Evaluating efficiency of cloud service providers in era of digital technologies

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Abstract

The rapid growth of advanced technologies such as cloud computing in the Industry 4.0 era has provided numerous advantages. Cloud computing is one of the most significant technologies of Industry 4.0 for sustainable development. Numerous providers have developed various new services, which have become a crucial ingredient of information systems in many organizations. One of the challenges for cloud computing customers is evaluating potential providers. To date,

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considerable research has been undertaken to solve the problem of evaluating the efficiency of cloud service providers (CSPs). However, no study addresses the efficiency of providers in the context of an entire supply chain, where multiple services interact to achieve a business objective or goal. Data envelopment analysis (DEA) is a powerful method for efficiency measurement problems. However, the current models ignore undesirable outputs, integer-valued, and stochastic data which can lead to inaccurate results. As such, the primary objective of this paper is to design a decision support system that accurately evaluates the efficiency of multiple CSPs in a supply chain. The current study incorporates undesirable outputs, integer-valued, and stochastic data in a network DEA model for the efficiency measurement of service providers. The results from a case study illustrate the applicability of our new system. The results also show how taking undesirable outputs, integer-valued, and stochastic data into account changes the efficiency of service providers. The system is also able to provide the optimal composition of CSPs to suit a customer's priorities and requirements.

Keywords: Industry 4.0; Efficiency evaluation; Cloud service providers; Two-stage network data envelopment analysis (DEA).

1. Introduction

In the era of globalization, it is crucial to digitize operations and equipment (Paul et al. 2021). Operations management needs to be intelligent and enhanced with data-driven technologies (Culot et al. 2020). As such, manufacturing systems can be rebuilt and improved from the standpoint of digital platforms (Sarker and Datta, 2022). To do so, Industry 4.0 technologies such as blockchain, cloud computing, big data analytics, and artificial intelligence need to be applied in operations (Kamble et al. 2021). Applying these technologies can enhance sustainability in manufacturing organizations (Kumar et al. 2020). Sustainability and Industry 4.0 technologies have received substantial attention from academic scholars, policymakers, and industrial managers over the last two decades (Toktaş-Palut et al. 2022). Industry 4.0 technologies, using resources efficiently, enable manufacturing systems to produce sustainable products (Ardanza et al. 2019). These technologies can significantly optimize sustainable energy development and increase sustainability activities (Beltrami et al. 2021). Industry 4.0 technologies also can support decision-making processes, information, and data sharing process throughout supply chains, including sustainable purchasing and sustainable production in manufacturing systems (Tozanlı et al. 2020). Thus, there is a substantial interest in applying advanced Industry 4.0 technologies and exploring related advantages aimed at sustainable development (Kopyto et al. 2020). Cloud computing, as one of the advanced digital technologies, has a big impact on the information technology (IT) landscape and sustainability in industrial organizations and has reduced the cost of IT expenditure for many enterprises (Alam et al. 2020). Several leading IT companies, now offer cloud services to their customers. According to the National Institute of Standards and Technology, “Cloud computing is a model that allows ubiquity, convenience and on-demand access to a shared pool of configurable resources and can be quickly delivered with minimum managerial effort on the part of the clients.” (Katzan Jr, 2009).

Given the sustainability, agility, and flexibility that cloud services offer, many businesses are opting to transfer all or part of their information systems to the cloud (Zhao et al. 2019; Bazi et al. 2017). Yet the growing number of cloud service providers (CSPs) is making it increasingly difficult to decide, which CSPs can meet a customer’s requirements. To tackle this problem, several methods for selecting and measuring the performance of CSPs have been developed (Ramachandran and Chang, 2016; Azadi et al. 2022). However, these methods typically evaluate the performance of IaaS, PaaS, and SaaS services separately, ignoring the interactions between them. To counter this problem, in this study, we evaluate the performance of CSPs while considering their role within a supply chain.

Data envelopment analysis (DEA) is a powerful and useful method for efficiency measurement problems (Amirteimoori & Emrouznejad, 2012). However, despite DEA’s advantages, the conventional DEA models consider decision-making units (DMUs) as “black boxes” and the internal structure of the DMUs are not considered. Additionally, DEA assumes that a DMU is a one-stage production process. However, many practical applications involve a network structure. Therefore, evaluating efficiency across a cloud supply chain demands a productivity analysis tool that is capable of assessing a CSP’s individual and overall efficiency within a network system (Liu, Zhou, Ma, Liu, & Shen, 2015). Also, traditional DEA models assume that all outputs are desirable (i.e., the more the better), continuous, and deterministic. These assumptions are not correct in many real-world cases, particularly those with undesirable, discrete, and/or non-deterministic variables (Azadi & Saen, 2011); Chen, Du, Huo, & Zhu (2012).

In the cloud computing service market, many providers supply a variety of services with the same feature. This can be a major challenge in selecting CSPs. Although significant research has been carried out for addressing the problem of evaluating the efficiency of CSPs, no study addresses the efficiency of providers in the context of an entire supply chain. As such, the main motivation of this study is to present a set of network DEA models based on a two-stage slacks-based measure (SBM) network, that considers undesirable outputs, integer-valued data, and stochastic data. The proposed models not only provide reliable insights into the performance of CSPs, but also provide the opportunity to conduct further analysis for managerial decision-making. The main contributions of this study are as follows:

- This is the first work to propose a method for evaluating the overall efficiency of providers within a cloud supply chain.
- The network DEA models concurrently consider undesirable outputs, integer-valued data, and stochastic data.
- The proposed models provide cloud computing customers with an optimal CSP composition given their priorities, such as cost or latency.
- The applicability and capability of the proposed models are evaluated through a case study.

This article is set out as follows. Section 2 contains the existing works. Section 3 describes the cloud environment and the cloud supply chain. Section 4 presents CSP-PE, the new support system for evaluating CSP performance. Section 5 defines the new models. Section 6 presents the results of the case study evaluation. In Section 7, we discuss the theoretical and practical implications of the proposed models. Finally, our concluding remarks are provided in Section 8.

2. Literature review

There is a rich body of literature on sustainability and Industry 4.0 technologies, evaluating the efficiency of CSPs and DEA and network DEA, along with its associated undesirable outputs, integer-valued data, and stochastic data. This literature review provides a background on these issues and identifies the gaps in the research this article aims to fill.

2.1 Sustainability and Industry 4.0 technologies

Sustainable operations management addresses the sustainability aspects such as economic, ecological, and social (Shou et al. 2019). Recently, companies around the globe have concentrated on sustainable operations in their supply chains (SCs) (Culot et al. 2020). Reducing manufacturing costs, minimizing waste of materials and products, and predicting unexpected disruptions are some advantages of sustainable operations management (Magon et al. 2018). To overcome these challenges, Industry 4.0 technologies, including the Internet of Things (IoT), big data analytics, and cloud computing are applied (Azadi et al. 2021). IoT is an interconnected device that works with the Internet and shares information and data throughout the network (Basaure et al. 2020). It reduces production costs, pollution, and energy and increases efficiency and sustainability standards (Bhatia et al. 2020). Big data analytics are ways of analyzing and extracting information and data systematically from large or complex datasets and help future growth and business improvement (Chang et al. 2021). Cloud computing is a model that provides anywhere, convenience, and on-demand access to a shared pool of configurable sources (Katzan Jr, 2009). It improves ethical and sustainable operations and eases production processes (Kumar et al. 2020). Typically, CSPs offer three types of services: IaaS[2], PaaS[3], and SaaS[4] (Mell & Grance, 2011). IaaS abstracts physical hardware, such as servers and networks, in the form of virtual servers or virtual storage, providing cloud customers with various components of a computing environment. PaaS provides a platform on top of abstracted hardware for developing cloud applications. SaaS provides software applications, providing access to use specific software without the need for installation or configuration (Somu, Kirthivasan, & VS (2017).

2.2. Performance evaluation of CSPs

Alhamad, Dillon, and Chang (2011) proposed a model for evaluating IaaS providers using the fuzzy set theory. They used a Sugeno fuzzy-inference approach to develop an overall measure of CSPs that allows cloud service customers to assess the trustworthiness of CSPs when creating or shifting their distributed systems to cloud data centers. To evaluate and select an appropriate SaaS provider, Martens and Teuteberg (2012) consider cost and risk factors in the decision-making process. Using an analytical hierarchy process (AHP) approach, they consider the risks associated with implementing a model given a sustainable decision-making approach, then validate the model with a simulation study that considers realistic SaaS scenarios. Kumar and Agarwal (2014) presented a framework for evaluating and selecting cloud services that act as a tool for selecting the most suitable CSP from the Web Repository. Their approach is based on AHP and multi-criteria quality of service (QoS) decision-making to accelerate the evaluation and selection process. Aruna & Aramudhan (2016) proposed a mechanism for ranking and selecting CSPs based on a fuzzy set approach with three general phases including problem decomposition, judgment of priorities, and an aggregation of these priorities. Supriya, Sangeeta, and Patra (2016) assessed the efficiency of IaaS providers using MCDM models. The process of determining a service provider's efficiency level relies on parameters provided by the Cloud Service Measurement Initiative Consortium, with priority given to the finance, security, and performance criteria. Somu et al. (2017)) proposed a model for evaluating and ranking CSPs using a hypergraph-based computational model and a minimum-distance Helly property

[2] Infrastructure as a service
[3] Platform as a service
[4] Software as a service

algorithm. They address the issue of missing values in CSP rankings with an expectation-maximization algorithm and arithmetic residue. Filiopoulou et al. (2018) suggested a DEA approach to evaluate the performance of CSPs. Azadi et al. (2020) developed a mixed ideal and anti-ideal DEA model to assess CSPs. The author used pessimistic and optimistic technique in their developed DEA model. Azadi et al. (2021) presented a DEA model to assess sustainable CSPs in the presence of quasi-fixed inputs and integer data. The model considers the manager's opinions on the indicators' weights based on the trade-off principle. Azadi et al. (2022) proposed a network DEA model for measuring the efficiency of CSPs. The model measures the efficiency of CSPs that provide their customer with a specific service such as IaaS or PaaS. Although these studies demonstrate progress in evaluating and selecting CSPs for specific components of a cloud supply chain, no model or framework is able to evaluate the efficiency of a CSP in the context of an entire supply chain with a unified model. Nor do existing studies address the performance measurement of CSPs across a supply chain while taking QoS indicators into account. Further, most existing models for evaluating and selecting CSPs suffer from complex calculations, require intensive user effort, and are time-consuming. Table 1 presents the approaches used for performance evaluation of CSPs.

