Selecting the Right ERP System for SMEs: An Intelligent Ranking Engine of Cloud SaaS Service Providers based on Fuzziness Quality Attributes

Mahmoud Ibrahim Fallatah† **and Mohammed Ikram**††,

Umm Al-Qura University, **Makkah,** Saudi Arabia

Summary
Small and Medium Enterprises (SMEs) are increasingly using ERP systems to connect and manage all their functions, whether internally between the different departments, or externally with customers in electronic commerce. However, the selection of the right ERP system is usually an issue, due to the complexities of identifying the criteria, weighting them, and selecting the best system and provider. Because cost is usually important for SMEs, ERP systems based on Cloud Software as a Service (SaaS) has been adopted by many SMEs. However, SMEs face an issue of selecting the right system. Therefore, this paper proposes a fuzziness ranking engine system in order to match the SMEs requirements with the most suitable service provider. The extensive experimental result shows that our approach has better result compared with traditional approaches.
Key words: *ERP; SME; Fuzzy Logic; Cloud Services; Ranking System*

1. Introduction

Small and Medium-sized Enterprises (SMEs) represent the majority of enterprises in most countries [1]. Thus, it is paramount to study factors related to their success. Oneof those factors is the adoption of suitable Information and Communication Technologies (ICT) that allows them to compete with larger firms [2,3]. Specifically, it is vital for SMEsto select an Enterprise Resource Planning (ERP) system that help them manage the various functions of their business [4]. While research on ERP adoption is relatively rich, research on selecting the right ERP system by SMEs is scarce [5]. Particularly, limitedresearch exists on the selection of cloud-based ERP system, known as Software as a Service (SaaS), by SMEs.

The Cloud SaaS is a cloud software application that runs and operates over a cloud computing infrastructure [6]. Cloud SaaS is a relatively new software delivery model for software applications, also known as software on-demand. Cloud SaaS is accessed and utilized by the global network infrastructure (i.e., the Internet) rather than installing software on computer hardware on-premises as known as licensed software [7]. Cloud SaaS reduces the cost of building software applications and services, and also eliminates hidden costs associated with running the software [8]. Thus, there has been significant growth in the adoption of Cloud SaaS among businesses.

While the adoption of Cloud SaaS is common among businesses of different types, SMEs in particular, tend to prefer Cloud SaaS when selecting an Enterprise Resource Planning (ERP) software. This is mainly due to the fact that due they have limited resources, compared to big companies [9,10]. SMEs also lack the administrative systemsthat help larger companies in their decision-making processes and usually depends on the ability of their managers [11]. That being said, bounded rationality suggests that managers have cognitive limitations that restrict their ability to absorb all required knowledge that allows them to evaluated alternatives and calculate the consequences of their decisions. Thus, when selecting among different SaaS ERP systems, not all managers are equipped and capable of making the right decisions.

Therefore, the objective of the extant paper is to provide a ranking system that helps managers of SMEs in selecting the appropriate SaaS ERP for their firm. Specifically, we propose a ranking system of Cloud SaaS service providers based on measuring the shortest distance to consumer's preferences. In addition, our proposed system uses the linguistic terms of non-functional attributes in terms of weighting the favourite quality attributes for SMEs. This classification helps SMEs to expose the main non-functional factors that should be considered when selecting an SaaS ERP software. With those objectives, our paper contributes to the literature by complementing prior studies on the importance of cloud-based software for SMEs as a

Manuscript received June 5, 2021
Manuscript revised June 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.6.7

strategic choice.

The rest of the paper is organized as follows. Section 2 discusses the related-on SMEs, as well as related works on cloud SaaS selection and ranking. Next, Section 3 describes the proposed architectural framework. The experimental setup and results are presented in section 4, while Section 5 discusses the experiment results. The conclusion of the paper is provided in section 6.

2. Literature Review

2.1. ERPs in SMEs

Ample research has studied ERPs in SMEs, focusing on issues of adoption, selection, implementation, and maintenance of ERPs by SMEs, among other issues [12].While a complete review of ERPs in SMEs is beyond the scope of our paper, we will briefly discuss the literature, focusing on how they relate to our focus in this paper.

Studies on SMEs adoption of ERPs focused on the factors that enable SMEs to adopt ERP systems, including internal factors such as organizational and technological factors [13], and external factors related to the uncertainty in their environment [14]. Recently, as cloud-based ERP systems are trending, a study developed a model for adopting cloud- based ERP by SMEs [4]. Based on firm qualities, internal pressure, external pressure, technology features, organizational readiness and external support.

On the other hand, studies on the selection of ERP systems by SMEs identified factors that impact the selection process. Such factors include business complexity, change management, and external factors like supply chain partners, and the pressure of value networks [25], cost drivers, functional requirements, flexibility, and scalability, the degree of ERP alignment/fit with the business processes [7]. A more recent paper focused on the selection of cloud-based ERP systems by SMEs and found that vendor's reputation and willingness to support the SMEs throughout the product life-cycle, and ability to co-create value with the SMEs to be major factors that influence SMEs decision on which system to adopt [3].

