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Research Article

CloudConsumerism: A Consumer-Centric Ranking Model for Efficient Service Mapping in Cloud

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In cloud, service providers and consumers are primary stakeholders that maintain a business liaison. Cloud service providers (CSPs) offer the services, and consumer uses the services on a payment basis. From a business perspective, the selection of a service based on mutual evaluation benefits both the CSPs and consumers. This paper presents an efficient CloudConsumerism model where the multicriteria decision-making method (MCDM) method, TOPSIS, is used for evaluating the performance of CSPs and consumers. For performance evaluation of CSPs, the performance attributes defined by Cloud Service Measurement Initiative Consortium (CSMIC) are exploited. For evaluating the consumers, this paper is the first approach towards identifying the behavioral attributes for evaluating the cloud consumers analogous to the business models. A service mapping algorithm is proposed for efficient (less overhead and higher robustness) mapping. Extensive simulation experiments are conducted; the results show that the proposed framework can be used for the online cloud-based platform due to limited overhead and high robustness.

1. Introduction

Cloud computing is a business model [1] where provider-consumer liaison is formed. The consumer goes through the services from the catalog of the multiple cloud service providers (CSPs) and selects the services from the CSP, which can provide higher performance at the lowest rate. The services offered by the CSPs fall in one of three categories, i.e., infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS) [2]. Manually selecting a service having multiple attributes offered from different CSPs is very tedious for the consumers. A new entity, broker, is evolved, which selects the services from the different CSPs on behalf of the consumer. The broker organization can be a third party or a part of the participating organizations. Some well-known organizations, namely, AWS Service Broker (https://http://aws.amazon.com/partners/servicebroker/), IBM Multicloud Management Services (https://www.ibm.com/in-en/services/cloud/multicloud), Cloudmore (https://web.cloudmore.com/cloud-broker-cloudmore), Cloud Services Brokerage (https://www.jamcracker.com/cloud-service-brokerage) etc., are playing the role of cloud broker.

The demand for cloud-based services is increasing day by day. COVID-19 disruption has also accelerated the usage of cloud-based services [3]. To fulfill the ever-increasing demand for cloud-based services and generate more revenue, many big IT organizations are playing the role of CSPs, namely, Amazon, Microsoft, Google, IBM, etc. [4]. Due to enormous expansion in the number of CSPs and consumers, their efficient selection while mapping has become complicated. In literature, quality of service (QoS)-based selection of a CSP for a consumer is recommended for the efficient service mapping [5–7]. The selection of a CSP for the consumer is a unidirectional approach where the selection of the service is based on the CSP's evaluation in the context of the QoS requirements of a consumer. For making the cloud business successful, the bidirectional evaluation of the participating entities (CSPs and consumers) involved in the mapping process is necessary for increasing their satisfaction.

For evaluating the CSPs, Cloud Service Measurement Initiative Consortium (CSMIC) has introduced performance metrics that are combined in the form of Service Measurement Index (SMI) [8]. In contrast, no standard parameters are defined for evaluating the behavior of consumers for the CSPs. Consumer behavior is about the approach of how people buy and use merchandise and services [9]. Consumer behavior helps in identifying whom to target, how to target when to reach them, and what message is to be given to them to reach the target consumers to buy the product. Analyzing consumer behavior helps the CSPs in improving brand equity and boosting sales. For evaluating consumer behavior, some consumer behavior analytics tools such as Mixpanel (https://mixpanel.com/), Google Analytics (https://support.google.com/analytics/answer/7126596?hl=en), and Kissmetrics (https://www.kissmetrics.io/) are exploited. These tools maintain the complete profile of consumers from website usage to social media engagement. In marketing research, RFM (recency, frequency, and monetary) model [10] [11, 12] is also proposed for evaluating consumer behavior.

Consumer evaluation plays an important role to make the business successful. Earlier frameworks are proposed for the evaluation of CSPs and consumers. The TRCSM framework is presented for evaluating the CSPs and consumers during service mapping [7]. The proposed framework uses prepurchase transaction attributes turnover, duration, and transaction for evaluating the cloud consumers. Another framework, MECSM [12], is proposed which uses a standard RFM model for evaluating the consumers parallel to the CSPs. RFM model uses prepurchase behavior attributes, recency, frequency, and monetary attributes for evaluating the consumers. The prepurchase behavior shows their behavior in past transactions. In the cloud, the same service is offered from different geographical regions, and sometimes service is available in some geographical regions, and it is not available in another geographical region. Observe the consumer behavior during the owning of the service (in-purchase behavior) while the change in service, location, price, and quality is also important. To improve the service quality and increase the consumer base, it is also necessary to observe consumer postpurchase behaviors.

Due to the dynamic need of the current IT industry, the demand of IT resources varies frequently [6, 13]. For example, for a large computing task, efficiency is the main deciding factor. For time-critical tasks, distance is a high priority. Further, a server's distance is different from different consumers. Also, a consumer may have multiple demands with different priorities. On the other hand, service providers may also have multiple different criteria for evaluating a consumer, e.g., consumers involved for a long duration, consumers with a high transaction amount, and a consumer with less retention rate. Evaluating an entity based on multiple attributes is a multicriteria decision-making problem (MCDM) [14–17]. The glaringly used MCDM methods in the cloud environment are AHP [18], TOPSIS [19], VIKOR [20], and PROMETHEE II [21]. These MCDM methods can be used for ranking both the provider as well as the consumer. Since cloud computing is an internet-based technology, therefore, the execution time of the MCDM method will greatly impact the service performance. In our previous work [6], the TOPSIS method is suggested in terms of lower execution time and higher robustness.

In this paper, CloudConsumerism model is proposed which evaluates the CSPs by exploiting the QoS attributes defined by CSMIC framework 2.0 [8], and consumer behavior attributes are defined for evaluating the consumers in the cloud environment. The service mapping algorithm is developed for efficient service mapping covering all the mapping scenarios (one to one, one to many, many to one, and many to many). A case study is presented for showing the process of service mapping. The experimental analysis is performed on large-scale synthetic dataset for showing its applicability in online cloud-based service selection.

1.1. Motivation and Contribution. Cloud-based services are geographically distributed to support the service consumer organizations in terms of lower upfront cost and dynamic change of hardware/software needs. The COVID-19 disruption has also accelerated the usage of cloud-based services [3]. According to a Gartner report [22], end-user spending on CSPs is forecast to grow 23.1% in 2021 to total $332.3 billion, up from $270 billion that was in 2020. The extensive adoption of cloud-based services in various emerging domains is imposing new challenges and forcing researchers to think about new strategies. To the best of our knowledge, a few research [7, 12] has been conducted where cloud consumers are analyzed parallel to the CSP. The main aim of this paper is to identify the consumer behavior attributes for evaluating the cloud consumer parallel to the CSPs. After the performance evaluation of both the CSPs and consumers, a ranking-based service mapping algorithm is designed which maps a large-scale CSPs and consumers within the limited time overhead of 10 seconds.

The next section discusses the performance evaluation attributes of cloud consumers. Section 3 presents a system model. In Section 4, a case study is presented to show the process of service mapping and the satisfaction of mapped CSPs, and consumers are also evaluated. The experimental analysis is presented in Section 5. The last section concludes the research paper with some future directions.

2. Consumerism in Cloud

In the cloud, consumers can be an individual or an organization. In this work, small organizations are considered as consumers. Organizational buying behavior is mostly a group process. In an organization, a single person does not typically make a buying decision. The service provider must understand group behavior. This group of people may be actual buyers, the people who impact directly or indirectly on the buying behavior, and the employees of the organization who are going to use these services. For evaluating the group behavior, the attributes are defined in three categories as presented in Figure 1.