Table 1. The approaches used for performance evaluation of CSPs

Authors	Approaches	Structures
Alhamad et al. (2011)	Fuzzy set theory	Black Box
Martens & Teuteberg (2012)	AHP	Black Box
Kumar & Agarwal (2014)	AHP	Black Box
Aruna & Aramudhan (2016)	Fuzzy set theory	Black Box
Supriya et al. (2016)	AHP and Fuzzy set theory	Black Box
Somu et al. (2017)	Hypergraph-based technique (HBT)	Black Box
Filiopoulou et al. (2018)	DEA	Black Box
Azadi et al. (2020)	DEA	Black Box
Azadi et al. (2021)	DEA	Black Box
Azadi et al. (2022)	DEA	Black Box
This study	Network DEA	Network

2.3. DEA and network DEA

DEA is a rigorous technique for measuring the relative efficiency of a set of decision-making units where multiple inputs produce multiple outputs. DEA forms an efficient combination of input and output variables by analyzing historical data and constructing an efficiency boundary. A DMU is deemed efficient if it lies on the boundary; otherwise, it is deemed inefficient. As Kao & Hwang (2010) discuss, in the last few decades many DEA models have been developed and applied, e.g., business performance measurement (Serrano-Cinca, Fuertes-Callén, & Mar-Molinero, 2005), decision-making performance with group decision support systems (Barkhi & Kao, 2010), evaluating supply chain management (Toloo, 2014; Toloo & Barat, 2015; Mirhedayatian et al. 2014), efficiency evaluation of sustainable suppliers (Azadi et al. 2015), technology selection (Wu et al. 2016a), allocation of emission reduction tasks (Wu et al. 2016b), measuring the performance of humanitarian supply chains (Izadikhah et al. (2019), and measuring the impact of enterprise integration on firm performance (Fazlollahi & Franke, 2018). However, the conventional DEA models only consider inputs and outputs; the operations of the internal components are ignored when measuring efficiency. When a system consists of several components operating interdependently, ignoring the operations within a component may result in misleading efficiency measurements (Kao, 2016). Hence, the operations of the components need to be considered when measuring performance in a network structure. When a DEA method is applied to systems with internal structures, it becomes a network DEA method as proposed by Färe & Grosskopf (2000). Related models have subsequently been developed for applications ranging from supply chain management to banking (Kao, 2014; Kao 2016). Though, despite the several advantages DEA and network DEA bring, their application to areas such as cloud computing is scarce.

DEA assumes that producing more output relative to less input is one criterion of efficiency. However, some outputs may be undesirable, such as pollution or noise (Cooper, 2007). Therefore, the results of an efficiency evaluation are likely to be less than optimal if bad outputs are not addressed in the model. Seiford & Zhu (2002) presented a DEA model for improving model performance by increasing the desirable outputs and decreasing the undesirable outputs. Jahanshahloo, Lotfi, Shoja, Tohidi, & Razavyan (2005) presented a non-radial DEA model that simultaneously considers both undesirable inputs and outputs. Other studies on undesirable outputs include Li et al. (2017); Chen et al. (2017); Khoshroo et al. (2018); and Toloo & Hanclova (2019).

Conventional DEA models also assume all inputs and outputs have real values. Although, in many real-world applications, some inputs and outputs only have integer values. As an example, analyzing the efficiency of hospitals requires inputs like the number of doctors and nurses and outputs such as the number of surgeries. These attributes are integer-valued data (Du, Chen, Chen, Cook, & Zhu, 2012). Integer-valued data was first incorporated into DEA by Lozano & Villa (2006). Matin & Kuosmanen (2009) improved Lozano & Villa's model by composing a new axiomatic foundation, which resulted in a mixed-integer linear programming (MILP) DEA model that is consistent with the minimum extrapolation principle in the Banker-Charnes-Cooper model (Wu & Zhou, 2015). Chen et al. (2012) incorporated undesirable factors into integer-valued DEA to evaluate the operational efficiencies of city bus systems considering safety records.

Further, many observations in the real world are stochastic. Consequently, the resulting efficiencies are stochastic as well (Kao & Liu, 2009). A case in point is the stock market, in which some observations, such as prices, change dramatically due to uncertainty in the environment. Talluri, Narasimhan, and Nair (2006) proposed a chance-constrained DEA for supplier selection by incorporating stochastic considerations into evaluation decisions. Izadikhah & Saen (2018) proposed a two-stage chance-constrained DEA for evaluating the sustainability of supply chains in the presence of undesirable factors. Although there has been some research into undesirable outputs, integer-valued data, and stochastic data with respect to DEA and network DEA, no studies address these conditions in an integrated DEA or network DEA framework. Table 2 exhibits various studies in the DEA literature for dealing with undesirable outputs, integer data, and stochastic data.

Table 2. DEA models with undesirable outputs, integer data, and stochastic data

Studies	Undesirable output	Integer data	Stochastic data
Seiford & Zhu (2002)	×		
Jahanshahloo et al. (2005)	×		
Li et al. (2017)	×		
Chen et al. (2017)	×		
Khoshroo et al. (2018)	×		
Toloo & Hanclova (2019)	×		
Lozano & Villa (2006)		×	
Matin & Kuosmanen (200)		×	
Chen et al. (2012)	×	×	
Talluri et al. (2006)			×
Izadikhah & Saen (2018)			×
This study	×	×	×

2.5 The cloud environment and its supply chain

As is shown in Figure 1, cloud computing services can be divided into three categories according to the abstraction level of the service provided and the provider’s business model. These categories are IaaS, PaaS, and SaaS (Buyya, Broberg, & Goscinski, 2011).

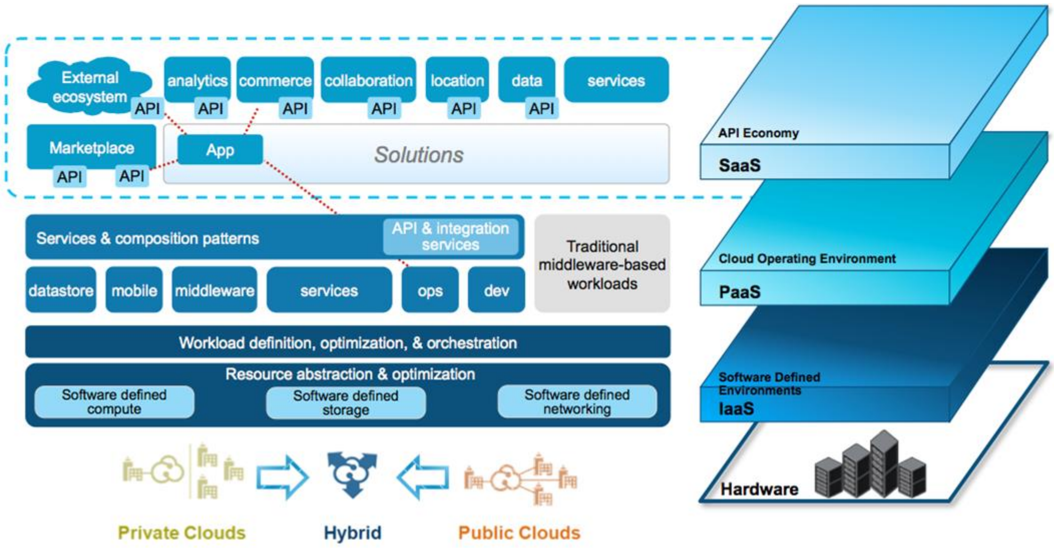

Figure 1. Cloud computing services (Angel Diaz & Chris Ferris, 2013)

IaaS offers on-demand virtual resources, such as processing, storage, or network infrastructure. Infrastructure services are considered to be the bottom layer of a cloud computing system (Buyya et al., 2011), providing customers with a choice of servers, operating systems, and a customized software stack. Although customers do not manage or control the underlying infrastructure, they do control the operating systems, storage, and deployed applications. They may also have limited control of selected networking components (e.g., host firewalls). In short, IaaS focuses on operations. EC2 is a good example of an IaaS (Ramezani, 2016). Beyond infrastructure, the next category of cloud services offers a higher level of abstraction for developing cloud-based applications – i.e., an environment where developers can create and deploy applications using programming languages, libraries, services, and tools. These types of services are known as PaaS. Here, PaaS customers do not need to know how many processors or how much memory an application might be using. Customers do not manage or control the underlying cloud infrastructure, but they do control the deployed applications and possibly the configuration settings of the hosting environment. PaaS is designed for developers. Examples include CloudBees, dotCloud, and AppFog (Ramezani, 2016). On-premises software, often abbreviated as on-prem software, is installed and executed on a personal computer rather than at a remote facility, such as a server farm or cloud. On-premises software is sometimes referred to as "shrinkwrap" software, while off-premises software is commonly called SaaS or "computing in the cloud" (Mangaiyarkarasi, Sureshkumar, & Elango, 2013). In SaaS, the applications reside at the top of the cloud stack and are accessed through a web browser. Given the benefits of SaaS, consumers are increasingly shifting from traditional desktop applications, such as word processing, spreadsheets, and email clients, to online software offered as a service. For customers, this option reduces the burden of software maintenance. For CSPs, this option simplifies development and testing (Buyya et al., 2011). SaaS consumers do not manage or control the underlying cloud infrastructure or the applications' capabilities, with the possible exception of limited configuration settings. SaaS focuses on end-users. Examples include Gmail, Microsoft Office 365, and Salesforce (Ramezani, 2016).

Figure 2 shows the responsibilities of the customer and the provider in four different types of service offerings. A supply chain is the system of organizations, people, activities, information, and resources involved in moving a product or service from a supplier to a customer (Reefke & Sundaram, 2018). Cloud supply chain activities include providing computing infrastructure, software development platforms, and software to the end customer. In a cloud supply chain, IaaS is often provided to PaaS suppliers; PaaS suppliers deliver their services to SaaS suppliers, and all services can be delivered to cloud service customers. Figure 3 illustrates the cloud supply chain. In terms of DEA, the three cloud services – IaaS, PaaS, and SaaS – are considered as three stages in the chain, while the providers are the decision-making units.

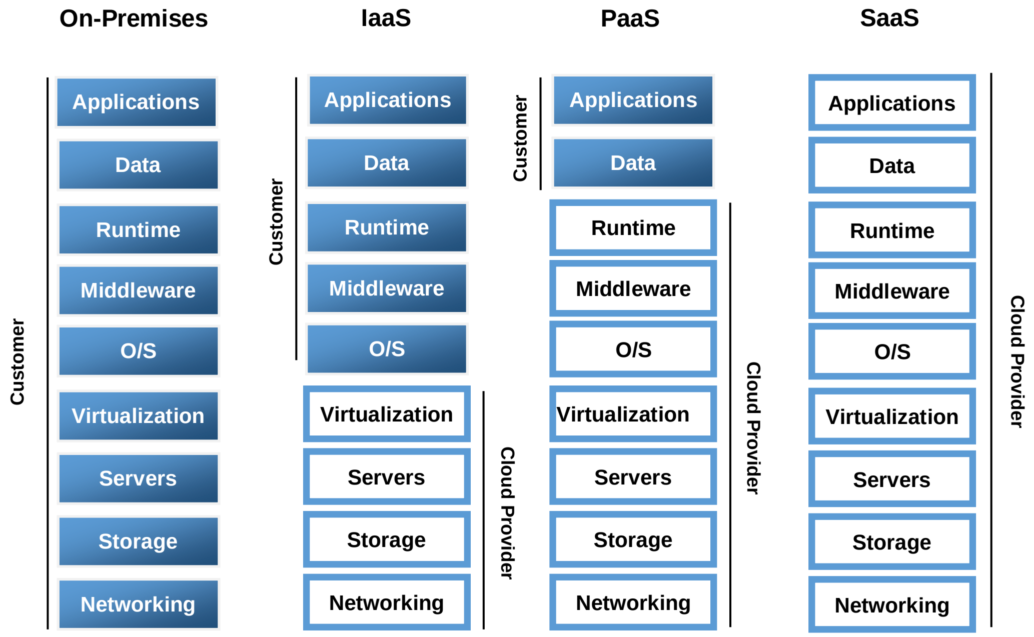

Figure 2. The responsibilities of customers and cloud providers given different service types (Ramezani, 2016)

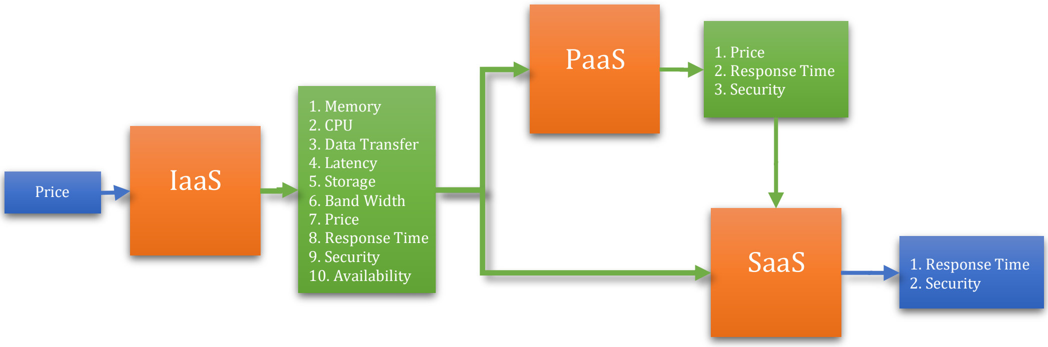

Figure 3. The cloud supply chain

2.6. Research gaps

In summary, although a great deal of work has been undertaken in evaluating and selecting CSPs, these methods and frameworks have various limitations and gaps. These are summarized as follows.