While studying the important factors in selecting ERP systems for SMEs is vital, understanding how to rank them in order to select the right one is equally important. The decision-making process that include identifying the criteria, weighting them, and selecting the optimal system is complex. Percin and Selcuk (2008)[15] used Analytic Network Process (ANP) to determine the weights of all criteria, and then, the obtained weights were used in the PROMETHEE method for optimal ranking of the alternative system choices. Another study identified 17 critical factors and categorized them on the basis of cost, security, organisational factors, performance and functionality of ERP, before using Analytic hierarchy process (AHP) to prioritize and rank the factors to be considered for adopting cloud ERP [16].

2.2. Software as a service (SaaS)

Service providers of cloud software as a service (SaaS) publish their services with the functional category of service and non-functional parameters (as known as QoS or QoE). An example of cloud SaaS functional service is a Salesforce cloud SaaS. This type of service provides customer relationship management (CRM) for a SaaS consumer. On the other hand, the non-functional parameters describe as the factors that a consumer may consider when making a decision and select a service such as the service price, service availability and more. The non-functional quality attributes can be classified into two categories-- qualitative and quantitative. The quantitative part of non-functional parameters is the quality of service (QoS) that can be measured numerically such as a service price, service availability. This category can be collected by using monitoring tools such as service availability or by the information from a service provider such as service price, whereas the qualitative types cannot be measured numerically and can be identified by a consumer's experience. Security, performance and supporting are examples of qualitative QoS.

Current research on the non-functional parameters of cloud software service is focused on selection of cloud service based on multiple attributes (i.e. non- functional factors) [17,18]. These works propose several criteria that should be considered when selecting a service, and propose a service selection mechanism to select a service.

Although there has been some work related to the non-functional parameters or the quality of service that should a consumer considers when selecting the cloud software service [19–21]. These works consider either multiple factors to investigate quality when selecting a service or by trying to identify some methods to measures the quality. Burkon proposes quality attributes based on studying the differences between SaaS and IT outsourcing software (ITO) to identify the main quality of service of a SaaS cloud service [19]. Therefore, the author concludes the main QoS that used for managing a SaaS service are as follows: availability, performance, reliability, scalability, security, support, interoperability, modifiability, usability and testability. In addition, Khanjani et al. [20] conducted a study on the quality of service for cloud Software as a Service (SaaS). These studies reviewed the following quality attributes for cloud software service: Adaptability, Extensibility, flexibility, customizability, scalability, changeability, composability, availability, maintainability, reliability, fault tolerance, recoverability, stability, serviceability, robustness, accuracy, efficiency, functionality, response time, suitability, data integrity, privacy, security, accessibility, learnability, commonality, multi-tenancy, operability, agility, assurance, performance, security management and usability. Finally, Al-Shammari & Al-Yasiri [21] provided valuable information on how to quantify the quality of experience in order to help a consumer and SaaS service provider obtain a service level agreement (SLA).

3. Fuzziness Ranking Engine Framework

Our proposed system consists of three main components as shown in figure (1). (1) Consumer Request Handler (CRH) is used to gathering all the information required from a consumer. (2) Ranking system engine (RSE) is the heart of our ranking system which is used for ranking and sorting the services to SMEs. Finally, (3) Service registry repository (SRR) is used to store all ERP Cloud SaaS services and non-functional quality attributes of ERP services.

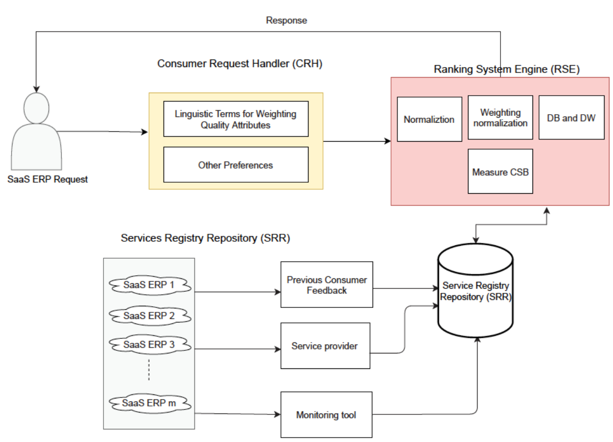


Figure 1. System Architecture Framework.

3.1. Consumer Request Handler (CRH):

The key objective for the CRH is to collect the main preferences of SMEs among conflict quality attributes. In order to achieve this, a service consumer first selects their preferences for quality attributes that must be considered during the ranking process. For example, if SME x selects attributes such as "service ratings", "service price" and "service founded" for as the main quality attributes to rank all services. Next, the SME weights the importance of these attributes based on linguistic terms such as the price of service is "Not Important", but the service availability is "Very Important". The second process is to assign a single value of these selected attributes. For example, the price of selected service needs to be within \$20 or service availability need to be %100.