2.1. Prepurchase Behavior. The prepurchase behavior of the consumer demonstrates the previous transactions with the provider organization and the complete history of the consumer buying behavior. The buying behavior of the consumer can be predicted by using the following attributes.

(i) Recency. Recency refers how recently a consumer had made a purchase. It is believed that the more recently a consumer has purchased with the CSP, the more likely he or she will continue to keep the service provider and their services in mind for consequent purchases. Compared with consumers who have not acquired from the CSP for a longer period, the probability of engaging in future transactions with recent consumers is arguably higher. Such information can be used to hark back recent consumers to review the business soon to continue meeting their purchase needs. The tendency of recency attribute is considered as negative (lower value is better)

(ii) Frequency. Frequency refers that within a given time, how many times the business deal has been made. The frequency of a consumer's transactions may be affected by factors such as the type of product, the price point for the purchase, and the need for replenishment or replacement. If the purchase cycle can be predicted, for example, when a customer needs to buy new services, marketing efforts could be directed towards reminding them to visit the business. The tendency of frequency attribute is considered as negative (lower value is better)

(iii) Monetary. Monetary value stems from the lucrativeness of expenditures the consumer makes with the business during their transactions. A natural tendency is to put more prominence on encouraging consumers who spend the most money to continue to do so. While this can produce a better return on investment in marketing and consumer service, it also helps in separating those consumers who have been consistent but have not spent as much with each transaction. The tendency of monetary attribute is considered as positive (higher value is better)

(iv) Duration. Duration shows the time the consumer is engaged with the CSP. According to some theories, a consistent consumer buys the services slowly and returns small profit regularly. The tendency of duration attribute is considered as negative (lower value is better)

(v) Churn rate. It is defined as the percentage rate of consumers who cancel or do not subscribe to a service or consumer cancelation over time, usually on an annual basis. The consumer organization which has a lower churn rate will have a constant or higher demand for services. Also, the probability that a single consumer will cancel during a specific time is less. The tendency of churn rate attribute is considered as negative (lower value is better).

$$churn\ rate = a = \frac{\Delta C_{cancel}}{C \times \Delta t}, \tag{1}$$

where C denotes the number of consumers, Δt is the amount of elapsed time, and ΔC_{cancel} is the number of consumers canceling in time Δt

(vi) Consumer acquisition cost. It is defined as the total marketing cost of acquiring a new consumer. Total marketing expenses contain advertising costs, commissions and bonuses paid, and salaries of marketers and sales managers. The tendency of customer acquisition cost attribute is considered as negative (lower value is better). The consumer acquisition cost is defined as

$$Consumer\ Acquisition\ Cost = \frac{Total\ Marketing\ expenses}{number\ \text{of}\ new\ consumers}. \tag{2}$$

(vii) Retention cost. Consumer retention cost (CRC) is defined as the total cost of retaining a consumer. It is assumed that a 5% increase in retention rate boosts the organization's profitability by 25% to 95%. A strategic organization manager should not only focus on retaining the consumers but also focused on the CRC used for retaining the consumer. The tendency of retention cost attribute is considered as negative (lower value is better)

(viii) Recurring revenue. Recurring revenue is the economy metric of subscription of the service over a fixed time. The consumer organization which has higher recurring revenue will have a higher monetary value. The tendency of recurring revenue attribute is considered as positive (higher value is better). The amount of subscription revenue owed by a consumer over a fixed time, usually measured monthly (MRR), quarterly (QRR), or annually (ARR).

$$\begin{gathered} Recurring\ revenue = RR = \frac{R}{\Delta t}, \\ ARR = 4 \times QRR = 12 \times MRR, \end{gathered} \tag{3}$$

where R denotes the subscription revenue owed during the amount of elapsed time Δt

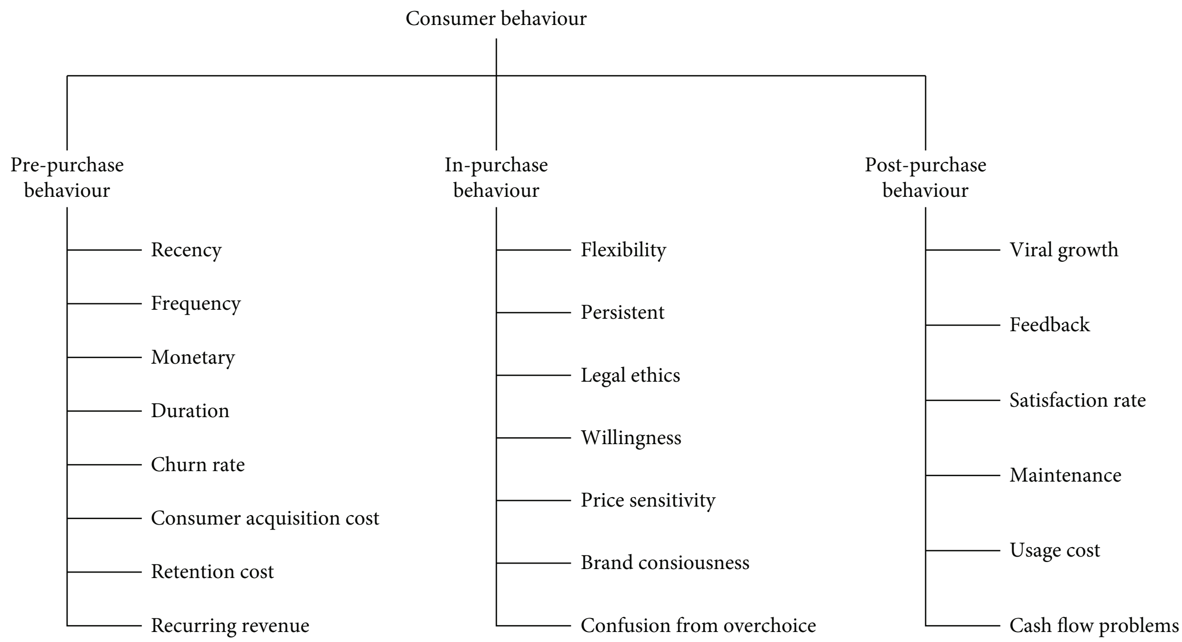

Figure 1: Consumer's behavioral attributes.

2.2. In-Purchase Behavior. In-purchase behavior of the consumer describes the behavior of the consumer during the purchase of services. The behavior of consumers during the purchase can be estimated by the following attributes.

(i) Flexibility. Flexibility is the inherent ability of the consumer to change or adapt or react to a decision-making environment with little change in cloud service cost and performance. The tendency of attribute is considered as positive (higher value is better)

(ii) Persistent. Despite a little difficulty in in-service performance, the consumer is continuing firmly with the existing CSP. The tendency of the attribute is considered as positive (higher value is better)

(iii) Legal ethics. Legal ethics are principles and values which, together with rules of conduct and laws, regulate a profession, such as the legal profession. A consumer, who is aware of the legal ethics of the geographical region from where the services are provisioned, does not blame the CSP regarding privacy issues. The tendency of attribute is considered as positive (higher value is better)

(iv) Willingness. The different consumers have different willingness to purchase a service and to pay for the service. The willingness of the consumer for the modified old services is lesser than the new technology-based services. A consumer who is willing to adopt the changes in technology is considered good for the perspective of the CSP. The tendency of attribute is considered as positive (higher value is better)

(v) Price sensitivity. Many consumers are price-centric if they do not see any deal; they are not going to make a transaction. The consumers who are focused on the performance of the service without the rigid boundary cost are considered good consumers. The tendency of attribute is considered as negative (lower value is better)

(vi) Brand consciousness. Consumers who are purchasing the services from the nationally renowned, expensive, and best-selling brands come in this category. These consumers are also called "price equals quality." Consumers assume that a high price tag is an indicator of a product of higher quality

(vii) Confusion from over choice. Consumers are very quick in deciding on the service selection among the available services, but due to largely available competitors, sometimes consumers get confused. The consumers who are clear about their demand and goals are beneficial for the CSP

2.3. Postpurchase Behavior. Postpurchase behavior describes the behavior of the consumer, such as the way of consumer thinks, feels, and act after provisioning the service.