(a) Previous research has developed and used different methods for evaluating the efficiency of CSPs. Yet none can evaluate CSPs in a supply chain as a unified system.

(b) Most existing models for the selection and performance measurement of CSPs suffer from complex calculations, are effort-intensive, and are time-consuming.

(c) No existing model can provide customers with an optimal CSP composition given their QoS priorities, such as cost or latency.

(d) The techniques for evaluating and selecting CSPs have ranged from simple weighted scoring methods to advanced mathematical programming methods. However, despite the importance of undesirable outputs, integer-valued data, and stochastic data as part of an efficiency evaluation, these factors have not received attention and no studies address these conditions in terms of CSPs or DEA.

As discussed, cloud computing can improve the sustainability of operations and eases production processes (Kumar et al. 2020).

3. A decision support system for evaluating the performance of CSPs

The decision-making system for evaluating CSPs across a cloud supply chain is summarized in the following algorithm.

Begin.

Step 1: Construct the cloud supply chain.

Step 2: Determine the decision-making variables (i.e., the inputs, the intermediate, and the outputs variables).

Step 3: Build three separate DEA ranking models to consider the undesirable, integer, and stochastic variables (further described in Section 5).

Step 4: Integrate the three models from Step 3 into one model that considers all three variables.

Step 5: Identify the three different variable types.

Step 6: Determine the scope of the problem, i.e., the number of stages (services) in the supply chain that need to be considered given the customer's priorities.

Step 7: Select the relevant DEA ranking models based on the number of stages and the type of decision-making variables.

Step 8: Analyse the results of the evaluation.

Step 9: Recommend the highest-ranking CSPs.

End.

Figure 4 shows the flowchart for the proposed model for evaluating CSPs in network structure.

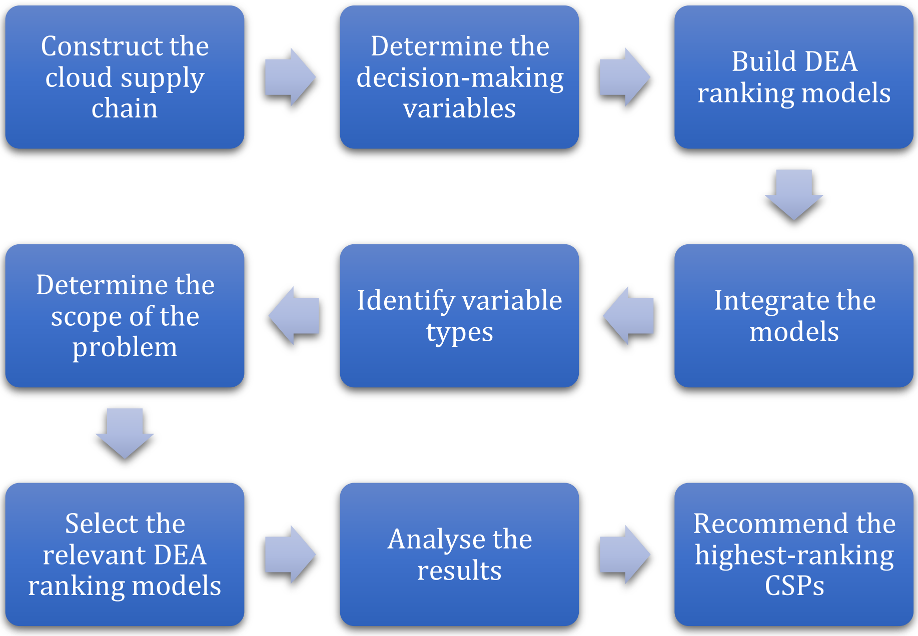

Figure 4. The flowchart for the proposed model

Figure 5 illustrates the decision support system based on this algorithm, hereafter referred to as the CSP performance evaluation system (CSP-PE). The input variables are:

1. The decision-making variables in the constructed cloud supply chain.
2. The types of decision-making variables (integer, undesirable, stochastic).
3. The customer's priorities. For example, low response times or cost reduction.
4. The number of stages, i.e., how many different types of cloud services are included in the supply chain (IaaS, PaaS, and SaaS). Depending on the scope of the evaluation problem, there can be between one and three stages.

The system's engine comprises four main components:

(a) Component 1: This component considers a two-stage SBM network DEA. It comprises two models – Models (1) and (2).
(b) Component 2: This component considers only integer-valued data. It comprises two models – Models (3) and (4).
(c) Component 3: This component considers deterministic undesirable outputs and integer-valued data and comprises Models (3) and (4).
(d) Component 4 is a unified, deterministic equivalent for Models (5) and (6). This component considers each of the three types of decision-making variables with two models – Models (7) and (8).

Each of these components and their models is discussed in more detail in Section 4. CSP-PE's structure is based on the cloud supply chain. Its output is a ranked list of CSPs and the optimal composition of those CSPs given the customer's requirements. For example, a customer may benefit more from choosing IaaS_1, PaaS_5, and SaaS_3 rather than choosing one provider that offers all three services.

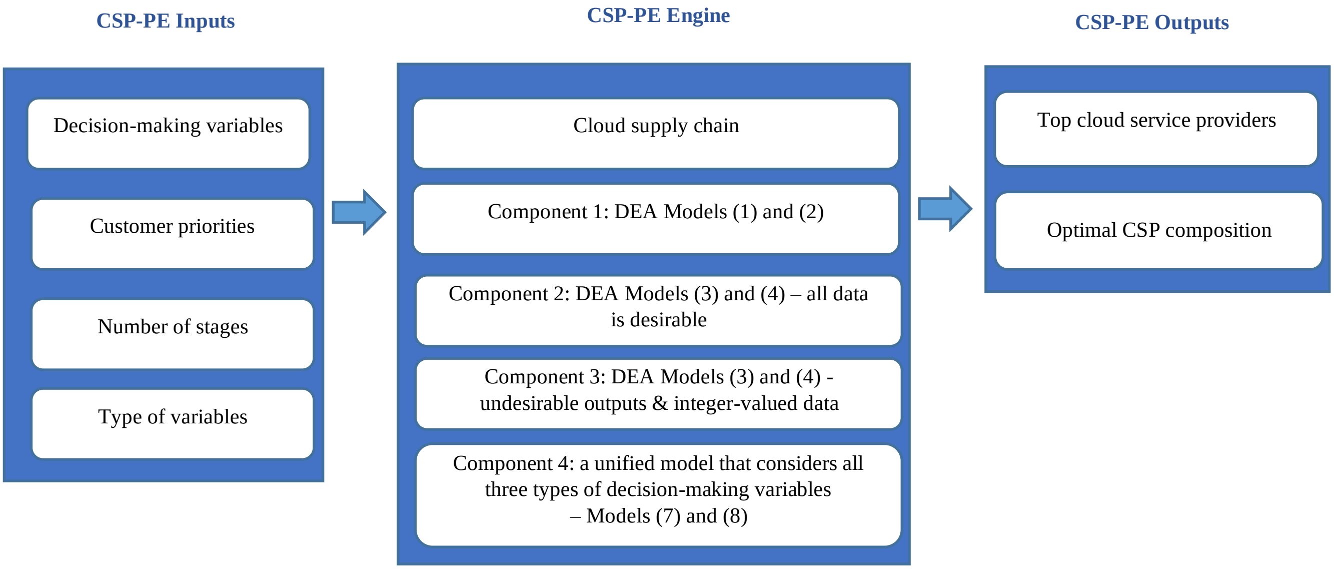

Figure 5. The suggested decision support system

4. The proposed DEA models

4.1. Two-stage SBM network DEA models with undesirable outputs and integer-valued data

The method of the current article is based on the SBM network DEA approach proposed by Tone & Tsutsui (2009). SBM network DEA is a powerful approach for evaluating both individual and overall efficiency. We begin by introducing the notations used in this paper. Suppose that *n* decision-making units (DMUs) ($j = 1, \dots, n$) somehow need to be evaluated over a set of inputs $I(= \{1, \dots, |I|\})$ and a set of outputs $R(= \{1, \dots, |R|\})$. Each observation of DMU_k is characterized by the magnitudes of the inputs to be consumed $\boldsymbol{x}_k = \left(x_{1k}, \dots, x_{|I|k}\right)$ and the outputs to be produced $\boldsymbol{y}_k = \left(y_{1k}, \dots, y_{|R|k}\right)$. Moreover, it is assumed that each DMU is divided into two sub-DMUs (Stage 1 and Stage 2), where Stage 1 of DMU_k uses $\boldsymbol{x}_k$ and Stage 2 of DMU_j produces $\boldsymbol{y}_k$. There is also a set of intermediate measures $L(= \{1, \dots, |L|\})$, where each $\boldsymbol{z}_k = (z_{1k}, \dots, z_{|L|k})$ simultaneously plays the role of the outputs and inputs for Stage 1 and Stage 2, respectively. In these two-stage network DEA models, the SBM efficiency of Stage 1 is formulated as follows:

$$
\begin{aligned}
&\rho_1^* = \min \tau - \frac{1}{|I|}\left(\sum_{i\in I}\frac{s_i^-}{x_{io}}\right) && \\
&\tau + \frac{1}{|L|}\left(\sum_{l\in L}\frac{s_l^+}{z_{lo}}\right) = 1 && \\
&\tau x_{io} - s_i^- = \sum_{j=1}^{n} x_{ij}\lambda_j && \forall i \in I \\
&\tau z_{lo} + s_l^+ = \sum_{j=1}^{n} z_{lj}\lambda_j && \forall l \in L \\
&\sum_{j\in J}\lambda_j = \tau && \\
&\lambda_j \geq 0 && \forall j \in J \\
&s_i^- \geq 0 && \forall i \in I \\
&s_l^+ \geq 0 && \forall l \in L
\end{aligned} \tag{1}
$$

where $\boldsymbol{s}^- = \left(s_1^-, \dots, s_{|I|}^-\right)$ are the input excesses and $\boldsymbol{s}^+ = \left(s_1^+, \dots, s_{|L|}^+\right)$ are the output (intermediate) shortfalls, also known as slacks. Let an optimal solution for Model (1) be $\left(\boldsymbol{\lambda}^*, \boldsymbol{s}^{-*}, \boldsymbol{s}^{+*}\right) \in \mathbb{R}^{n+|I|+|L|}$. Similarly, the SBM efficiency of Stage 2 can be measured by

$$
\begin{aligned}
&\rho_2^* = \min \tau - \frac{1}{|L|}\left(\sum_{l\in L}\frac{s_l^-}{z_{lo}}\right) && \\
&\tau + \frac{1}{|R|}\left(\sum_{r\in R}\frac{s_r^+}{y_{ro}}\right) = 1 && \\
&\tau z_{lo} - s_l^- = \sum_{j=1}^{n} z_{lj}\lambda_j && \forall l \in L \\
&\tau y_{ro} + s_r^+ = \sum_{j=1}^{n} y_{rj}\lambda_j && \forall r \in R \\
&\sum_{j\in J}\lambda_j = \tau && \\
&\lambda_j \geq 0 && \forall j \in J \\
&s_l^- \geq 0 && \forall l \in L \\
&s_r^+ \geq 0 && \forall r \in R
\end{aligned} \tag{2}
$$

Here, $\boldsymbol{s}^- = \left(s_1^-, \dots, s_{|L|}^-\right)$ are the input (intermediate) excesses, and $\boldsymbol{s}^+ = \left(s_1^+, \dots, s_{|R|}^+\right)$ are the output shortfalls, again, known as slacks. Also, λ is the intensity vector. Let an optimal solution for Model (2) be $\left(\boldsymbol{\lambda}^*, \boldsymbol{s}^{-*}, \boldsymbol{s}^{+*}\right) \in \mathbb{R}^{n+|L|+|R|}$.