After gathering this information from SMEs, the CRH generates the best-ideal service BIS_i, worse-ideal service WIS_i and weighting quality attributes vector Wi and transmits this information to the ranking system engine RSE which interacts with the service registry repository and ranks all services for the SME.

Non-functional quality attributes can be classified into two types: (1) Positive non- functional attributes are those that have the best amount when they increase such as availability, number of service reviewers and service ratings. (2) Negative non-functional attributes are those that have the best amount when they decrease, such as price and service response time. Therefore, the BIS and WIS will be based on these classifications. It means that if the SME chooses the service price, the system will rank the services from the price that the SME select and goes to the highest price.

3.1.1. Linguistic Terms for Weighting Non-Functional Attributes:

A number of approaches have been used to measure the importance of quality attributes, such as ranking the importance of attributes or based on the min and max in the weighting approach. Since SME's non-functional preferences are usually described as linguistic values which can be ambiguous, such as "extremely important" or "not important," our proposal framework weight the important of quality attributes as linguistic terms. Our framework classifies the linguistic variable of weighting attribute into seven linguistic terms as follows: extremely important (EI), very important (VI), important (I), somewhat important (SI), not important (NI), not very important (NVI) and not important at all (NIA). In order to translate these linguistic terms into numerical quantity for further analysis, the fuzzy logic concept is proposed. Moreover, the triangular fuzzynumber $\hat{A} = (a, b, c)$ has been launched to compute the membership function, as shown in figure (2). Table (1) describes the linguistic terms with a set of fuzzy numbers.

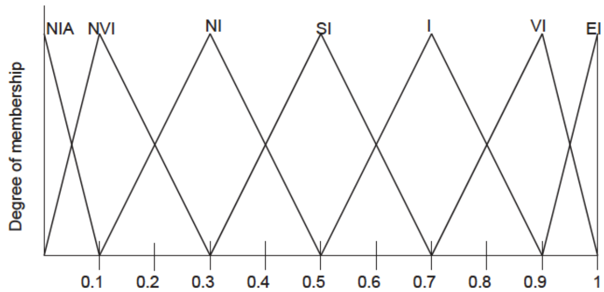


Figure 2. Degree of membership function

Table 1: Linguistic terms with their fuzzy numbers

Linguistic terms	Triangular fuzzy number
Extremely important (EI)	(0.9,1.0,1.0)
Very important (VI)	(0.7,0.9,1.0)
Important (I)	(0.5,0.7,0.9)
Somewhat important (SI)	(0.3,0.5,0.7)
Not important (NI)	(0.1,0.3,0.5)
Not very important (NVI)	(0.0,0.1,0.3)
Not important at all (NIA)	(0.0,0.0,0.1)

Defuzzification is a process to convert fuzzy numbers defined over an output universe of discourse into a non-fuzzy (crisp) value. It generates a crisp value that best represents the possibility distribution of an inferred fuzzy number. There are many different defuzzification methods such as RCOM (Random Choice Of Maximum), FOM (First of Maximum), LOM (Last Of Maximum), COG (Center Of Gravity), MeOM (Mean Of Maxima), WFM (Weighted Fuzzy Mean), QM (Quality Method), EQM (Extended Quality Method), and COA (Center Of Area) [22].

To obtain the crisp value of a triangular fuzzy number Aˆ = (a, b, c),we compute the COG of Aˆ using the following formula (1):

$$d(\hat{A}) = a + \frac{(a-b)+(c-b)}{3}$$

Finally, the crisp weight of non-functional (w_i) is calculated using the following formula (2):

$$w_j = \frac{d(\hat{A}_j)}{\sum_{j=1}^{n} d(\hat{A}_j)}$$

As a result, the list of weighting attributes W = w_1, w_2, w_n is generated to the ranking system to identify the importance of non-functional attributes. Algorithm (1) is used to weight the importance of quality attributes.

Algorithm 1: Algorithm for weighting attributes using linguistic values

Input: Linguistic values with their fuzzy number and importance of criteria;
Output: List of Weighting criteria (W) ;
foreach *non-functional attribute* **do**
  match the linguistic values; Fuzzy number;
  $(a,b,c),(a',b',c')and(a'',b'',c'')$ compute the membership function $(membership(criteria_i))$;
end
return list of membership function for each criteria;
Calculate the summation of membership function $sum(membership(criteria_i))$;
foreach *non-functional attribute* **do**
  calculate the weighting criteria $w_i = membership(criteria_i)/sum(membership(criteria_i))$
end
return the list of (W)

3.1.2. Quality Value of Non-Functional Attributes based on SME's Preferences

The second input by a service consumer is the non-functional requirements as a numerical value such as the service price needs to be $100. The reason for this input is to use for ranking the services based on the measuring the shortest distance to the SME's requirements. Therefore, after obtaining all the requirements from the SME, our ranking system sort all the services based on the shortest distance to the consumer's requirements.

