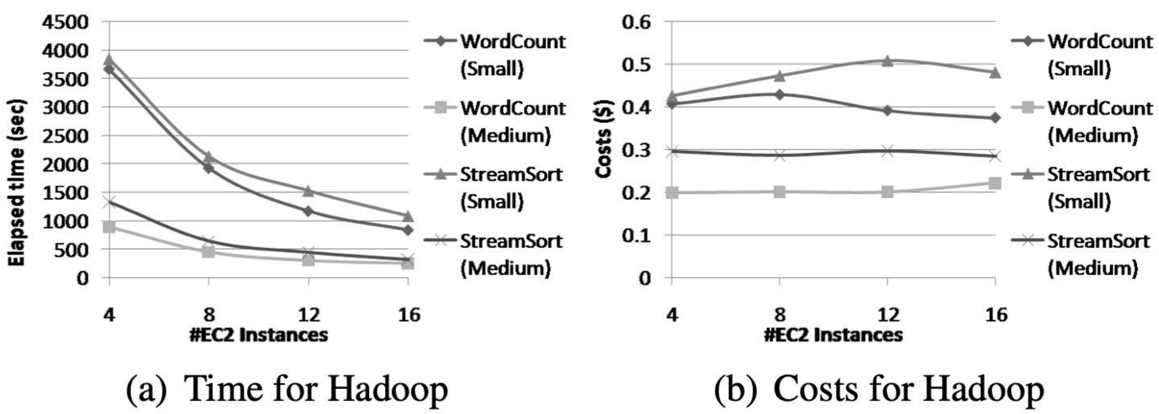

Figure 2. Performance and costs for Hadoop vs. the number of same-type instances on EC2

Table 4: Effects of virtual-machine consolidation in Spring (every four Postmark, small VM type)

#VM per physical machine	One VM	Two VMs	Four VMs
Average elapsed time (sec)	127	125.5	425
Average cost per task ($)	0.004	0.004	0.012
Total cost of users ($)	0.014	0.014	0.047
P_{raw} (kWh)	0.046	0.024	0.038
$Cost_{provider}$ ($)	0.024	0.012	0.020
Profit ($)	-0.009	0.002	0.028
ROI (%)	-40.0%	17.2%	142.0%
Throughput (tasks/h)	28.3	56.4	33.9

Application-Level Optimizations and Instance Selection: On Amazon EC2, user optimizations can be categorized into application-level adjustments, choosing the appropriate instance type, and tuning the number of instances [32].For a fixed instance type, tuning parameters such as the number of threads can impact performance and cost. For example, optimizing these parameters for Postmark and PARSEC improved performance and reduced user costs. Notably, with current consumption-based pricing models, optimizing for performance aligns closely with optimizing for cost.

Instance Type and Number of Instances: Selecting the optimal instance type is critical in balancing performance and cost. As shown in Table 4, Postmark exhibits slightly longer elapsed times on smaller instances but incurs nearly 50% lower costs compared to medium instances, highlighting a trade-off between performance and cost. Conversely, for Dedup and Black-Scholes, medium instances offer faster execution times and lower costs than small instances. This demonstrates that the choice of instance type can affect performance and cost, with no single instance type being the best choice for all scenarios. Figure 1 illustrates that varying the number of instances from four to sixteen in Hadoop does not yield a consistent pattern in cost, suggesting that optimal settings for cost may differ from those for performance.

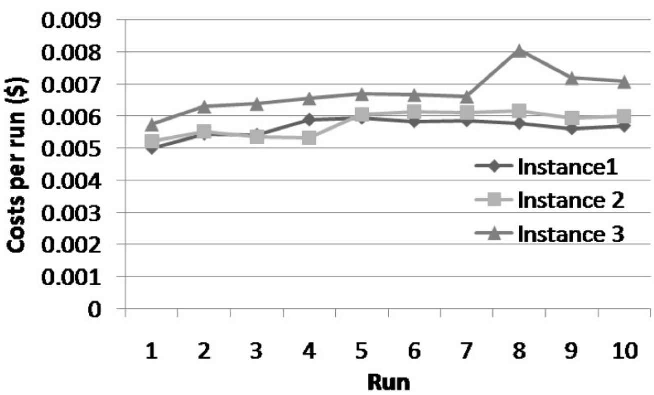

Figure 3: Variations among three instances (Postmark) on EC2

Provider Optimizations on Spring

Virtual-Machine Consolidation and Cost Implications: In our study of virtual-machine (VM) consolidation in Spring, we examined the impact of running multiple VMs on the same physical machine. We observed significant effects on power consumption and provider profitability by varying the number of VMs from one to four. Consolidation notably reduced power consumption by up to 150% for BlackScholes and 21% for Postmark. This reduction in power usage led to substantial increases in provider profit and return on investment (ROI), with improvements of 180% and 340% for Postmark and Black-Scholes, respectively. However, as more tasks were consolidated, system throughput peaked with two VMs. Then, it declined, highlighting a potential issue in pricing strategies that maximize profit at the expense of system performance.

Hadoop Benchmarks and Variability: Similar trends were observed when analyzing multi-machine benchmarks with Hadoop.Consolidation increased provider ROI by 135% and 118% for WordCount and StreamSort, respectively, but also resulted in significant throughput degradation—up to 350% for StreamSort. This degradation confirms the earlier findings from single-machine benchmarks. Additionally, cost variations among different instances on EC2, such as discrepancies in running Postmark across different small instances and similar patterns in Spring, indicate a disparity in pricing fairness. These findings underscore the broader implications of pricing schemes on cloud computing and distributed systems, revealing inconsistencies that could affect both user costs and system efficiency.

Conclusion

Exploring pricing models in cloud and distributed systems reveals a significant impact on system efficiency and user satisfaction. Our findings indicate that the pay-as-you-go model, prevalent in cloud computing, introduces a complex interplay between cost management and system optimization. While resource-consumption-based pricing aligns closely with performance optimization, it also underscores challenges in achieving cost efficiency without compromising system effectiveness. This dynamic calls for a nuanced approach to pricing strategies that balance cost control with optimal resource utilization.

Furthermore, the comparative analysis of grid and cloud computing economic models highlights the limitations of existing pricing structures. Despite technological advancements, the lack of comprehensive and practical economic models hinders widespread adoption. Addressing this gap requires the development of sustainable tariff structures that align with legal, regulatory, and business objectives, ultimately fostering greater operational efficiency and market competitiveness.

Finally, our study underscores the importance of continuous innovation in pricing schemes. The evolution of cloud pricing models, including dynamic and auction-based strategies, reflects ongoing efforts to optimize resource allocation and improve cost management. Future research should focus on refining these models to enhance fairness and competitiveness while ensuring that they effectively address the diverse needs of users and providers. By advancing pricing mechanisms, we can better support the growth and efficiency of cloud and distributed computing environments.

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In addition, the innovative idea of applying deep learning technology to emotion analysis in the article also brings a new perspective to my work. These advanced methods not only provide theoretical support for the design of emotion-driven recommendation systems, but also promote my exploration in enhancing the accuracy and personalization level of recommendation systems. Thanks to the contributions of these researchers, their work has provided a solid foundation and valuable guidance for my research in the field of artificial intelligence application.