Definition 1. The optimal objective values $\boldsymbol{\rho_1^*}$ and $\boldsymbol{\rho_2^*}$ are the SBM efficiency of Stages 1 and 2, respectively, for $\mathbf{DMU}_{\boldsymbol{o}}$.

Definition 2. The overall SBM efficiency of DMU_o is $\frac{\rho_1^*+\rho_2^*}{2}$. If we have $\rho_1^* = \rho_2^* = 1$, then DMU_o shows SBM efficiency overall.

Two types of integer and non-integer measures are considered. It is assumed that I^{IN} and I^{NI} are two mutually exclusive and collectively exhaustive input subsets for integer and non-integer-valued inputs. Mathematically, $I^{IN} \cup I^{NI} = I$ and $I^{IN} \cap I^{NI} = \phi$. Similarly, we let the integer- and non-integer-valued of outputs and intermediate measures be respectively R^{IN}, R^{NI} and L^{IN}, L^{NI}. In addition, all the outputs and intermediate measures are partitioned into four subsets ($R^{INU}, R^{NIU}, R^{IND}, R^{NID}$ and $L^{INU}, L^{NIU}, L^{IND}, L^{NID}$) to consider the undesirable outputs, where the superscript INU represents the integer-valued undesirable variables, NIU denotes the non-integer-valued undesirable variables, INU, IND, NID, integer-valued desirable, and non-integer-valued desirable measures. We suggest the following mixed-integer linear programming to measure the SBM efficiency of Stage 1 in the presence of integer-valued inputs and (un)desirable intermediate variables:

$$
\begin{array}{ll}
\rho_1^* = \min \tau - \frac{1}{|I^{NI}|+|I^{IN}|}\left(\sum_{i\in I^{NI}}\frac{s_i^-}{x_{io}} + \sum_{i\in I^{IN}}\frac{(s_i^-+t_i^-)}{x_{io}}\right) & \\
1 = \tau + \frac{\left(\sum_{l\in L^{NID}}\frac{s_l^{+D}}{z_{lo}}+\sum_{l\in L^{IND}}\frac{(s_l^{+D}+t_l^{+D})}{z_{lo}}+\sum_{l\in L^{NIU}}\frac{s_l^{-U}}{z_{lo}}+\sum_{l\in L^{INU}}\frac{(s_l^{-U}+t_l^{-U})}{z_{lo}}\right)}{|L^{NID}|+|L^{IND}|+|L^{NIU}|+|L^{INU}|} & \\
\tau x_{io} - s_i^- = \sum_{j=1}^n x_{ij}\lambda_j & \forall i \in I^{NI} \\
\bar{x}_i - s_i^- = \sum_{j=1}^n x_{ij}\lambda_j & \forall i \in I^{IN} \\
\tau x_{io} - t_i^- = \bar{x}_i & \forall i \in I^{IN} \\
\tau z_{lo} + s_l^{+D} = \sum_{j=1}^n z_{lj}\lambda_j & \forall l \in L^{NID} \\
\bar{z}_l + s_l^{+D} = \sum_{j=1}^n z_{lj}\lambda_j & \forall l \in L^{IND} \\
\tau z_{lo} + t_l^{+D} = \bar{z}_l & \forall l \in L^{IND} \\
\tau z_{lo} - s_l^{-U} = \sum_{j=1}^n z_{lj}\lambda_j & \forall l \in L^{NIU} \\
\bar{z}_l - s_l^{-U} = \sum_{j=1}^n z_{lj}\lambda_j & \forall l \in L^{INU} \\
\tau z_{lo} - t_l^{-U} = \bar{z}_l & \forall l \in L^{INU} \\
\sum_{j\in J}\lambda_j = \tau & \\
\lambda_j \geq 0 & \forall j \in J \\
s_i^- \geq 0 & \forall i \in I \\
t_i^- \geq 0 & \forall i \in I^{IN} \\
s_l^{+D} \geq 0 & \forall l \in L^D \\
t_l^{+D} \geq 0 & \forall l \in L^{IND} \\
s_l^{-U} \geq 0 & \forall l \in L^U \\
t_l^{-U} \geq 0 & \forall l \in L^{INU} \\
\bar{x}_i \in \mathbb{Z}_+ & \forall i \in I^{IN} \\
\bar{z}_l \in \mathbb{Z}_+ & \forall l \in L^{IN}
\end{array}
\tag{3}
$$

where $L^D = L^{IND} \cup L^{NID}$, $L^U = L^{INU} \cup L^{NIU}$, $\bar{x}_i$ and $\bar{z}_l$ are integer decision variables that indicate integer-valued reference points for input $i \in I^{IN}$ and intermediate $l \in L^{IN}$. It should be noted that, here, there are two types of slacks: one for the integer-valued inputs and the other for the intermediate variables. The first type of slack, $i \in I^{IN}$, i.e., s_i^-, is the difference between the combination $\sum_{j=1}^n x_{ij}\lambda_j$ and the integer-valued $\bar{x}_i$. The second type of slack t_i^- is the difference between the integer-valued $\bar{x}_i$ and the projection τx_{io}. As a result, $s_i^- + t_i^-$ is the total slack for an integer-valued x_i. Similarly, the total slack for the integer-valued desirable measures and the undesirable intermediate measures are, $s_l^{+D} + t_l^{+D}$ and $s_l^{-U} + t_l^{-U}$, respectively. These values are considered in the objective function of Model (3) along with a set of normalization constraints.

Analogously, Model (2) evaluates efficiency in Stage 2 according to the integer-valued intermediate variables and the (un)desirable outputs. Model (2) is formulated as follows:

$$
\begin{aligned}
&\rho_2^* = \min \tau - \frac{1}{|L^{NI}|+|L^{IN}|}\left(\sum_{l\in L^{NI}} \frac{s_l^-}{z_{lo}} + \sum_{l\in L^{IN}} \frac{(s_l^- + t_l^-)}{z_{lo}}\right) && \\
&1 = \tau + \frac{\left(\sum_{r\in R^{NID}} \frac{s_r^{+D}}{y_{ro}} + \sum_{r\in R^{IND}} \frac{(s_r^{+D}+t_r^{+D})}{y_{ro}} + \sum_{r\in R^{NIU}} \frac{t_r^{-U}}{y_{ro}} + \sum_{r\in R^{INU}} \frac{(s_r^{-U}+t_r^{-U})}{y_{ro}}\right)}{|R^{NID}|+|R^{IND}|+|R^{NIU}|+|R^{INU}|} && \\
&\tau z_{lo} - s_l^- = \textstyle\sum_{j=1}^{n} z_{lj}\lambda_j && \forall l \in L^{NI} \\
&\bar{z}_l - s_l^- = \textstyle\sum_{j=1}^{n} z_{lj}\lambda_j && \forall l \in L^{IN} \\
&\tau z_{lo} - t_l^- = \bar{z}_l && \forall l \in L^{IN} \\
&\tau y_{ro} + s_r^{+D} = \textstyle\sum_{j=1}^{n} y_{rj}\lambda_j && \forall r \in R^{NID} \\
&\bar{y}_r + s_r^{+D} = \textstyle\sum_{j=1}^{n} y_{rj}\lambda_j && \forall r \in R^{IND} \\
&\tau y_{ro} + t_r^{+D} = \bar{y}_r && \forall r \in R^{IND} \\
&\tau y_{ro} - s_r^{+U} = \textstyle\sum_{j=1}^{n} y_{rj}\lambda_j && \forall r \in R^{NIU} \\
&\bar{y}_r - s_r^{+U} = \textstyle\sum_{j=1}^{n} y_{rj}\lambda_j && \forall r \in R^{INU} \qquad (4) \\
&\tau y_{ro} - t_r^{+U} = \bar{y}_r && \forall r \in R^{INU} \\
&\textstyle\sum_{j\in J} \lambda_j = \tau && \\
&\lambda_j \geq 0 && \forall j \in J \\
&s_l^- \geq 0 && \forall l \in L \\
&t_l^- \geq 0 && \forall l \in L^{IN} \\
&s_r^{+D} \geq 0 && \forall r \in R^D \\
&t_r^{+D} \geq 0 && \forall r \in R^{IND} \\
&s_r^{+U} \geq 0 && \forall r \in R^U \\
&t_r^{+U} \geq 0 && \forall r \in R^{INU} \\
&z_l \in \mathbb{Z}_+ && \forall l \in L^{IN} \\
&y_r \in \mathbb{Z}_+ && \forall r \in R^{IN}
\end{aligned}
$$

where $R^D = R^{IND} \cup R^{NID}$ and $R^U = R^{INU} \cup R^{NIU}$. Models (3) and (4) evaluate the individual efficiency of each DMU_o in Stage 1 and Stage 2, respectively, given integer-valued and undesirable data. The overall SBM efficiency of a DMU_o is derived from an average of the efficiency in Stages 1 and 2 (see Definition 2).

4.2. Two-stage SBM network DEA models with undesirable outputs, integer-valued data, and stochastic data

Most DEA and network DEA models treat data as being deterministic. Subsequently, the relative efficiencies of the DMUs are also deterministic. However, measuring the efficiency of CSPs in practical applications often involves random variables and uncertainty. Hence, Models (5) and (6) rely on a chance-constrained programming approach that allows for random variations in the data. As discussed by Zha et al. (2016), chance-constrained programming can robustly deal with data uncertainty when that uncertainty is caused by random errors in the data set. By incorporating different levels of random errors into the model, chance-constrained programming can show the influence the “randomness” has had on the evaluation results. Moreover, this approach focuses on real units and the uncertainty inherent in individual inputs, intermediate variables, and outputs.