Consider q_1, q_2, ..., q_n is the set of non-functional attributes in the service list min_1, min_2, ..., min_n is the set of minimum values of the quality attributes, and max_1, max_2,..,max_n is the set of maximum value of quality attributes. In addition, assume cp_1, cp_2,…, cp_n are the selected attributes by an SME as preferences for service selection. Moreover, assume Cr_1, Cr_2,… , Cr_n are the list of non-functional attributes which is used for calculating the distance from each service. Note that the SME's requirements must be in the range from minimum to maximum in all selected attributes. Finally, assume LWi is the linguistic terms for weighting quality attributes from the SME's perspective. Using all these inputs, the CRH will generate a set of BIS, and the worse-ideal service WIS to rank and sort all services for the service consumer. The proposed system generates the BIS with two options:

1. In case the selected attributes are positive according to the SME's preferences, theset of *BIS* is calculated using equation (3), and the set of *WIS* is calculated using equation (4).

$$BIS = Cr_{cp}^{\alpha_1}, Cr_{cp}^{\alpha_2}, \ldots\ldots, Cr_{cp}^{\alpha_i}, \ldots\ldots, Cr_{cp}^{\alpha_n}$$

where $Cr_{cp}^{\alpha i}$ is the consumer quality requested by a service consumer for the selected attributes preferences.

$$WIS = min_{cp}^{\alpha_1}, min_{cp}^{\alpha_2}, \ldots\ldots, min_{cp}^{\alpha_i}, \ldots.., min_{cp}^{\alpha_n}$$

where $min_{cp}^{\alpha i}$ is the minimum value of quality attributes.

2. In case the selected attributes are negative according to the SME's preferences, the BIS and WIS can be calculated as follows:

$$BIS = Cr_{cp}^{\beta_1}, Cr_{cp}^{\beta_2}, \ldots\ldots, Cr_{cp}^{\beta_i}, \ldots.., Cr_{cp}^{\beta_n}$$

Where $Cr_{cp}^{\beta i}$ the consumer quality requested by a service consumer for the selected quality attributes as preferences.

$$WIS = max_{qp}^{\beta_1}, max_{qp}^{\beta_2}, \ldots\ldots, max_{qp}^{\beta_i}, \ldots.., max_{qp}^{\beta_n}$$

Finally, $max_{qp}^{\beta i}$ is the maximum value of selected quality attributes.

3.2. Ranking System Engine (RSE)

The ranking system engine of our proposal system is the core component for ranking and sorting the services for SMEs. It is responsible for filtering and classifies each service to obtain the most matches with the SME's preferences. In addition, the RSE proposed is based on measuring the shortest distance to quality attributes of the SME's preferences.

Let's assume that BIS = $bis_1, bis_2, \ldots, bis_n$ is the vector of best-ideal service and WIS = $wis_1, wis_2, \ldots, wis_n$ is the vector for the worse-ideal service. Moreover, $W = w_1, w_2, \ldots, w_n$ is the vector of weighting the importance of quality attributes based on the consumer's preferences. These parameters are transmitted by the CRH to the RSE. The RSE processes in detail as follows:

1. The BIS vector and WIS vector are combined to the pool of software services. This step is necessary to consider the SME's preferences for ranking and sorting the services.

2. The normalization step takes place to normalize all metrics to keep all values in range [0,1]. It uses equation (7) to normalize the positive quality attributes such as the availability factor. In addition, equation (8) is used to normalize the negative quality attributes such as service price.

$$r_ij = \frac{NF_ij}{\sqrt{\sum_{i=1}^{m} NF_ij^2}}$$

$$r_ij = \frac{1/NF_ij}{\sqrt{\sum_{i=1}^{m} 1/NF_ij^2}}$$

3. In order to consider the weighting of quality attributes for the SME's preferences, this step calculates the weighted normalized ratings. Equation (9) is used for this purpose.

$$v_ij = w_j . r_ij$$

where w_j is the weighting of quality attributes j, and r_{ij} refers to the normalized value for service i and quality j.

4. The Euclidean distance have been used to measure the distance to the best-ideal service and to worse-ideal service.
Therefore, to measure the distance to the best-ideal service, equation (10) is used. The result of this equation will be one matrix size (1 × n) which includes the distance of each service to the best-ideal service. It is called the Distance to Best DB.

$$DB_j = \sqrt{\sum_{i=1}^{n} (v_ij - bis_i^*)^2}$$

where v_{ij} is the weighted normalized non-functional parameters of service i and quality j. Also, bis_i^* denotes the best-ideal service vector for quality i.

Moreover, equation (11) is used to measure the distance to the worse-ideal service. The result of this equation is also one matrix size (1 × n), called the Distance to Worse DW.

$$DW_j = \sqrt{\sum_{i=1}^{n} (v_ij - wis_i^*)^2}$$

where v_{ij} is the weighted normalized non-functional parameters of service i and quality j. Moreover, wis_i^* denotes the worse-ideal service vector for quality i.