(i) Viral growth. Viral growth refers to the number of new consumers an existing consumer brings to your services/product in a defined period. These consumers are also called an advocate of the service

(ii) Feedback. Consumer feedback is the information provided by the consumer about the experience of usage of the service. Positive feedback on the service motivates other consumers to make a purchase

(iii) Satisfaction rate. The repurchase of the services by the consumer is a positive sign of satisfaction rate. The repurchase of the services from the same brand also helps the CSPs in generating more revenue

(iv) Maintenance. Maintenance cost refers to any cost incurred by an organization to keep its services in operational condition. These costs may be for general maintenance like running antivirus software, or they may be fixing some hardware/software problems. A consumer who requires low maintenance of services is beneficial for the service provider

(v) Usage cost. Cloud services have usage-based pricing. Consumers whose usage of the services after provisioning is more is considered beneficial for the service providers

(vi) Cash flow problems. A cash flow problem arises when an organization is unable to pay its debt due to late and slow-paying consumers. A consumer is considered valuable in terms of cash flow if he pays fast

3. CloudConsumerism: A Consumer-Centric Ranking Model for Efficient Service Mapping

This section presents the hypothesis and components such as possible service mapping scenarios, MCDM method TOPSIS used for ranking the CSPs as well as consumers, and Algorithm 1: service mapping algorithm for efficiently mapping the CSPs to the consumer in all the possible scenarios.

3.1. Service Mapping Scenarios. In the brokerage-based service selection, the number of cloud entities that needs to be evaluated is two; therefore, the degree of mapping is two, and the number of possible scenarios is four. The proposed CloudConsumerism model deals efficiently with all possible scenarios.

Case 1. One to one mapping. In this case the single cloud broker provides service that is provisioned by one cloud service provider to a consumer as shown in Figure 2.

Case 2. One to many mapping. In this case a cloud broker provides service that is provisioned by a cloud service provider to many consumers as shown in Figure 3.

Case 3. Many to one mapping. In this case many consumers request a service to the cloud broker, and only one cloud service provider is available for the service provisioning as shown in Figure 4.

Case 4. Many to many mapping. In this case many consumers are requesting a service to the cloud brokers, and many cloud service providers are available for the service provisioning as shown in Figure 5.

3.2. MCDM Method TOPSIS. CloudConsumerism model uses TOPSIS method [23] for evaluating the stakeholders. The method is based on the idea that the selected CSP must be closest to the positive ideal solution and farthest from the negative ideal solution. The steps of TOPSIS methods are the following:

Step 1. Normalize the decision matrix $DM_{\text{norm}} = [nv_{ij}]$, where nv_{ij} for i^{th}CSP for j^{th} attributes are given by

$$nv_{ij} = \frac{v_{ij}}{\sqrt{\sum_{i=1}^{m} v_{ij}^2}}, \tag{4}$$

$$nm = \begin{pmatrix} nv_{11} & \cdots & nv_{1n} \\ \vdots & \ddots & \vdots \\ nv_{m1} & \cdots & nv_{mn} \end{pmatrix}. \tag{5}$$

Step 2. Calculate the weighted normalized decision matrix $WDM_{\text{norm}} = [r_{ij}]$, where r_{ij} for i^{th}CSP for j^{th} attribute is given by

$$\mathrm{r_{ij}} = \mathrm{nv_{ij}} \times \mathrm{w_j}, \tag{6}$$

$$WDM_{\text{norm}} = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix}. \tag{7}$$

Step 3. Calculate the positive ideal solution A_p and the negative ideal solution A_n.

$$A_p = \left(\min \left(r_{ij} | i = 1, 2, 3, \cdots \cdots \cdots m\right) | j \in J_-, \max \cdot \left(r_{ij} | i = 1, 2, 3, \cdots \cdots \cdots m\right) | j \in J_+\right) \cong \left(r_{pj} | j = 1, 2, 3, \cdots n\right), \tag{8}$$

$$A_n = \left(\max \left(r_{ij} | i = 1, 2, 3, \cdots \cdots \cdots m\right) | j \in J_-, \min \cdot \left(r_{ij} | i = 1, 2, 3, \cdots \cdots \cdots m\right) | j \in J_+\right) \cong \left(r_{nj} | j = 1, 2, 3, \cdots n\right), \tag{9}$$

where

$J_+ = \{j = 1, 2, \cdots..n | j$ is associated to the attribute which is beneficial attribute.

$J_- = \{j = 1, 2, \cdots..n | j$ is associated to the attribute which is cost attribute.

Step 4. Evaluate the separation distance from positive ideal solution S_{ip} and negative ideal solution S_{in}.

$$S_{ip} = \sqrt{\sum_{j=1}^{n} \left(r_{ij} - r_{bj}\right)^2}, i = 1, 2, \cdots \cdots ..m, \tag{10}$$

```
Input: Directory of CSPs and Consumers.
Output: Service mapping of CSPs and Consumers.
Begin
 For all the available CSPs set flagCSP ←1.
   IF CSPs ==1 && consumers ==1 THEN
     bind consumer to CSP
     flagCSP ←0.
   END IF
   IF CSPs >1 && consumers ==1 THEN
     get the ranking score of the CSPs using TOPSIS;
     sort the ranking score of CSPs and find top rank CSP;
     map the consumer to CSP;
     flagCSP ← 0;
   END IF
   IF CSPs ==1 && consumers > 1 THEN
     get the ranking score of consumers using TOPSIS;
     sort the ranking score of consumers and find top rank consumers;
     map the consumer to CSP;
     flagCSP ← 0;
   END IF
   IF CSPs >1 && consumers > 1 THEN
     FOR each consumer DO
       get the ranking score of CSPs using TOPSIS Method;
       sort the ranking score of CSPs and find top rank CSP;
     END FOR
     FOR each CSP DO
       get the list of competitive consumers;
     END FOR
     FOR each CSP DO
       IF competitive consumers list is empty THEN
         continue;
       ELSE IF competitive consumers ==1 and flagCSP ==1 THEN
         map the consumer to CSP;
         flagCSP ← 0;
     END IF
     ELSE flagCSP ==1 THEN
       get the score of competitive consumers using TOPSIS;
       rank the consumers and get the top rank consumer;
       map the consumer to CSP;
       flagCSP ← 0;
     END FOR
   END IF
   After completion of the service the flagCSP is set to 1;
End
```

Algorithm 1: Service mapping algorithm.

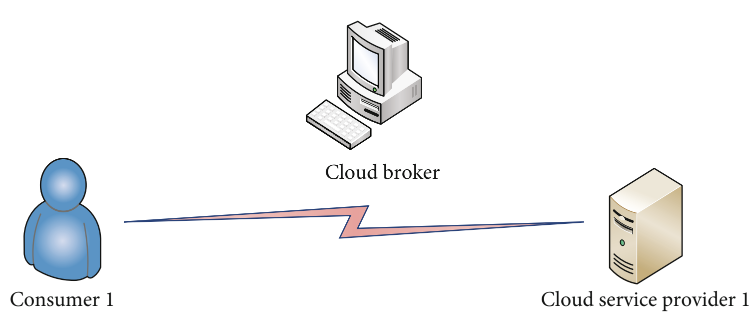

Figure 2: One to one mapping.