To this end, we use $\tilde{\boldsymbol{x}}_j = (\tilde{x}_{1j}, \dots, \tilde{x}_{|I|j})$, $\tilde{\boldsymbol{y}}_j = (\tilde{y}_{1j}, \dots, \tilde{y}_{|R|j})$, and $\tilde{\boldsymbol{z}}_j = (z_{1j}, \dots, \tilde{z}_{|L|j})$ to represent random input, output, and intermediate vectors, respectively. We presume these random variables follow a normal distribution with known parameters as the normal distribution is less restrictive and can be used to transform other types of distributions into approximately normal forms (Zhou et al., 2017). Let $\boldsymbol{x}_j = (x_{1j}, \dots, x_{|I|j})$, $\boldsymbol{y}_j = (y_{1j}, \dots, y_{|R|j})$, and $\boldsymbol{z}_j = (z_{1j}, \dots, z_{|L|j})$ represent the expected input, output, and intermediate vector values for each $\text{DMU}_j; j = 1, \dots, n$. Mathematically, we assume $E(\tilde{\boldsymbol{x}}_j) = \boldsymbol{x}_j, E(\tilde{\boldsymbol{y}}_j) = \boldsymbol{y}_j$, and $E(\tilde{\boldsymbol{z}}_j) = z_j$. Moreover, for the sake of notation simplicity, we set $\sigma_{\tilde{\mathbf{x}}_{ij}} = \sigma_{ij}^{x}$, $\sigma_{\tilde{\mathbf{y}}_{rj}} = \sigma_{rj}^{y}$, and $\sigma_{\tilde{\mathbf{z}}_{lj}} = \sigma_{lj}^{z}$, $\forall i, \forall r, \forall l, \forall j$. We formulate the following pair of stochastic SBM models to evaluate the SBM efficiency of Stages 1 and 2, respectively[5]:

$$
\begin{array}{lr}
\rho_1^* = \min \rho_1 & \\
P\left\{\rho_1 - \tau + \dfrac{\left(\sum_{i\in I^{NI}} \frac{s_i^-}{x_{io}} + \sum_{i\in I^{IN}} \frac{(s_i^- + t_i^-)}{x_{io}}\right)}{|I^{NI}| + |I^{IN}|} \le 0\right\} \ge 1-\alpha & \\
P\left\{\tau + \dfrac{\left(\sum_{l\in L^{NID}} \frac{s_l^{+D}}{z_{lo}} + \sum_{l\in L^{IND}} \frac{(s_l^{+D} + t_l^{+D})}{z_{lo}} + \sum_{l\in L^{NIU}} \frac{s_l^{-U}}{z_{lo}} + \sum_{l\in L^{INU}} \frac{(s_l^{-U} + t_l^{-U})}{z_{lo}}\right)}{|L^{NID}| + |L^{IND}| + |L^{NIU}| + |L^{INU}|} = 1\right\} \ge 1-\alpha & \\
P\left\{\sum_{j=1}^{n} \tilde{x}_{ij}\lambda_j + s_i^- \le \tau \tilde{x}_{io}\right\} \ge 1-\alpha & \forall i \in I^{NI} \\
P\left\{\sum_{j=1}^{n} \tilde{x}_{ij}\lambda_j + s_i^- \le \bar{x}_i\right\} \ge 1-\alpha & \forall i \in I^{IN} \\
P\left\{\bar{x}_i + t_i^- \le \tau \tilde{x}_{io}\right\} \ge 1-\alpha & \forall i \in I^{IN} \\
P\left\{\sum_{j=1}^{n} \tilde{z}_{lj}\lambda_j - \tau \tilde{z}_{lo} \ge s_l^{+D}\right\} \ge 1-\alpha & \forall l \in L^{NID} \\
P\left\{\sum_{j=1}^{n} \tilde{z}_{lj}\lambda_j - \bar{z}_l \ge s_l^{+D}\right\} \ge 1-\alpha & \forall l \in L^{IND} \\
P\left\{\bar{z}_l - \tau \tilde{z}_{lo} \ge t_l^{+D}\right\} \ge 1-\alpha & \forall l \in L^{IND} \\
P\left\{\sum_{j=1}^{n} \tilde{z}_{lj}\lambda_j + s_l^{+U} \ge \tau \tilde{z}_{lo}\right\} \ge 1-\alpha & \forall l \in L^{NIU} \\
P\left\{\sum_{j=1}^{n} \tilde{z}_{lj}\lambda_j + s_l^{+U} \ge \bar{z}_l\right\} \ge 1-\alpha & \forall l \in L^{INU} \\
P\left\{\tau \tilde{z}_{lo} - t_l^{+U} \le \bar{z}_l\right\} \ge 1-\alpha & \forall l \in L^{INU} \\
\sum_{j\in J} \lambda_j = \tau & \\
\lambda_j \ge 0 & \forall j \in J \\
s_i^- \ge 0 & \forall i \in I \\
t_i^- \ge 0 & \forall i \in I^{IN} \\
s_l^{+D} \ge 0 & \forall l \in L^{D} \\
t_l^{+D} \ge 0 & \forall l \in L^{IND} \\
s_l^{-U} \ge 0 & \forall l \in L^{U} \\
t_l^{-U} \ge 0 & \forall l \in L^{INU} \\
\bar{x}_i \in \mathbb{Z}_+ & \forall i \in I^{IN} \\
\bar{z}_l \in \mathbb{Z}_+ & \forall l \in L^{IN}
\end{array}
\tag{5}
$$

[5] For more details about the chance-constrained programming approach, see Cooper, Deng, Huang, & Li (2004) and Cooper, Deng, Huang, & Li (2002).

$$
\begin{array}{ll}
\rho_2^* = \min \rho_2 & \\
P\left\{\rho_2 - \tau \frac{1}{|L^{NI}|+|L^{IN}|}\left(\sum_{l\in L^{NI}} \frac{s_l^-}{z_{lo}} + \sum_{l\in L^{IN}} \frac{(s_l^- + t_l^-)}{z_{lo}}\right) \le 0\right\} \ge 1-\alpha & \\
P\left\{\tau + \frac{\left(\sum_{r\in R^{NID}} \frac{s_r^{+D}}{y_{ro}} + \sum_{r\in R^{IND}} \frac{(s_r^{+D} + t_r^{+D})}{y_{ro}} + \sum_{r\in R^{NIU}} \frac{t_r^{-U}}{y_{ro}} + \sum_{r\in R^{INU}} \frac{(s_r^{-U} + t_r^{-U})}{y_{ro}}\right)}{|R^{NID}|+|R^{IND}|+|R^{NIU}|+|R^{INU}|} = 1\right\} \ge 1-\alpha & \\
P\left\{\sum_{j=1}^n \tilde{z}_{lj}\lambda_j + s_l^- \le \tau\tilde{z}_{lo}\right\} \ge 1-\alpha & \forall l \in L^{NI} \\
P\left\{\sum_{j=1}^n \tilde{z}_{lj}\lambda_j + s_l^- \le \bar{z}_l\right\} \ge 1-\alpha & \forall l \in L^{IN} \\
P\{\bar{z}_l + t_l^- \le \tau\tilde{z}_{lo}\} \ge 1-\alpha & \forall l \in L^{IN} \\
P\left\{\sum_{j=1}^n \tilde{y}_{rj}\lambda_j - \tau\tilde{y}_{ro} \ge s_r^{+D}\right\} \ge 1-\alpha & \forall r \in R^{NID} \\
P\left\{\sum_{j=1}^n \tilde{y}_{rj}\lambda_j - \bar{y}_r \ge s_r^{+D}\right\} \ge 1-\alpha & \forall r \in R^{IND} \\
P\{\bar{y}_r - \tau\tilde{y}_{ro} \ge t_r^{+D}\} \ge 1-\alpha & \forall r \in R^{IND} \\
P\left\{\sum_{j=1}^n \tilde{y}_{rj}\lambda_j + s_r^{+U} \ge \tau\tilde{y}_{ro}\right\} \ge 1-\alpha & \forall r \in R^{NIU} \\
P\left\{\sum_{j=1}^n \tilde{y}_{rj}\lambda_j + s_r^{+U} \ge \bar{y}_r\right\} \ge 1-\alpha & \forall r \in R^{INU} \\
P\{\tau\tilde{y}_{ro} - t_r^{+U} \le \bar{y}_r\} \ge 1-\alpha & \forall r \in R^{INU} \\
\sum_{j\in J} \lambda_j = \tau & \\
\lambda_j \ge 0 & \forall j \in J \\
s_l^- \ge 0 & \forall l \in L \\
t_l^- \ge 0 & \forall l \in L^{IN} \\
s_r^{+D} \ge 0 & \forall r \in R^D \\
t_r^{+D} \ge 0 & \forall r \in R^{IND} \\
s_r^{+U} \ge 0 & \forall r \in R^U \\
t_r^{+U} \ge 0 & \forall r \in R^{INU} \\
\bar{z}_l \in \mathbb{Z}_+ & \forall l \in L^{IN} \\
\bar{y}_r \in \mathbb{Z}_+ & \forall r \in R^{IN}
\end{array}
\tag{6}
$$

where P means probability and $\alpha \in (0,1)$ is a predetermined number. Chance constraints prevent violations with a probability of at most α (Zhou, Lin, Xiao, Ma, & Wu, 2017).

To formulate equivalent deterministic models of (5) and (6), we follow the method of (Cooper, Huang, & Li, 1996). For instance, consider the constraint $P\left\{\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- \le \tau\tilde{x}_{io}\right\} \ge 1 - \alpha$ of model (5), which can be written as $\alpha = P\left\{\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- - \tau\tilde{x}_{io} \ge 0\right\}$ with a pessimistic stand point. By standardization of the left side of the constraint, we obtain $\alpha = P\left\{Z_i \le \frac{E\left(\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- - \tau\tilde{x}_{io}\right)}{\sigma_{\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- - \tau\tilde{x}_{io}}}\right\}$, which leads to $\alpha = \Phi\left(\frac{E\left(\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- - \tau\tilde{x}_{io}\right)}{\sigma_{\sum_{j=1}^n \tilde{x}_{ij}\lambda_j + s_i^- - \tau\tilde{x}_{io}}}\right)$ where Z_i is a random variable from the standard normal distribution. $\Phi(.)$ is the normal distribution function. Employing the aforementioned notations for expected values and standard deviations of $\tilde{\boldsymbol{x}}_j$, we achieve $\alpha = \Phi\left(\frac{\sum_{j=1}^n x_{ij}\lambda_j + s_i^- - \tau x_{io}}{\sum_{j=1}^n \sigma_{ij}^x\lambda_j + \tau\sigma_{io}^x}\right)$, which is equivalent to the following deterministic constraint $\Phi^{-1}(\alpha)\left(\sum_{j=1}^n \sigma_{ij}^x\lambda_j + \tau\sigma_{io}^x\right) = \sum_{j=1}^n x_{ij}\lambda_j + s_i^- - \tau x_{io}$. In a similar manner, an equivalent deterministic version of the constraint of models (5) and (6) can be built. Readers interested in the more detailed development of these models can consult Cooper, Deng, Huang, and Li (2002).