5. The similarity to the best- ideal service has been measured to rank all software services for the service consumer. The DW vector is divided by the summation of the DB vector with DW using

equation (12). The result is the vector called CSB, size (1 × n).

$$CSB_j = \frac{DW_j}{DB_j + DW_j}$$

6. The last step is ranking and sorting all the services using the *CSB* vector. It ranksin descending order, which means the service that has the highest similarity will be ranked first.

   To describe the ranking system engine approach, algorithm (2) provides pseudocode for the *RSE*.

Algorithm 2: Ranking system of cloud services (SaaS) based on measuring the similarity to ideal-service

initialization;
Input: The pool of similar cloud software services,;
Set of the best-ideal service vector $BIS_t = (bis_1, bis_2, ..., bis_n)$,;
Set of the worse-ideal service vector $WIS_t = (wis_1, wis_2, ..., wis_n)$ and;
Set of weighting the most important of criteria $W_t = (w_1, w_2, ..., w_n)$;
Output: Ranking cloud services;
saas_services(update) = Combine the BIS vector and WIS vector with the pool of services;
for ∀ *saas_services(update)* j *in* $1:m$ **do**
  foreach $q_t ==$ *positive* **do**
    normalized_positive_data $= \frac{x_{tj}}{\sqrt{\sum_{t=1}^{m} x_{tj}^2}}$
  end
  return(normalized_positive_data)
  foreach $q_t ==$ *negative* **do**
    normalized_negative_data $= \sqrt{\sum_{t=1}^{m} 1/x_{tj}^2}$
  end
  return(normalized_negative_data)
end
saas_normalized = *Combinenormalized_positive_datawithnormalized_negative_data*
for ∀ *saas_normalized* j *in* $1:m$ **do**
  weighted_saas = *saas_normalized*$_{tj}$ × w_t
end
return (weighted_saas)
for ∀ *weighted_saas* j *in* $1:m$ **do**
  $Distance(best)_j = \sqrt{\sum_{t=1}^{n} (weighted\_saas_{tj} - bis(weighted\_saas)_t)^2}$
end
return(Distance(best))
for ∀ *weighted_saas* j *in* $1:m$ **do**
  $Distance(worse)_j = \sqrt{\sum_{t=1}^{n} (weighted\_saas_{tj} - wis(weighted\_saas)_t)^2}$
end
return (Distance(worse))
calculate $Similarity\_Best\_Service_j = \frac{Distance(worse)_j}{Distance(best)_j + Distance(worse)_j}$
Ranking services according to Similarity_Best_Service in descending order;

3.3. Service Registry Repository (SRR):

This section discusses the main quality of service providers that can be measured and calculated easily by different resources. In this paper, three main resources have been classified related to service vendor:service provider, monitoring tool and previous consumer feedback. The reason for this classification is due to the fact that the quality of cloud software services can be determined by the information that can be seen in the web page of a service provider, or by running a monitoring tool to collect some performance metrics such as availability, throughput and response time. In addition, since the cloud software service is multi-tenant service, it must consider the feedback from previous consumer experience.

- Service providers published its services along with multiple related quality parameters. For SMEs, as discussed above, one of the most important parameters is the price or the cost of using the service. Most of the pricing models for the cloud ser- vices today include the pay-as-you-go or pay based-consumption. However, cloud software service providers calculate their cost by renting the cloud infrastructure, marketing, and operation. After that, they launch their services by various cost categories, such as monthly payments per user, enterprise version or paying upfront. Also, service provider has different cost categories based on the supporting criteria and training mechanism. The majority of service providers offer a one-month free trial for customers before they require a full contract for their services. Mostly, the services offered during the one-month free trial come with limited features. A second criterion that we can obtain from a service provider is the history of a service or the date that a service founded. This provides a useful indicator about the quality of the service. Therefore, a cloud software with a longer history has a good impact and instils more confidence in SMEs when they are selecting an ERP system. Usually, services with longer lifespan result in more user feedback and more training resources which are available to the public. That being said, this does not mean that relatively new services are less credible, it just indicates that older service providers have more user feedback and ratings.

- Monitoring tools become a very valuable tool to help in understanding the performance of any service on the Internet. There are different options for applying monitoring tools either by contracting with the third party monitoring tool or running own monitoring tool. A number of web monitoring tools are available on the Internet such as up-down, statusOK and site24x7. All these services are available through subscription and can be used to monitor different resources on the Internet. The majority of monitoring tools measure the performance of cloud software services, web services or a specific network by measuring the service performance using availability, response time and throughput. We consider the following metrics: (1) Availability: This refers to the number of successful invoca-tions/total invocations and is calculated as a percentage; (2) Response time: This refers to the time taken to send a request and receive a response (in milliseconds), and (3) Throughput: This refers to the number of invocations for a given period of time.