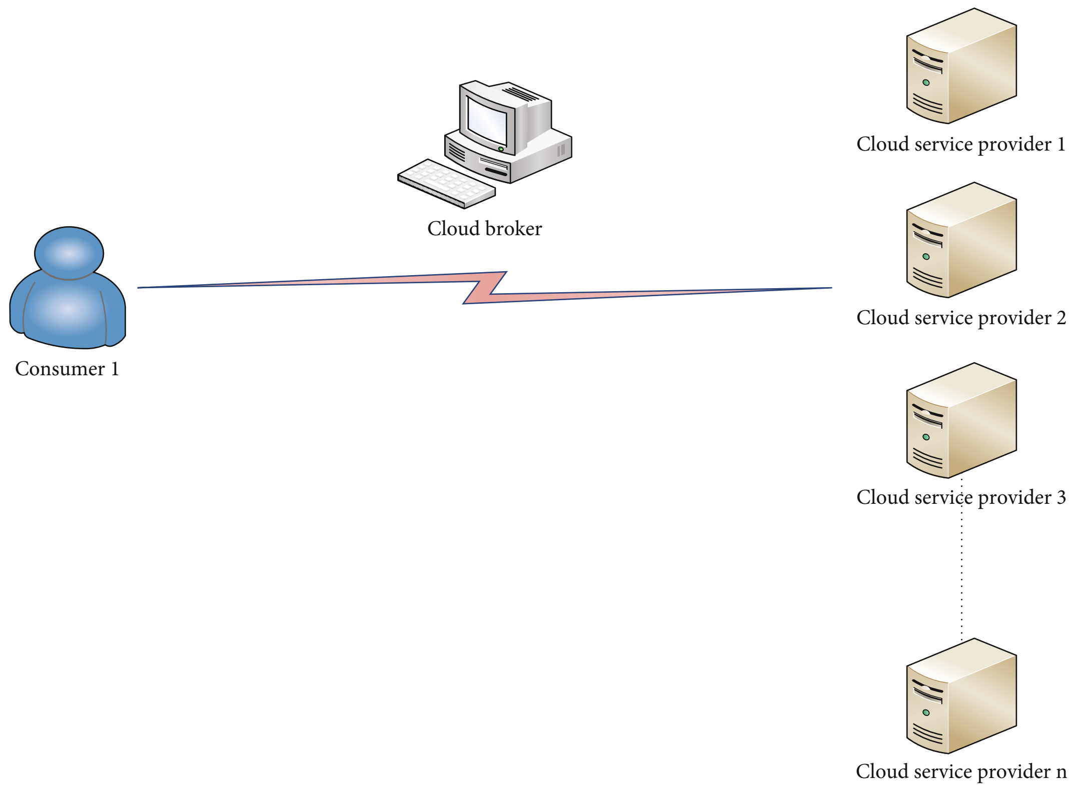

FIGURE 3: One to many mapping.

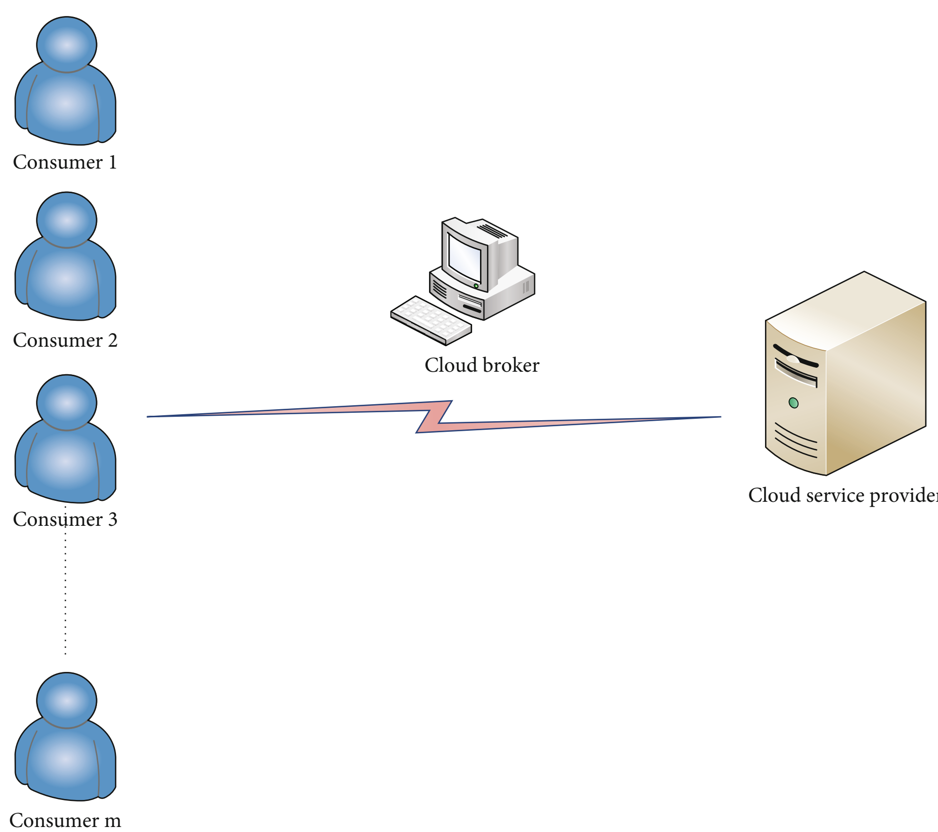

FIGURE 4: Many to one mapping.

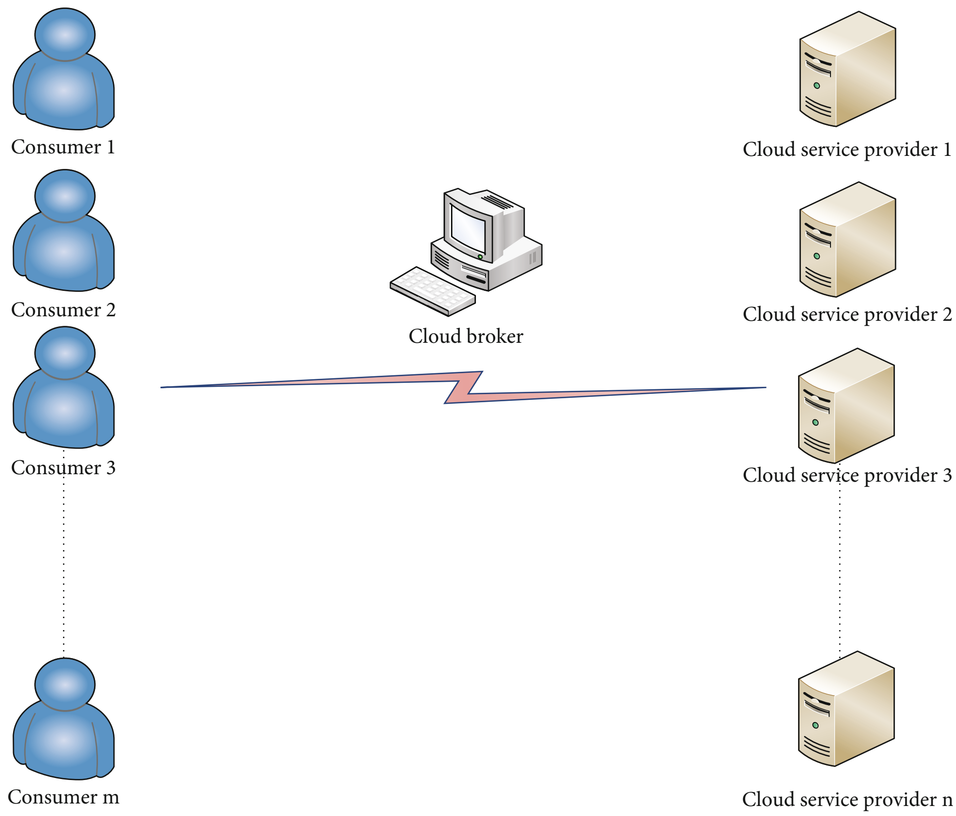

Figure 5: Many to many mapping.

$$S_{\text{in}} = \sqrt{\sum_{j=1}^{n} \left(r_{ij} - r_{nj}\right)^2}, i = 1, 2, \cdots \cdots ..m, \quad (11)$$

where S_{ip} and S_{in} are L2-norm distance of the i^{th} target CSP from the positive and negative ideal solution, respectively.