Models (7) and (8) are the deterministic equivalents of Models (5) and (6), which demonstrate how the optimal objective values ρ_1^* and ρ_2^* required for Definition 1 are determined.

$$
\begin{aligned}
&\rho_1^* = \min \tau - \frac{1}{|I^{NI}|+|I^{IN}|}\left(\sum_{i\in I^{NI}} \frac{s_i^-}{x'_{io}} + \sum_{i\in I^{IN}} \frac{(s_i^- + t_i^-)}{x'_{io}}\right) && && \\
&1 = \tau + \frac{\left(\sum_{l\in L^{NID}} \frac{s_l^{+D}}{z'_{lo}} + \sum_{l\in L^{IND}} \frac{(s_l^{+D}+t_l^{+D})}{z'_{lo}} + \sum_{l\in L^{NIU}} \frac{s_l^{-U}}{z'_{lo}} + \sum_{l\in L^{INU}} \frac{(s_l^{-U}+t_l^{-U})}{z'_{lo}}\right)}{|L^{NID}|+|L^{IND}|+|L^{NIU}|+|L^{INU}|} && && \\
&\tau x'_{io} - s_i^- = \sum_{j=1}^{n} x'_{ij}\lambda_j && \forall i \in I^{NI} && \\
&\bar{x}_i - s_i^- = \sum_{j=1}^{n} x'_{ij}\lambda_j && \forall i \in I^{IN} && \\
&\tau x'_{io} - t_i^- = \bar{x}_i && \forall i \in I^{IN} && \\
&\tau z'_{lo} + s_l^{+D} = \sum_{j=1}^{n} z'_{lj}\lambda_j && \forall l \in L^{NID} && \\
&\bar{z}_l + s_l^{+D} = \sum_{j=1}^{n} z'_{lj}\lambda_j && \forall l \in L^{IND} && \\
&\tau z'_{lo} + t_l^{+D} = \bar{z}_l && \forall l \in L^{IND} && \\
&\tau z'_{lo} - s_l^{-U} = \sum_{j=1}^{n} z'_{lj}\lambda_j && \forall l \in L^{NIU} && \\
&\bar{z}_l - s_l^{-U} = \sum_{j=1}^{n} z'_{lj}\lambda_j && \forall l \in L^{INU} && (7) \\
&\tau z'_{lo} - t_l^{-U} = \bar{z}_l && \forall l \in L^{INU} && \\
&\sum_{j\in J} \lambda_j = \tau && && \\
&\lambda_j \geq 0 && \forall j \in J && \\
&s_i^- \geq 0 && \forall i \in I && \\
&t_i^- \geq 0 && \forall i \in I^{IN} && \\
&s_l^{+D} \geq 0 && \forall l \in L^{D} && \\
&t_l^{+D} \geq 0 && \forall l \in L^{IND} && \\
&s_l^{-U} \geq 0 && \forall l \in L^{U} && \\
&t_l^{-U} \geq 0 && \forall l \in L^{INU} && \\
&\bar{x}_i \in \mathbb{Z}_+ && \forall i \in I^{IN} && \\
&\bar{z}_l \in \mathbb{Z}_+ && \forall l \in L^{IN} &&
\end{aligned}
$$

where

$$
x'_{ij} = \begin{cases} x_{io} + \sigma_{io}^{x}\Phi^{-1}(\alpha), & \text{if } i \in I^{NI}, j = o \\ x_{io} + \lceil \sigma_{io}^{x}\Phi^{-1}(\alpha) \rceil, & \text{if } i \in I^{IN}, j = o \\ x_{ij} - \sigma_{ij}^{x}\Phi^{-1}(\alpha), & \text{if } i \in I^{NI}, j \neq o \\ x_{ij} - \lceil \sigma_{ij}^{x}\Phi^{-1}(\alpha) \rceil, & \text{if } i \in I^{IN}, j \neq o \end{cases}
$$

$$
z'_{lo} = \begin{cases} z_{lo} - \sigma_{lo}^{z}\,\Phi^{-1}(\alpha), & \text{if } l \in L^{NID} \\ z_{lo} - \lceil \sigma_{lo}^{z}\,\Phi^{-1}(\alpha) \rceil, & \text{if } l \in L^{INU} \\ z_{lo} + \sigma_{lo}^{z}\,\Phi^{-1}(\alpha), & \text{if } l \in L^{NIU} \\ z_{lo} + \lceil \sigma_{lo}^{z}\,\Phi^{-1}(\alpha) \rceil, & \text{if } l \in L^{INU} \end{cases}
$$

$$
z'_{lj} = \begin{cases} z_{lj} + \sigma_{lj}^{z}\,\Phi^{-1}(\alpha), & \text{if } l \in L^{NID} \\ z_{lj} + \lceil \sigma_{lj}^{z}\,\Phi^{-1}(\alpha) \rceil, & \text{if } l \in L^{INU} \\ z_{lj} - \sigma_{lj}^{z}\,\Phi^{-1}(\alpha), & \text{if } l \in L^{NIU} \\ z_{lj} - \lceil \sigma_{lj}^{z}\,\Phi^{-1}(\alpha) \rceil, & \text{if } l \in L^{INU} \end{cases}
$$

$$
\begin{array}{ll}
\rho_2^* = \min \tau - \frac{1}{|L^{NI}|+|L^{IN}|}\left(\sum_{l \in L^{NI}} \frac{s_l^-}{z''_{lo}} + \sum_{l \in L^{IN}} \frac{\left(s_l^- + t_l^-\right)}{z''_{lo}}\right) & \\
1 = \tau + \frac{\left(\sum_{r \in R^{NID}} \frac{s_r^{+D}}{y''_{ro}} + \sum_{r \in R^{IND}} \frac{\left(s_r^{+D}+t_r^{+D}\right)}{y''_{ro}} + \sum_{r \in R^{NIU}} \frac{t_r^{-U}}{y''_{ro}} + \sum_{r \in R^{INU}} \frac{\left(s_r^{-U}+t_r^{-U}\right)}{y''_{ro}}\right)}{|R^{NID}|+|R^{IND}|+|R^{NIU}|+|R^{INU}|} & \\
\tau z''_{lo} - s_l^- = \sum_{j=1}^{n} z''_{lj} \lambda_j & \forall l \in L^{NI} \\
\bar{z}_l - s_l^- = \sum_{j=1}^{n} z''_{lj} \lambda_j & \forall l \in L^{IN} \\
\tau z''_{lo} - t_l^- = \bar{z}_l & \forall l \in L^{IN} \\
\tau y''_{ro} + s_r^{+D} = \sum_{j=1}^{n} y''_{rj} \lambda_j & \forall r \in R^{NID} \\
\bar{y}_r + s_r^{+D} = \sum_{j=1}^{n} y''_{rj} \lambda_j & \forall r \in R^{IND} \\
\tau y''_{ro} + t_r^{+D} = \bar{y}_r & \forall r \in R^{IND} \\
\tau y''_{ro} - s_r^{+U} = \sum_{j=1}^{n} y''_{rj} \lambda_j & \forall r \in R^{NIU} \\
\bar{y}_r - s_r^{+U} = \sum_{j=1}^{n} y''_{rj} \lambda_j & \forall r \in R^{INU} \\
\tau y''_{ro} - t_r^{+U} = \bar{y}_r & \forall r \in R^{INU} \\
\sum_{j \in J} \lambda_j = \tau & \\
\lambda_j \geq 0 & \forall j \in J \\
s_l^- \geq 0 & \forall l \in L \\
t_l^- \geq 0 & \forall l \in L^{IN} \\
s_r^{+D} \geq 0 & \forall r \in R^{D} \\
t_r^{+D} \geq 0 & \forall r \in R^{IND} \\
s_r^{+U} \geq 0 & \forall r \in R^{U} \\
t_r^{+U} \geq 0 & \forall r \in R^{INU} \\
z_l \in \mathbb{Z}_+ & \forall l \in L^{IN} \\
y_r \in \mathbb{Z}_+ & \forall r \in R^{IN}
\end{array}
\tag{8}
$$

where

$$
z''_{lj} = \begin{cases} z_{lo} + \sigma_{lo}^{z} \Phi^{-1}(\alpha), & \text{if } l \in L^{NI}, j = o \\ z_{lo} + \lceil \sigma_{lo}^{z} \Phi^{-1}(\alpha) \rceil, & \text{if } l \in L^{IN}, j = o \\ z_{lj} - \sigma_{lj}^{z} \Phi^{-1}(\alpha), & \text{if } l \in L^{NI}, j \neq o \\ z_{lj} - \left\lceil \sigma_{lj}^{z} \Phi^{-1}(\alpha) \right\rceil, & \text{if } l \in L^{IN}, j \neq o \end{cases}
$$

$$
y''_{ro} = \begin{cases} y_{ro} - \sigma_{ro}^{z}\, \Phi^{-1}(\alpha), & \text{if } r \in R^{NID} \\ y_{ro} - \lceil \sigma_{ro}^{z}\, \Phi^{-1}(\alpha) \rceil, & \text{if } r \in R^{INU} \\ y_{ro} + \sigma_{ro}^{z}\, \Phi^{-1}(\alpha), & \text{if } r \in R^{NIU} \\ y_{ro} + \lceil \sigma_{ro}^{z}\, \Phi^{-1}(\alpha) \rceil, & \text{if } r \in R^{INU} \end{cases}
$$

$$
y''_{rj} = \begin{cases} y_{rj} + \sigma_{lj}^{y}\, \Phi^{-1}(\alpha), & \text{if } r \in R^{NID} \\ y_{rj} + \left\lceil \sigma_{lj}^{y}\, \Phi^{-1}(\alpha) \right\rceil, & \text{if } r \in R^{INU} \\ y_{rj} - \sigma_{lj}^{y}\, \Phi^{-1}(\alpha), & \text{if } r \in R^{NIU} \\ y_{rj} - \left\lceil \sigma_{lj}^{y}\, \Phi^{-1}(\alpha) \right\rceil, & \text{if } r \in R^{INU} \end{cases}
$$

The feasibility of DEA models is a vital problem, which has been addressed in the DEA literature. Models (3) and (4) are feasible because there are two variants of the SBM model, which are always feasible (see Tone et al. 2020). When the constraint C (including random variables) is stochastic, then its probability is greater than zero or mathematically $P\{C\} \geq 1 - \alpha$ for any $0 < \alpha < 1$. We can conclude that Models (5) and (6) are both feasible because they possess such constraints.

Moreover, Models (7) and (8) inherit their feasibilities from the feasibility of their equivalent models, i.e., Models (5) and (6), respectively.

The following table exhibits the key defined indexes, parameters, and variables in the aforementioned models:

Table 3. List of the employed notations.

Type	Notation	Description	Type	Notation	Description
INDEX	j	DMUs index	**SET**	I	Total inputs
	i	Input index		I^{IN}	Integer-valued inputs
	r	Output index		I^{NI}	Non-integer-valued inputs
	l	Intermediate index		R	Total outputs
	o	DMU under evaluation index		R^{IN}	Integer-valued outputs
PARAMETER	x_{ij}	The i^{th} input of DMU_j		R^{NI}	Non-integer-valued outputs
	z_{lj}	The l^{th} intermediate of DMU_j		R^{INU}	Integer-valued undesirable outputs
	y_{rj}	The r^{th} output of DMU_j		R^{NIU}	Non-integer-valued undesirable outputs
	$\tilde{x}_{ij}$	The i^{th} random input of DMU_j		R^{IND}	Integer-valued desirable outputs
	$\tilde{z}_{lj}$	The l^{th} random intermediate of DMU_j		R^{NID}	Non-integer-valued desirable outputs
	$\tilde{y}_{rj}$	The r^{th} random output of DMU_j		$(R^U)R^D$	(Un)Desirable outputs
	$\sigma_{\tilde{x}_{ij}}$	Standard deviation of $\tilde{x}_{ij}$		L	Total intermediates
	$\sigma_{\tilde{z}_{lj}}$	Standard deviation of $\tilde{z}_{lj}$		L^{IN}	Integer intermediates
	$\sigma_{\tilde{y}_{rj}}$	Standard deviation of $\tilde{y}_{rj}$		L^{NI}	Non-integer intermediates
VARIABLE	λ_j	The j^{th} intensity component		L^{INU}	Integer-valued undesirable intermediates
	s_i^-	The i^{th} input excess		L^{NIU}	Non-integer-valued undesirable intermediates
	s_l^-	The l^{th} intermediate excess		L^{IND}	Integer-valued desirable intermediates
	s_l^+	The l^{th} intermediate shortfall		L^{NID}	Non-integer-valued desirable intermediates
	s_r^+	The r^{th} output shortfall		$(L^U)L^D$	(Un)Desirable intermediates