● The feedback of previous consumers of cloud software service is highly important to understand the performance of service in other clients' views. There are many parameters that can be obtained from the feedback of previous consumers, such as performance and support. Due to consumer privacy, many useful parameters cannot be obtained for assessment. However, two important attributes are very useful and can help to gather important information, such as service ratings and service reviewers. Typically, service ratings are in the range of 1 to 5, where 5 means the service has a high rating and a lower value means the service received a lower rating. The second criterion, service reviewers, is the number of previous consumers who assisted in the rating of the service. Normally, services with high popularity indicate a higher number of service reviewers.

4. Experiment Evaluation

4.1 Experiment setup:

The experiment was run on a MAC operating system (version 11.2.3) and by usingR language. We have been developed our algorithm to understand the SMEs request, and then rank and sort all the services using the proposed method and compared with two existing methods (FSSP [26] and CASCP [27]) as well as traditional methods (i.e. based on service price, based on service availability and etc.) for ranking all services. In addition, two datasets have been used as a benchmark for testing and evaluation:

- QWS is published by Al-Masri [23].
- CRM dataset: This dataset introduced by previous works published in AINA Conference in 2019 [24].

In order to measure the performance of our proposed method, the mean average precision *mAP*, as well as the normalized discounted cumulative gain *nDCG* have beenused for this purpose. The *mAP* is used to measure the accuracy of the object detectors, which is the average of the maximum precision at different recall values. The *mAP* metrics are used to evaluate our proposed method against the other ranking approaches with *QWS* dataset. To measure the *mAP* in the top-K services, we use the following equation:

$$MAP_k = \frac{1}{k}\sum_{j=1}^{k} P_j$$

Where P_j is the precision value for the service j.

$$mAP_k = \frac{1}{k}\sum_{i=1}^{k}\frac{1}{i}\sum_{r=1}^{i} rel_r$$

Moreover, the *nDCG* metric is widely used to evaluate the ranking system. *nDCG*works by providing the ideal descending services ranking and predicting descending services ranking. The *nDCG* is then calculated for the top-k using equation (15). How-ever, the *nDCG* metric has only been used to determine the performance of the rankingservice approach with the *CRM* dataset as it is difficult to generate *NDCG* metric with a large number of services which is the *QWS* (See section **??**) dataset own.

$$NDCG_k = \frac{DCG_k}{iDCG_k}$$

$$DCG_k = \sum_{j=1}^{k}\frac{rel_j}{log(1+R_j)}$$

where DCG_k is the discounted cumulative values of the top-k for the predicted service ranking system, while *iDCG* is the ideal value of the top-k for ideal service ranking. The value of DCG_k can be calculated using equation (16).

To calculate the relevant ranking services, Euclidean distance is used to calculate the distance between the consumer requirements of the preferences for each service. Tocalculate this, equation (17) is used.

$$d(Cr, NF) = \sqrt{\sum_{i=1}^{n}(Cr_i - NF_i)}$$

In order to test and evaluate our proposed method using the CRM dataset, threequeries for each ranking approach were conducted. The first query considers two at-tributes as quality preferences, the second query considers four attributes as quality preferences and the third query considers six attributes as non-functional preferences. In addition, we tested our ranking method with seven attributes as follows: service rating, service reviewers, service price (monthly subscription per user), service founded, availability, response time and throughput.

Consumer request (weight)	Service Reviewers	Service Rating	Service Price	Service Founded	Availability	Response time	Throughput
1	N/A	5 (VI)	30 (EI)	N/A	N/A	N/A	N/A
2	N/A	N/A	30 (EI)	N/A	100 (SI)	200 (SI)	N/A
3	500 (I)	5(EI)	30 (I)	2000 (SI)	100 (EI)	200 (I)	N/A

Table 2: SaaS SNFCP queries input

Table (2) shows the parameters of the queries for ranking the services using the ourproposed method approach. For example, in the first query, the ranking request considers two quality attributes for ranking the services, these being the service price and the service rating. Therefore, the *CRH* will obtain two parameters (5^{Rating} *AND* 30^{price}). This means the consumer considers a service rating of 5 out of 5 as a Very Importantpriority and a service price of $30 as an Important priority.

4.2: Experiment Results

We have studies the ranking services based on top (5,10,15 and 20) services gen- erated by our proposed method and compared the performance with another existing approach FSSP and CASCP using the nDCG metric. The experimental results are shown in Table 3. The following points summarize of important findings:

1. Our proposed method outperforms the FSSP and CASCP approaches in respect of nDCG in considering 2 and 4 criteria.

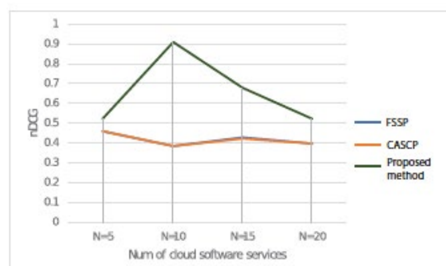
2. Our proposed method, in terms of ranking services considering 2-quality attributes, they are higher than existing approaches FSSP and CASCP in respect nDCG by approximately 50%.