Step 5. Calculate the relative closeness.

$$C_i = \frac{S_{\text{in}}}{S_{ip} + S_{\text{in}}}, 0 \leq C_i \leq 1, i = 1, 2, \cdots \cdots \cdots \cdots m.,$$

$$C_i = \begin{cases} 1, \text{if the } \textit{alterative solution has} \text{ the } \textit{best condition}, \\ 0, \text{if the } \textit{alterative solution has} \text{ the } \textit{worst condition}. \end{cases} \quad (12)$$

Step 6. Rank the CSP based on relative closeness.

$$Rank = sort(C_i). \quad (13)$$

3.3. Service Mapping Algorithm. This subsection presents the service mapping algorithm. The Algorithm 1 is used by the proposed CloudConsumerism model during the service mapping process.

4. Case Study

In the presented case study, the offered QoS data is collected from three IaaS public CSPs: Amazon EC2, Rackspace, and Windows Azure. The SMI attributes, namely, accountability, agility, assurance, cost, performance, and security, are considered for estimating the ranking the CSPs. The QoS data offered by CSP_1 (Amazon EC2), CSP_2 (Rackspace), CSP_3 (Microsoft), and relative weights of consumer's requirement is presented in Table 1. The QoS data is collected from the paper [5]. Due to unavailability of data of QoS attributes accountability and security, the values are randomly assigned. QoS attributes comparison rules and scaling are adopted from the paper [24]. For the ranking estimation of consumers, the transaction attributes recency, frequency, monetary, duration, recurring revenue, churn rate, and acquisition cost are considered, and data values are assigned randomly, as presented in Table 2. The preferences of CSPs for selecting the valuable consumers is presented in Table 3.

The TOPSIS method is applied to rank the CSPs and consumers based on the preferences of their counterparts. The ranking of CSPs is shown in Figure 6. In business perspective, every consumer follows a cost-quality trade-off. Thus, cost-quality-based service ranking is considered as the final stage of selection of CSPs. Since the offered cost of the CSP for the services is different, the ranking score of CSPs per unit cost is estimated as presented in Figure 7. From the figure, it is seen that CSP_1 is ranked as the first choice by all the consumers. The CSP_2 is ranked as the

Table 1: Offered QoS of the CSPs.

QoS attributes	Top-level QoS attributes required by the consumers 1	2	3	4	5	6	7	8	9	10	First level attributes (weights)	Second level attributes (weights)		Service 1 (S1)	Service 2 (S2)	Service 3 (S3)	Value type
Accountability	0.05	0.25	0.10	0.25	0.05	0.05	0.05	0.05	0.30	0.05	Level 0-10			4	8	4	Numeric
												CPU	0.5	9.6	12.8	8.8	Numeric
Agility	0.10	0.20	0.20	0.10	0.15	0.10	0.10	0.10	0.10	0.30	Capacity (0.6)	Memory	0.3	15	14	15	Numeric
												Disk	0.2	1690	2040	630	Numeric
											Elasticity (0.4)	Time	1	80-120	520-780	20-200	Range
											Availability (0.7)	0.7	0.7	99.95%	99.99%	100%	Numeric
												Upload time	0.3	13.6	15	21	Numeric
Assurance	0.30	0.10	0.15	0.20	0.20	0.20	0.45	0.20	0.20	0.20	Service stability (0.2)	CPU	0.4	17.9	16	23	Numeric
												Memory	0.3	7	12	5	Numeric
											Serviceability (0.1)	Free support	0.7	0	1	1	Boolean
												Type of support	0.3	24/7, diagnostic tools, phone, urgent response	24/7, diagnostic tools, phone, urgent response	24/7, phone, urgent response	Unordered set
												VM cost	0.6	$0.68	$0.96	$0.96	Numeric
Cost	0.30	0.05	0.30	0.10	0.25	0.50	0.05	0.10	0.05	0.10	Ongoing cost (1)	Data	Inbound	10	10	8	Numeric
													Outbound	11	15	18	
												Storage	0.2	12	15	15	Numeric
												Range	0.5	80-120	520-780	20-200	Range
Performance	0.30	0.30	0.10	0.30	0.30	0.10	0.30	0.30	0.30	0.30	Service response time (0.1)	Average value	0.5	100	600	30	Numeric
Security	0.05	0.10	0.15	0.05	0.05	0.05	0.05	0.25	0.05	0.05	Level: 0-10 (1)			4	8	4	Numeric

Table 2: Service transaction of consumers.

	Recency	Frequency	Monetary	Duration	Recurring revenue	Churn rate	Acquisition cost
Consumer_1	18	10	520	2	100	0.10	50
Consumer_2	4	1	190	5	500	0.15	50
Consumer_3	12	6	65	3	200	0.10	45
Consumer_4	7	3	2000	4	400	0.25	55
Consumer_5	9	4	250	7	700	0.05	35
Consumer_6	55	8	726	4	100	0.30	45
Consumer_7	17	14	580	3	200	0.20	30
Consumer_8	35	6	150	2	500	0.10	20
Consumer_9	23	1	325	4	1100	0.40	10
Consumer_{10}	3	15	140	2	1200	0.10	40

Table 3: Required transaction preferred by the CSPs.

	Recency	Frequency	Monetary	Duration	Recurring revenue	Churn rate	Acquisition cost
CSP 1	0.30	0.20	0.10	0.10	0.15	0.10	0.05
CSP 2	0.10	0.10	0.25	0.20	0.10	0.15	0.10
CSP 3	0.20	0.20	0.10	0.20	0.10	0.05	0.15

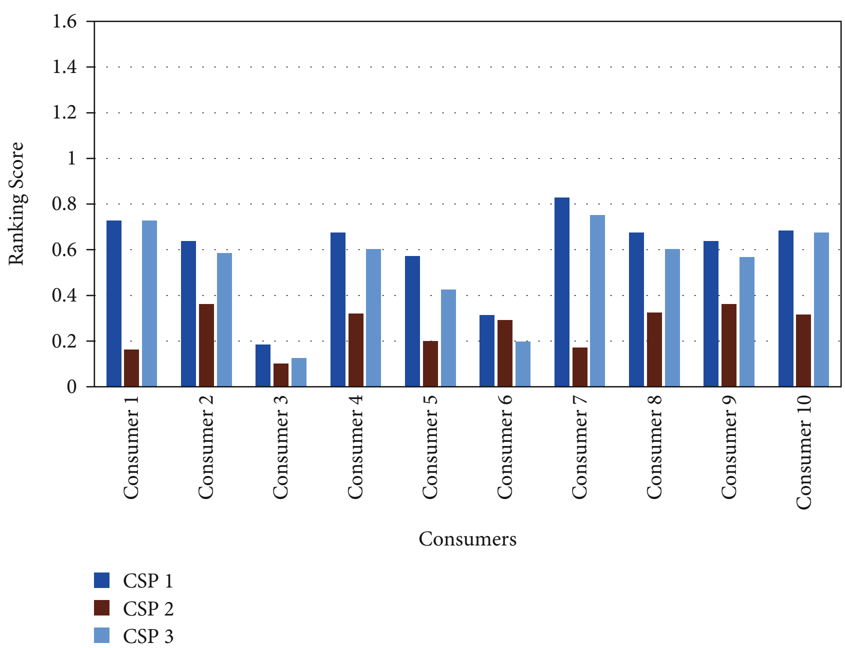

Figure 6: Ranking score of CSPs.