5. Data and evaluation of the proposed models

To evaluate the proposed models, we prepared a data set on a sample of the top IaaS and PaaS providers. From an initial list of 82 CSPs, a significant amount of QoS data was available for 24 of the companies, such as price, and cloud security. Hence, we removed the CSPs with no, or very little, QoS data and considered these 24 providers as the final research sample[6]. The dataset was collected from different resources such as reports, cloud computing experts, sales employees, and websites. Each company in this study was considered to be a DMU within a two-stage cloud supply chain comprising IaaS as Stage 1 and PaaS as Stage 2. Figure 6 shows the two stages of the cloud supply chain structure. The input variable for the first stage (IaaS) is the deterministic price (x_1). There are three intermediate deterministic variables: memory (z_1), CPU (z_2), and data transfer (z_3) along with one intermediate random variable latency $(\tilde{z}_4)$. The second stage (PaaS) also involves five inputs, i.e., the deterministic price (x_2) with the four intermediate variables, and an output deterministic variable,

[6] Note that the CSPs asked authors not to reveal their names. Hence, we had to remove their names in the Table 4.

the number of security certifications (y_1), and an output random variable, service time delays $(\tilde{y}_2)$. We assume that all random variables follow a normal distribution. Note that $\tilde{z}_4$ and $\tilde{y}_2$ are undesirable random variables and z_3 and y_1 are deterministic integer-valued variables. Details of the expected values and standard deviations of the dataset are provided in Table 4.

Table 4. The dataset for 24 CSPs

CSPs (DMUs)	Stage 1 (Input)	Stage 2 (Input)	Intermediates					Outputs		
	x_1	x_2	z_1	z_2	z_3	z_4	σ_4^z	y_1	y_2	σ_2^y
1	80	35	8	2	5	433	1.443	5	78	0.754
2	140.79	50	7	2	3.2	49	0.853	3	101	0.669
3	80	47	8	4	5	46	1.749	4	52	0.793
4	80	59	8	6	8	39	1.758	1	163	0.515
5	158	50	2	4	0.5	45	0.522	3	41	0.522
6	110	45	4	2	3	41	0.866	4	33	0.754
7	150	42	16	6	8	68	1.467	4	139	0.492
8	156.24	49	2	2	10	40	0.492	4	64	1.055
9	87.88	37	2.048	3	3	46	0.577	2	149	0.853
10	16.65	49	0.5	1	0.5	152	0.452	1	176	0.739
11	15	31	0.5	1	3	40	0.522	1	180	0.793
12	79	40	8	2	5	71	1.314	2	59	0.522
13	83	31	7	1	3	62	1.730	4	115	1.073
14	64.95	43	4	2	3	62	0.669	1	152	0.515
15	219	37	8	8	10	46	1.337	2	119	0.515
16	150	42	16	6	8	68	3.303	4	26	0.452
17	140	42	16	6	6	70	3.215	4	176	0.515
18	110	45	4	2	3	41	1.443	4	143	2.065
19	80	47	8	4	4	46	2.250	4	154	1.165
20	83	31	7	1	3	62	2.146	4	179	1.765
21	15	34	0.5	1	3	40	0.515	1	165	0.452
22	80	62	8	6	8	40	1.564	1	134	0.492
23	15	31	0.5	1	3	40	0.515	1	126	0.515
24	221	38	8	8	10	48	1.712	2	177	1.055

$\boldsymbol{z_4 = E(\tilde{z}_4)}$: Latency (Millisecond); $\boldsymbol{\sigma_4^z = \sigma_{\tilde{z}_4}}$: Standard deviation of intermediate random variable $\boldsymbol{\tilde{z}_4}$; $\boldsymbol{y_2 = E(\tilde{y}_2)}$: Delayed service time (second); $\boldsymbol{\sigma_2^y = \sigma_{\tilde{y}_2}}$: Standard deviation of output random variable $\boldsymbol{\tilde{y}_1}$.

In this study, price is considered a quantitative metric that plays an important role in the performance measurement of CSPs. Thus, it is desirable for expressing price concerning the features related to CSPs (Somu, Kirthivasan & VS 2017). CPU is the electronic circuit within a computer that performs the instructions of a computer program by performing the basic arithmetic, logic, controlling, and input/output operations specified by the optimized instructions (Maalej et al. 2020). Memory in cloud computing architecture is defined as a clustered structure of memory resources in the form of virtual entities. Data storage refers to saving data to a remote storage system maintained by a third party. The Internet provides the connection between the computer and the database. Cloud storage systems usually depend on hundreds of data servers. Since computers occasionally require maintenance or repair, it is important to store the same information on multiple machines, which is called redundancy. Bandwidth or data transfer refers to the amount of data that can be sent from one point to another in a certain period. It is measured as a bit rate expressed in bits per second (bits/s) or multiples of it (kbit/s, Mbit/s, etc.) (Thangappan et al. 2020). Cloud computing security is a wide-ranging set of policies, applications, technologies, and controls utilized for protecting virtualized IP, applications, data, services, and the associated infrastructure of cloud computing. It is a sub-domain of computer security, network security, and, more generally, information security (Mthunzi et al. 2020). Service availability refers to the probability of receiving the proper service at any given time. It is usually expressed as service level agreement (SLA) downtime in minutes per year or as the percentage of time the service will be up throughout the year. Thus, CSPs need to perform an availability analysis for quantifying the expected downtime that the service may experience over a while (Ghosh et al. 2014).

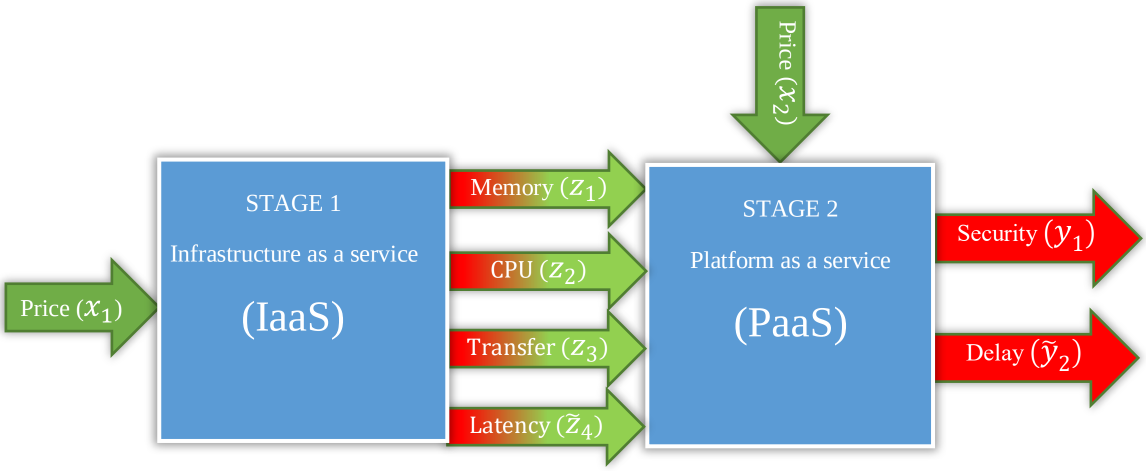

Figure 6. The two-stage cloud supply chain structure

5.1 Results and discussions

To illustrate the rationality of the proposed models, we compared the results of the efficiency evaluations along with their ranking scores for each of the 24 CSPs obtained using four approaches as shown in Table 5. Approach 1 calculates the efficiency scores for Stage 1 (IaaS) and Stage 2 (PaaS) using Models (1) and (2), respectively. The average of these two scores represents overall efficiency scores along with the reacted ranking scores within a pair of parentheses shown in the 4th column which points out that 4 out of the 24 CSPs (CSPs, 1, 8, 10, and 11) would operate efficiently in this supply chain. This is because these CSPs satisfy Definition 2 and, according to this definition, they are efficient in both stages. CSP 6 is ranked at the bottom of the ranking list, which means it is the worst overall efficient unit due to its low performance in both stages.

Approach 2 evaluates the overall efficiency scores by considering only integer-valued variables (y_1 and z_3). The 7th column of Table 5 summarizes the overall efficiency and ranking scores without this condition. There are 5 efficient CSPs, i.e., CSPs 1, 4, 8, 11, and 23. Moreover, CSPs 4 and 23 turn from inefficient to efficient, and CSP 10 becomes inefficient once the integer-valued assumption is included in the evaluation.

Approach 3 measures the efficiency scores of Stages 1 and 2 along with the overall efficiency and ranking scores that consider both undesirable outputs and integer-valued deterministic variables that are shown in columns 8-10 of Table 5, respectively. Reference to Columns 7 and 10 illustrates that in comparison to Approach 2, CSP 16 becomes efficient in Approach 3 and conversely CSP 1 turned out to be inefficient.

Approach 4 considers undesirable outputs, integer-valued, and stochastic latency ($\tilde{z}_4$) and service time delays ($\tilde{y}_2$) into account to evaluate the overall efficiency scores when $\alpha = 0.2$. There are only three overall efficient CSPs 11, 16, and 23. This means that considering the new condition of stochastic data increases the discrimination power in DEA which is one of the challenging problems in the DEA literature (for a deeper discussion of discrimination power in DEA, see Toloo and Salahi, 2018).

CSP 8 and 11 are overall efficient in all the approaches. Therefore, these CSPs may serve as a benchmark for other CSPs wishing to improve their performance in different approaches. Note that this does not necessarily mean that cloud customers should purchase both IaaS and PaaS services from these providers. In this regard, CSP-PE provides the customer with a range of different CSP compositions for purchasing cloud services. For example, the IaaS option (Stage 1) provided by CSP 20 leads to a more optimal composition when combined with the PaaS option (Stage 2) provided by CSP 21. The worst unit is CSP 2, which has poor overall performance in all approaches.