3. It is worth noting that ranking services in terms of matching the quality attributesconsidering more than four criteria still challenging. However, if a consumer request ranking services by specific consumer non-functional requirements, they may some services matching their requirements and may not. It dependents the pool of service list.

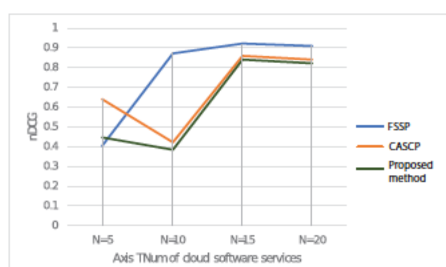
4. In general, the nDCG values of all approaches decrease with the increasing number of quality attributes concerns when ranking the services.

5. In general, the nDCG values decrease with the increasing number of services.

a) nDCG ranking services with 2 quality attributes



b) nDCG ranking services with 4 quality attributes



c) nDCG ranking services with 6 quality attributes

Figure 3. nDCG result for Find SaaS SNFCP and compared with FSSP and CASCP

The experiment results for nDCG matrices for our proposed method with compared of FSSP and CASCP approach are shown in Figure (3). The result proves that our proposed method in terms of considering two and four quality attributes for ranking theservices outperform the other approaches using different given numbers with respect to nDCG. Figure (3a,3b) show our proposed method is higher than other approaches by approximately 50% when using two and four criteria for ranking the services. On the other hand, figure (3c) shows our proposed method of using six criteria lose the performance compared to other approaches.

Approach	2-Criteria				4-Criteria				6-Criteria			
	N=5	N=10	N=15	N=20	N=5	N=10	N=15	N=20	N=5	N=10	N=15	N=20
FSSP	0.4717532	0.3971027	0.3687536	0.3624668	0.4556533	0.3825136	0.4255493	0.3968845	0.4037312	0.8699604	0.9160177	0.9040686
CASCP	0.4717532	0.5154495	0.4989939	0.493587	0.4556533	0.3825129	0.4237599	0.3956011	0.6360104	0.4223828	0.8579019	0.8373529
Find SNFCP	1	0.9997387	0.9974817	0.9871743	0.5211027	0.9083838	0.6749247	0.5222999	0.4443679	0.381437	0.8376763	0.8194429

Table 3: Results of CRM analysis

4.3: The experiment result for QWS:

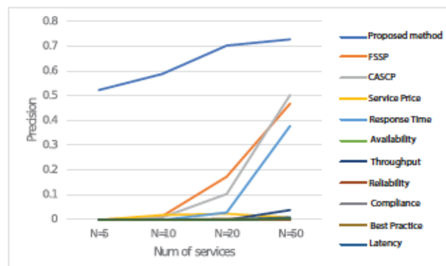
This section explained the results of our proposed method of ranking services andcompared the results with other existing approaches FSSP and CASCP. We also com- pared our proposed method by ranking the services based on consumer's preferences such as ranking the services beginning with the lowest price to the highest price. We study the mean average precision (mAP) for ranking services on top-(5,10, 20 and 50) in order to measure the performance of the ranking approaches. The result of performancefor Find SaaS SNFCP and compared with FSSP and CASCP are shown in figure (4). We can summarize the main findings into the following points:

1. In general, our proposed method outperforms the other ranking system approaches. The average precision of proposed method is approximately 75%, whereas the FSSP has 12% and CASCP has 9%. Therefore, ranking services considering the specific value of the non-functional attribute or as known as the consumer non-functional requirements in this research is crucial to determine the service that matches withthe non-functional preferences.

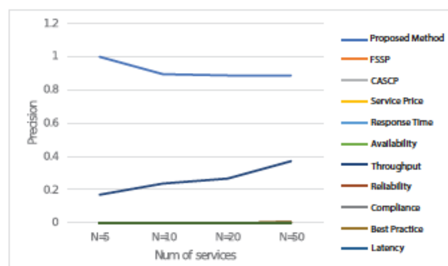
2. Ranking services based on the non-functional preferences such as based on serviceprice is not a proper way to find the service match with a consumer preference.

3. Since the pool of service is large in QWS dataset, the ranking services considering the specific amount of non-functional parameters obtain very close to consumer'spreferences of non-functional attributes.

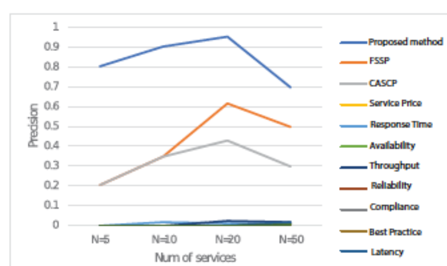
4. Results in Figure (4a,4b,4c, 4d and 4e) show that the increase in the services has generally a positive impact on the proposed method approach accuracy in respectof precision.