second choice except for consumer_6, and CSP_3 is ranked as the last choice by all consumers except consumer_6. Thus, for CSP_1, all the consumers are in competition. Therefore, consumers are ranked based on the consumers transaction behavior attribute value and desired consumer weighting by the CSPs. Ranking results of consumers are shown in Figure 8. The duration of the transactions differs from consumer to consumer. The ranking score per unit time is generated for the healthy comparison as shown in Figure 9, which is considered at the final stage of ranking. From the results, it is observed that consumer_{10} is ranked at first choice by the CSP_1 and others also. Considering the mutual choice, the consumer_{10} is mapped to the CSP_1. CSP_2 is preferred at second choice only by consumer_6; therefore, consumer_6 is directly mapped (no need of ranking the consumer because of no competition) to the CSP_2. CSP_3 is preferred as the second choice by the rest consumers. The rest of consumers are ranked based on the requirement of CSP_3, and it is found that CSP_3 prefers consumer_1 as their second choice (first choice is consumer_{10} which is already

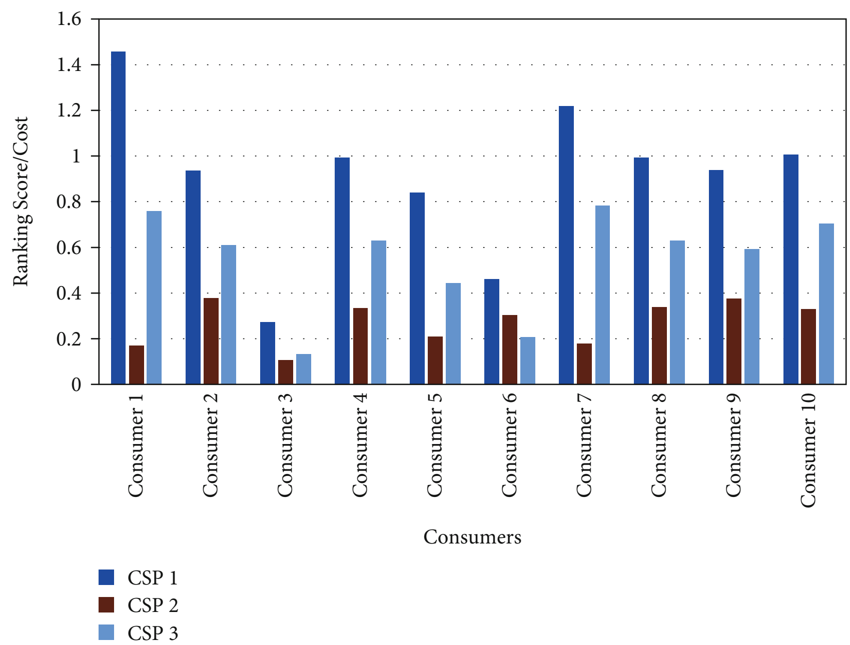

Figure 7: Ranking of CSPs per unit cost.

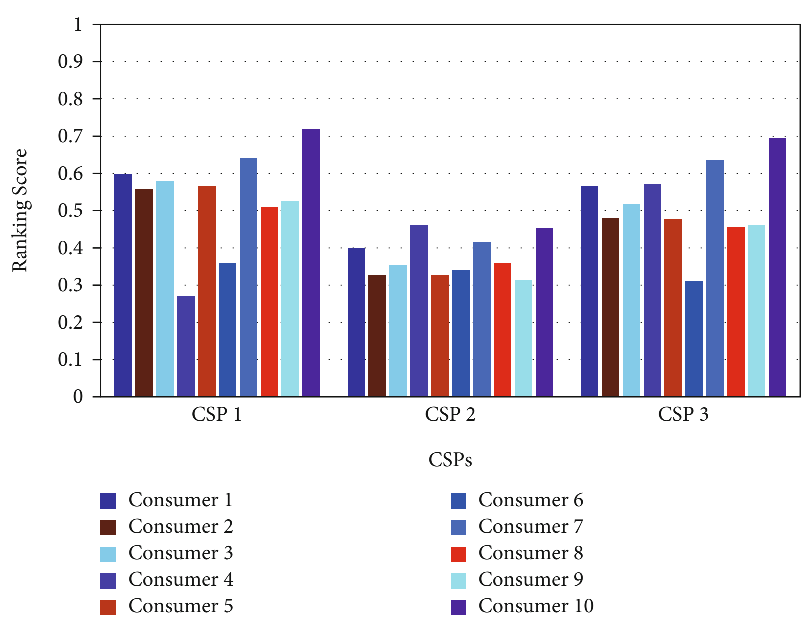

Figure 8: Ranking score of consumers.

mapped), so consumer$_1$ (second choice) is mapped with the CSP$_3$. The mapping of consumers and CSPs after considering mutual evaluation is presented in Figure 10.

4.1. Satisfaction of Mapped Consumers and CSPs. After mapping the of consumers and CSPs, the service satisfaction of consumers and CSPs are computed [12]. For computing the satisfaction, the ranking score of the CSPs/consumers is considered. The satisfaction of the CSP/consumer is calculated using the offered and received performance. For the satisfaction of consumers, the ranking score of CSP, which is at the first choice based on the requirement of a consumer, is considered as offered performance for the consumer. The ranking score of actual mapped CSP after considering the ranking of consumers based on the requirement of CSP is considered as received performance and vice versa. The case study results show that consumer$_1$ is mapped to CSP$_3$, consumer$_6$ is mapped to CSP$_2$, and consumer$_{10}$ is mapped to CSP$_1$.

The CSP$_1$ is ranked as the first choice by consumer$_1$. The ranking score of CSP$_1$ (1.4577) is considered as the desired/offered performance for the consumer$_1$, and at the final stage

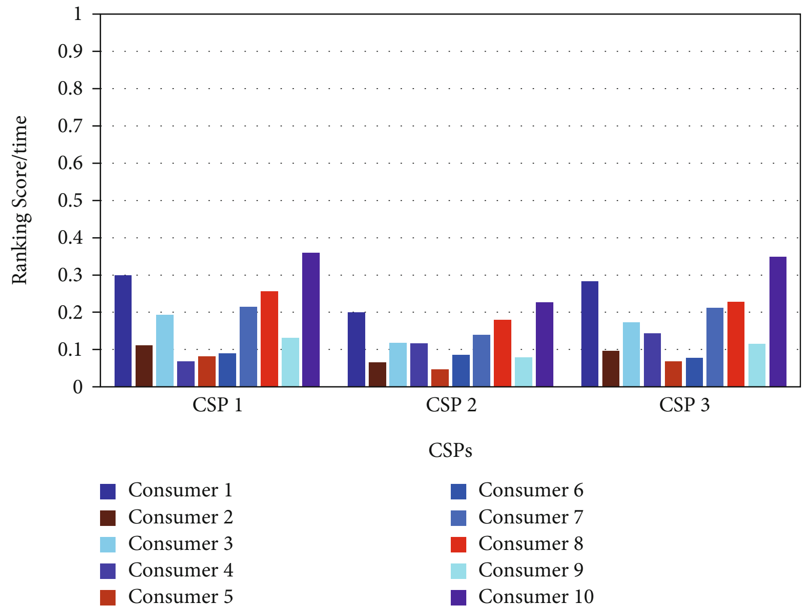

Figure 9: Ranking sore of consumers per unit time or duration.