Table 5. The obtained results

CSPs (DMUs)	Approach 1			Approach 2			Approach 3			Approach 4		
				(All data is desirable)								
	Model (1)	**Model (2)**	**Overall (Rank)**	**Model (3)**	**Model (4)**	**Overall (Rank)**	**Model (3)**	**Model (4)**	**Overall (Rank)**	**Model (7)**	**Model (8)**	$\alpha = 0.2$
	Stage 1	**Stage 2**		**Stage 1**	**Stage 2**		**Stage 1**	**Stage 2**		**Stage 1**	**Stage 2**	**Overall (Rank)**
1	1	1	1.000(1)	1	1	1.000(1)	0.5326	1	0.766(8)	0.531	1	0.766(6)
2	0.1812	0.5737	0.378(23)	0.195	0.4648	0.330(23)	0.2831	0.4648	0.374(24)	0.2745	0.434	0.354(23)
3	0.4739	0.3593	0.417(20)	0.4739	0.4423	0.458(21)	0.7616	0.5898	0.676(11)	0.7289	0.56	0.645(13)
4	0.9936	1	0.997(5)	1	1	1.000(1)	1	1	1.000(1)	1	0.1802	0.590(16)
5	0.0835	1	0.542(18)	0.0835	1	0.542(20)	0.0822	1	0.541(22)	0.0812	0.1802	0.131(24)
6	0.191	0.375	0.283(24)	0.191	1	0.596(15)	0.3085	1	0.654(14)	0.2915	1	0.646(12)
7	1	0.4597	0.730(10)	1	0.2898	0.645(14)	1	0.2898	0.645(16)	1	0.2592	0.630(14)
8	1	1	1.000(1)	1	1	1.000(1)	1	1	1.000(1)	1	1	1.000(1)
9	0.2582	0.7715	0.515(19)	0.2582	0.8316	0.545(18)	0.3451	0.8316	0.588(20)	0.331	0.7995	0.565(19)
10	1	1	1.000(1)	0.2582	0.8316	0.545(18)	0.3701	0.8316	0.601(19)	0.3684	0.7995	0.584(18)
11	1	1	1.000(1)	1	1	1.000(1)	1	1	1.000(1)	1	1	1.000(1)
12	0.5043	0.2843	0.394(22)	0.5408	0.0805	0.311(24)	0.6098	1	0.805(7)	0.5964	0.444	0.520(21)
13	0.3219	0.7823	0.552(17)	0.3312	1	0.666(11)	0.3388	1	0.669(12)	0.3329	1	0.667(9)
14	0.4231	0.3905	0.407(21)	0.4291	0.3844	0.407(22)	0.4866	0.3479	0.417(23)	0.4691	0.3374	0.403(22)
15	1	0.4047	0.702(12)	1	0.4056	0.703(9)	1	0.4159	0.708(9)	1	0.3694	0.685(7)
16	1	0.1334	0.567(16)	1	0.1449	0.572(17)	1	1	1.000(1)	1	1	1.000(1)
17	1	0.541	0.771(8)	1	0.3531	0.677(10)	1	0.2332	0.617(18)	1	0.2166	0.608(15)
18	0.191	1	0.596(15)	0.191	1	0.596(15)	0.3085	1	0.654(14)	0.2919	1	0.646(11)
19	0.4563	1	0.728(11)	0.4563	1	0.728(8)	0.7077	0.4648	0.586(21)	0.6751	0.4357	0.555(20)
20	0.3219	1	0.661(14)	0.3312	1	0.666(11)	0.3388	1	0.669(12)	0.332	1	0.666(10)
21	1	0.9396	0.970(6)	1	0.9824	0.991(6)	1	0.9824	0.991(6)	1	0.9361	0.968(5)
22	1	0.3394	0.670(13)	1	0.3034	0.652(13)	1	0.2678	0.634(17)	1	0.1743	0.587(17)
23	1	0.8235	0.912(7)	1	1	1.000(1)	1	1	1.000(1)	1	1	1.000(1)
24	1	0.4959	0.748(9)	1	0.5073	0.754(7)	1	0.3655	0.683(10)	1	0.3337	0.667(8)

A box chart is a method for graphically illustrating the locality, spread, and skewness of groups of numerical data through their quartiles. It is also a prominent method to compare different groups of data with details. Figure 8 plots a box chart to compare and contrast the overall efficiency scores obtained by various approaches. As can be seen, the interquartile ranges of overall efficiency scores obtained by the first three approaches are wider than those for the last approach.

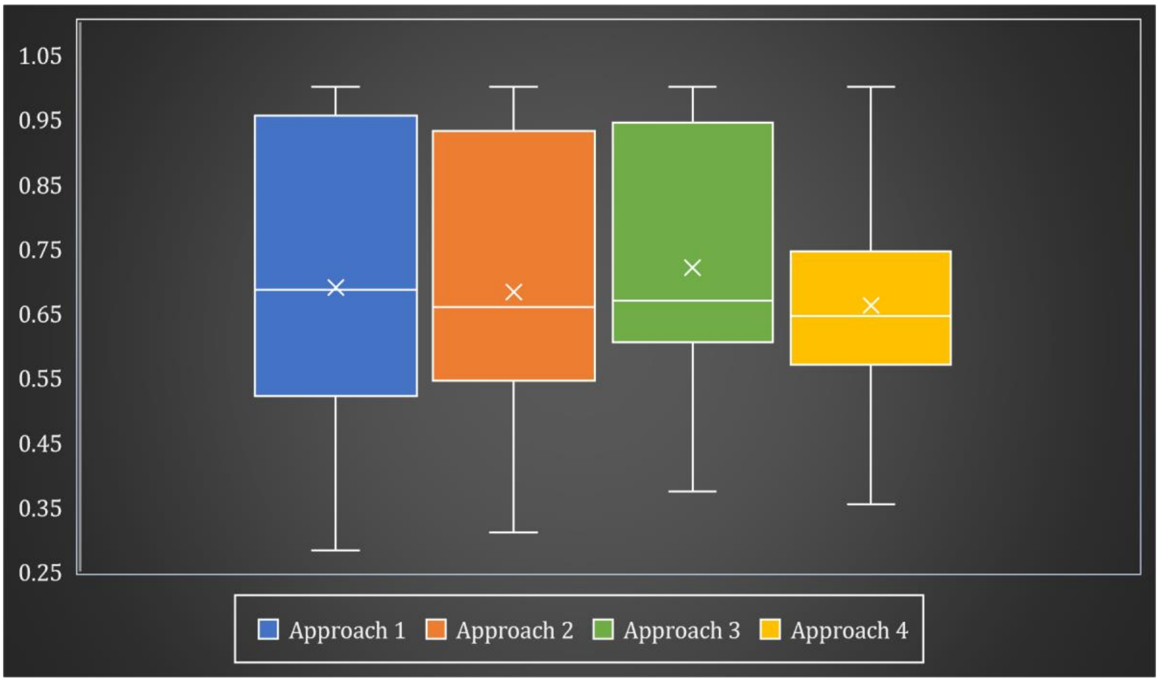

Figure 8. Box plot of overall efficiency scores with different approaches

At this juncture, we compare the ranking scores of CSPs by different approaches. To this end, we employ Spearman's rank correlation test, which has been developed to describe how well each pair of approaches are related using a monotonic function. Figure 9 represents a scatter plot of overall efficiency scores obtained by each pair of approaches. The Spearman correlation coefficient between the first two approaches is 0.81, which is statistically significant showing a positive and strong linear relationship. As a result, the ranking score of a unit almost remains the same for Approaches 1 and 2. In addition, the same relation exists for Approaches 3 and 4.

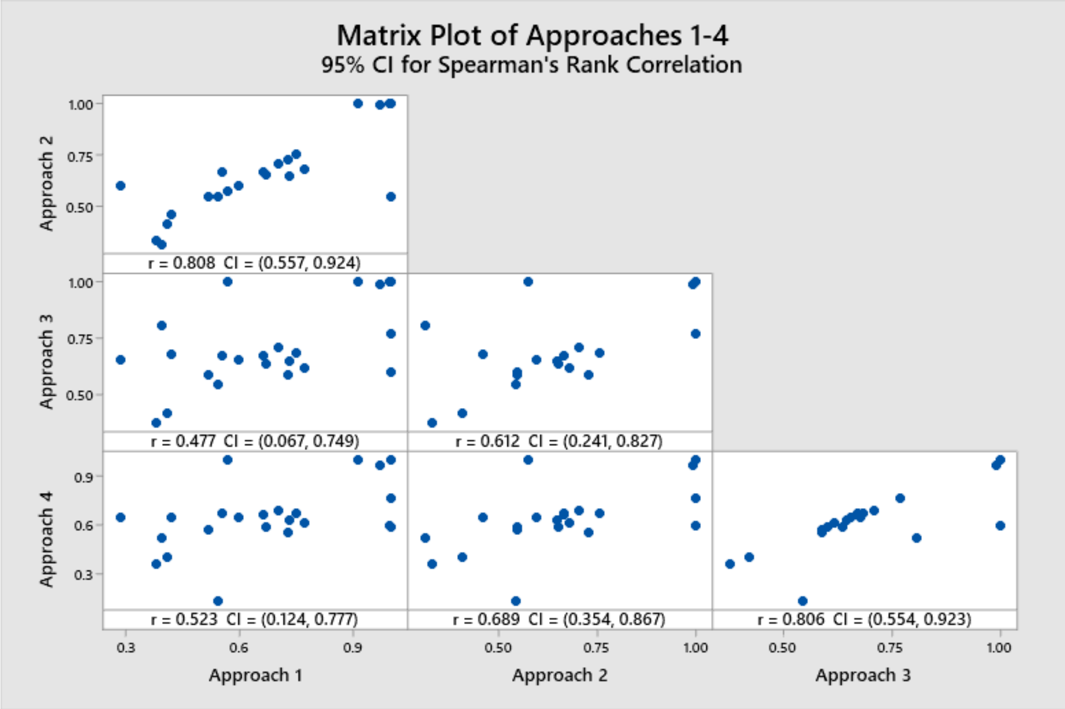

Figure 9. Matrix plot of overall efficiency scores obtained by various approaches

5.2 Managerial insights

Many businesses today are opting for cloud services over on-premises computing facilities due to their competitive advantages. The models proposed and applied in this study have been designed to help managers and decision-makers select specific CSPs to form the optimal cloud supply chain for their needs and to minimize potential service disruptions as a result of selecting the wrong CSP. Further, these models assist CSPs in recognizing their weaknesses divisionally and taking steps to improve their service offerings. As investing in cloud computing technologies is costly, efficiency measurement methods, including network DEA provide support for managerial decisions. However, while the focus of this study is to evaluate and construct cloud supply chains, decision-makers and managers could also use these tools for supply chain management or with other types of supply chains. The results show our model can assess the performance of CSPs in a cloud supply chain in separate stages of the chain and overall, based on QoS indicators effectively. Evaluating and selecting CSPs to form a cloud supply chain is a multi-criteria decision-making problem that many managers find difficult to navigate. Tools that are easy to apply and simple to understand are needed. The models proposed in this study are appropriate tools for meeting this need.

6. Conclusions and future works

Industry 4.0 technologies such as IoT, cloud computing, and blockchain can contribute significantly to the sustainable performance of organizations by considering key factors such as material consumption, green gas emissions, labor practices, and shared information (Beltrami et al. 2021). The main contribution of this study is a reliable method for evaluating the performance of multiple CSPs from a supply chain perspective. Using this method, each CSP is individually assessed with an efficiency measure as part of a logical and sequential process using a series of two-stage SBM network DEA models. Additionally, the supply chain's inputs, intermediate, and outputs variables are concurrently considered, along with undesirable factors, integer-valued data, and stochastic data, to result in an overall performance measure in the context of the chain.

Our findings demonstrate the advantages of network DEA as a tool for determining performance efficiency at each stage of a cloud supply chain as well as the chain's overall efficiency. This technique offers rigor to studies on efficiency assessment in cloud supply chains, but can also be used as a basic reference for researchers and practitioners when developing and applying DEA models to evaluate cloud network performance. Furthermore, addressing other significant issues in the cloud computing domain. For managers, the proposed models can identify inefficient CSPs or aspects of a CSP's service that need to be improved. Such insights provide valuable information for helping cloud customers optimize the composition of their cloud services.

In this study, we focussed on the efficiency of IaaS and PaaS using two-stage network DEA. Exploring some improved network DEA models that incorporate non-deterministic techniques, such as fuzzy systems, would be an interesting research avenue. Moreover, alternative future research can be to extend the trust-based CSP evaluations of cloud supply chains using network DEA models and other optimization methods, as well as data sets spanning different periods of the cloud supply chain to develop dynamic network DEA models. Developing some optimization methods for addressing the data selection problem in supply chain evaluation is also an attractive further research topic (see Toloo et al. 2022, 2023)

Compliance with Ethical Standards:

Conflict of Interest: Authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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