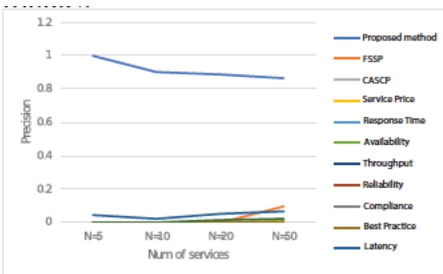
a) Ranking services with 2 quality attributes



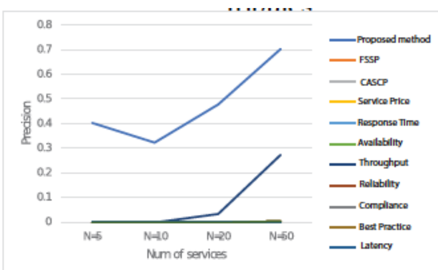
b) Ranking services with 4 quality attributes



c) Ranking services with 6 quality attributes



d) Ranking services with 8 quality attributes



e) Ranking services with 10 quality attributes

4.3 Experiment Discussion:

Ranking cloud software services takes into account the weighting non-functional attributes with consumer non-functional requirements, which obtains different resulst compared to the case when taking into account only weighting non-functional attributes. Figure (5) show the meanvalue of nDCG value for all ranking requests regarding Find Saas (SNFCP, M2NFCP and LNFCP) compared with FSSP and CASCP. The figure proves that FSSP and CASCP obtain similar performance since FSSP is using the SAW for the ranking engine and CASCP is using the TOPSIS mathematical approach for ranking the services,

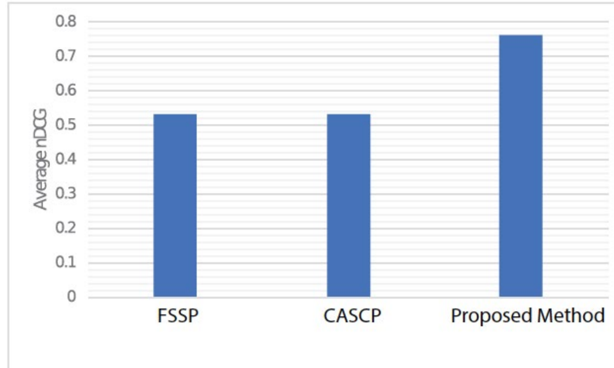


Figure 5. The average nDCG for our proposed approaches and compared with the existingresearch approaches

Figure (**5**) shows the bar chart of average value for Find SaaS (SNFCP), FSSP andCASCP for all ranking request. It can be seen that the average of Find SaaS SNFCP is77%, FSSP and CASCP are approximately similar by 53%.

This section compares the performance of Find SaaS ranking approaches comparedwith the other ranking approaches.

Figure (**5**) shows the precision curves for each ranking method including Find SaaS SNFCP for each experiment. The figure shows the high performance of our proposed method in matching ranked services compared with the other approaches. The other ranking approaches do not have stable performance results. FSSP and CASCP have the second-best performance results compared with ranking the services based on selectedQoS.

5. Conclusions

The paper focused on helping SMEs in selecting the cloud-based ERP system that fits their requirements. Specifically, it proposed a fuzziness ranking engine system in order to match the SMEs requirements with the most suitable service provider. Our extensive experimental result shows that our suggested approach produced better result compared with other approaches suggested in the literature. That being said, future research should continue to propose new methods that SMEs (i.e. users) could rely on in choosing a preferred ERP system.

Acknowledgments

The authors would like to thank Al-Muallem Mohammed Bin Ladin Chair for Creativity and Entrepreneurship and the Deanship of Scientific Research at Umm Al-Qura University for the continuous support. This work was supported financially by the chair (Grant number: DSR-UQU-BLIE-011)

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Mahmoud Ibrahim Fallatah is an Associate Professor of strategy and innovation at the College of Business, Umm Al-Qura University. He is the professor of the MBL Chair for Creativity and Entrepreneurship. Dr.Fallatah earned his PhD from The University of Texas at Arlington in 2016, and an MBA degree and a Master of Science degree in Engineering Management from The University of New Orleans in 2010. His research interests lie primarily in the area of knowledge creation, innovation and

entrepreneurship, utilizing the social capital and network theories. His work has been published in highly ranked ISI journals and top conferences. Dr.Fallatah is an active member of the Academy of Management and the Southern Management Association.

Mohammed Ikram is an Assistant Professor in the school of computer science, Al-Jamoum collage at Umm Al-Qura University. He received his PhD degree from the computer science department at University of Technology Sydney, Australia in 2020, and his masters from the same university in 2015. His research interests include, but are not limited to Cloud Computing, Internet of Things, networking system and data science. He published several publications in these fields.