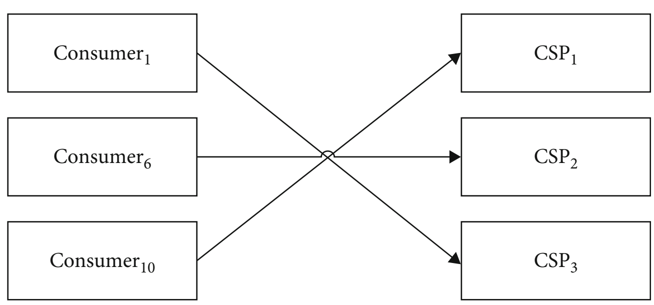

Figure 10: Mapping of consumers and CSPs.

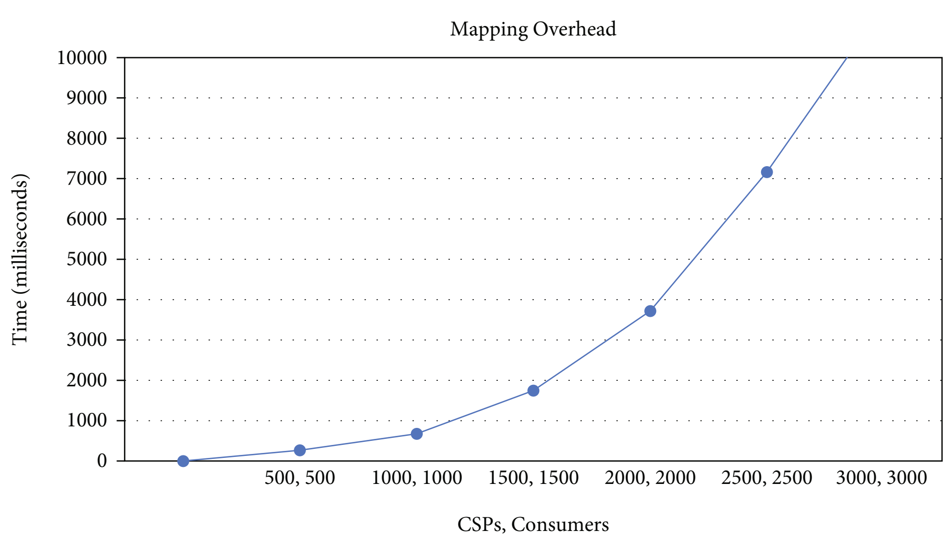

Figure 11: The number of CSPs and consumers is fixed to 2500.

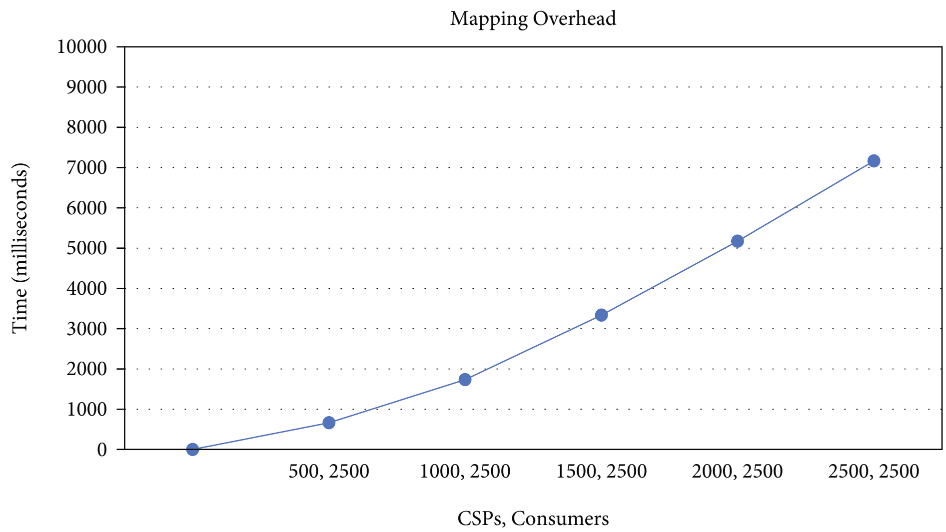

Figure 12: The CSPs are varied from 500 to 2500 and consumers are fixed to 2500.

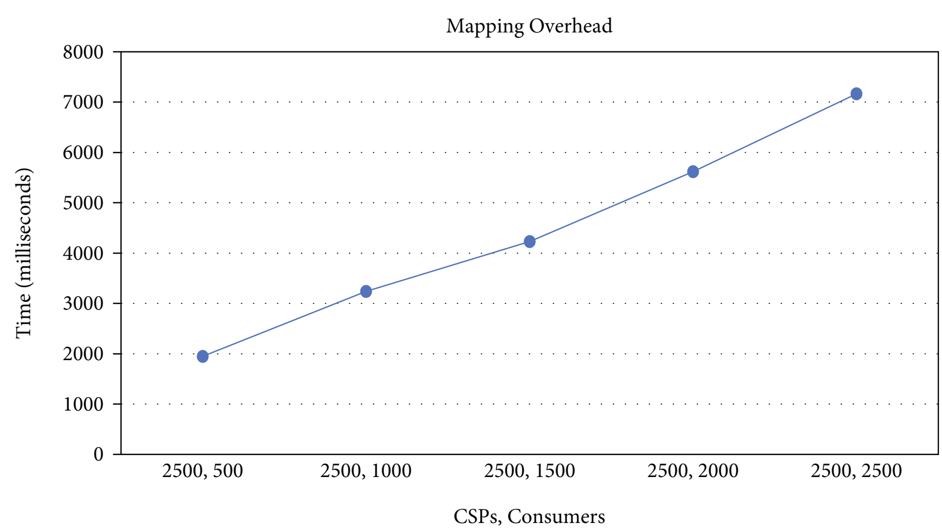

Figure 13: The number of CSPs is varied from 500 to 2500, and the number of consumers is fixed to 2500.

Table 4: Comparative analysis with existing frameworks.

Framework	Number of CSPs	Number of consumers
SMICloud [5]	1000	1
TRCSM [7]	700	700
MECSM [12]	1800	1800
Modified MECSM	2500	2500

of mapping, CSP_3 (0.7592) is mapped to the $consumer_1$, which is considered as actual received performance; therefore, the satisfaction of $consumer_1$ is evaluated as:

$$e^{-\left|\frac{1.4577-0.7592}{0.7592}\right|} = 0.6193 = 61.93\%. \quad (14)$$

The CSP_1 is ranked as the first choice by the $consumer_6$. The ranking score of CSP_1 (0.4605) is considered as the desired/offered performance for the $consumer_6$, and at the final stage of mapping, CSP_6 (0.3040) is mapped to the $consumer_6$, which is considered as received performance for the $consumer_6$; therefore, the satisfaction of $consumer_6$ is evaluated as

$$e^{-\left|\frac{0.3040-0.4605}{0.4605}\right|} = 0.7119 = 71.19\%. \quad (15)$$

The CSP_1 is ranked as the first choice by the $consumer_{10}$. The ranking score of CSP_1 (1.0058) is considered as the desired/offered performance for the $consumer_{10}$, and at the final stage of mapping, CSP_1 (1.0058) is mapped to the $consumer_{10}$, which is considered as the received performance. For $consumer_{10}$, the offered performance and the received is equal; therefore, the satisfaction of $consumer_{10}$ is 100%.

5. Experimental Results and Discussion

For experimental analysis, the MCDM methods are implemented in JAVA, running on Windows 10 Home Single Language with Intel Core i7-4510U @ 2.00GHz 2.60 GHz having 8 GB RAM. The ranking overhead is evaluated with variations in the number of CSPs and the number of consumers. The number of attributes for CSPs as well as consumers is fixed. The benchmark for ranking overhead is considered 10 seconds. The mapping overhead of three different scenarios (by varying the number of CSPs and consumers) is recorded. In the first scenario, the number of consumers and CSPs are considered equal, i.e., 500 each and the ranking overhead is recorded. The results show that within a limited time overhead of 10 milliseconds, the mapping overhead increases linearly and scales mapping up to 2500 consumers and 2500 CSPs, as shown in Figure 11. In the second scenario, the number of CSPs is fixed to 2500 (considering as a scaling limit as obtained from the first scenario), and the number of consumers is varied from 500 to 2500 with a step size of 500. The results show that the ranking overhead increases linearly, as shown in Figure 12, and within a time overhead of 8 milliseconds, the 2500 consumers and 2500 provides are mapped. In the third scenario, the number of consumers is fixed to 2500, and the number of CSPs is varied from 500 to 2500 with a step size of 500. The ranking overhead increases linearly as the number of CSPs increases, and within 8 milliseconds, 2500 consumers and 2500 CSPs are mapped as shown in Figure 13. For each data value, the results are taken 40 times, and the average execution time is considered the final ranking overhead in each scenario.

6. Conclusion and Future Work

In this paper, we have addressed a consumer-centric quality of service-based service mapping model, CloudConsumerism. In the proposed model, for evaluating the consumers, the behavioral attributes of consumers are defined, and while mapping, the consumers and CSPs both are evaluated. The number of consumers and service providers is scaleup up to 2500 consumers and 2500 providers. We demonstrate the applicability of our work in the online cloud service selection model by increasing the scaleup of the number of consumer and the number of providers within the limited time overhead of 10 seconds. By applying the requirement filtering from both the side, i.e., cloud consumer as well as CSP, it is shown that the valuable consumers are mapped to the high-performance service provider and hence the satisfaction of the cloud consumer and CSP is increased. The comparative analysis with existing frameworks has been presented in Table 4. In the future, the separate broker for each consumer and provider will be involved so that the third-party broker can also be evaluated from both the side consumer as well as provider. For evaluating the broker, the new attribute will also be defined. From Table 4, it is concluded that the modified MECSM is more efficient in terms of overhead and robustness.

Data Availability

The data used to support the findings of this study are currently under embargo, while the research findings are commercialized. Requests for data, 12 months after the publication of this article, will be considered by the corresponding author.

Conflicts of Interest

There is no conflicts of interest of any authors.

References

[1] C. Madhavaiah, "Defining cloud computing in business perspective : a review of research," *Metamorphosis*, vol. 11, no. 2, pp. 50–65, 2012.

[2] T. Leadership and W. Paper, "Defining a framework for cloud adoption: How common ground can help enterprises drive success with cloud computing," *IBM Global Technology Services*, 2010.

[3] Z. R. Alashhab, M. Anbar, M. M. Singh, Y. B. Leau, Z. A. Al-Sai, and S. A. Alhayja'a, "Impact of coronavirus pandemic crisis on technologies and cloud computing applications," *Journal of Electronic Science and Technology*, vol. 19, no. 1, article 100059, 2021.

[4] M. S. Kumar, I. Gupta, S. K. Panda Gupta, and P. K. Jana, "Granularity-based workflow scheduling algorithm for cloud computing," *The Journal of Supercomputing*, vol. 73, no. 12, pp. 5440–5464, 2017.

[5] S. Kumar, S. Versteeg, and R. Buyya, "A framework for ranking of cloud computing services," *Future Generation Computer Systems*, vol. 29, no. 4, pp. 1012–1023, 2013.

[6] M. Neeraj, S. Goraya, and D. Singh, "A comparative analysis of prominently used MCDM methods in cloud environment," *Journal of Supercomputing*, vol. 77, no. 4, pp. 3422–3449, 2020.

[7] N. Yadav and M. S. Goraya, "Two-way ranking based service mapping in cloud environment," *Future Generation Computer Systems*, vol. 81, pp. 53–66, 2018.

[8] "The Cloud Service Measurement Initiative Consortium Service Measurement Index Introducing the Service Measurement Index," 2011, http://www.cloudcommons.com/about-smi.

[9] D. L. Motherbaugh, D. L. Hawkins, and A. Mookerjee, "Consumer behaviour, building marketing," *Strategies*, 2010.

[10] W. Jianping, "Research on VIP customer classification rule base on RFM model," in *MSIE 2011*, pp. 336–338, Harbin, Jan 2011.

[11] J. Wei, S. Lin, and H. Wu, "A review of the application of RFM model," *African Journal of Business Management*, vol. 4, no. 19, pp. 4199–4206, 2010.

[12] M. S. Goraya and D. Singh, "Satisfaction aware QoS-based bidirectional service mapping in cloud environment," *Cluster Computing*, vol. 23, no. 4, pp. 2991–3011, 2020.

[13] H. Shen, G. Liu, S. S. Member, G. Liu, and S. S. Member, "An efficient and trustworthy resource sharing platform for collaborative cloud computing," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 4, pp. 862–875, 2014.

[14] M. Azadi, M. Izadikhah, F. Ramezani, and F. K. Hussain, "A mixed ideal and anti-ideal DEA model: an application to

evaluate cloud service providers," *IMA Journal of Management Mathematics*, vol. 31, pp. 233–256, 2019.

[15] S. Ramadass, R. Krishankumar, K. S. Ravichandran, H. Liao, S. Kar, and E. Herrera-Viedma, "Evaluation of cloud vendors from probabilistic linguistic information with unknown/partial weight values," *Applied Soft Computing*, vol. 97, article 106801, 2020.

[16] R. Ranjan, K. Siba, and C. Kumar, "Prioritizing the solution of cloud service selection using integrated MCDM methods under fuzzy environment," *The Journal of Supercomputing*, vol. 73, no. 11, pp. 4652–4682, 2017.

[17] L. Sun, J. Ma, Y. Zhang, H. Dong, and F. Khadeer, "Cloud-FuSeR: fuzzy ontology and MCDM based cloud service selection," *Future Generation Computer Systems*, vol. 57, pp. 42–55, 2016.

[18] T. L. Saaty, "The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making," in *Multiple criteria decision analysis*, pp. 363–419, Springer, New York, NY, 2016.

[19] K. Yoon, "A reconciliation among discrete compromise solutions," *Journal of the Operational Research Society*, vol. 38, no. 3, pp. 277–286, 1987.

[20] A. Mardani, E. K. Zavadskas, K. Govindan, A. A. Senin, and A. Jusoh, "VIKOR technique: a systematic review of the state of the art literature on methodologies and applications," *Sustainability*, vol. 8, pp. 37-38, 2016.

[21] J. P. Brans and P. Vincke, "Note—a preference ranking organisation method," *Management Science*, vol. 31, no. 6, pp. 647–656, 1985.

[22] C. Gartner, "STAMFORD, Gartner Forecasts Worldwide Public Cloud End-User Spending to Grow 21% in 2021," 2021.

[23] B. Lee, K. H. Oh, H. J. Park, U. M. Kim, and H. Y. Youn, "Resource reallocation of virtual machine in cloud computing with MCDM algorithm," in *2014 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*, Oct 2014.

[24] V. Xuan, H. Tsuji, and R. Masuda, "A new QoS ontology and its QoS-based ranking algorithm for Web services," *Simulation Modelling Practice and Theory*, vol. 17, no. 8, pp. 1378–1398, 2009.