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A Fuzzy Logic Multi-Criteria Decision Framework for Selecting IT Service Providers

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Abstract

Selecting IT service providers in information systems outsourcing involves both qualitative and quantitative evaluations. This paper proposes an integrated multi-criteria decision-making (MCDM) framework to effectively handle uncertainty and subjectivity in the vendor selection process. The proposed methods apply fuzzy logic approach to integrate qualitative survey data into traditional multi-criteria decision models such as data envelope analysis (DEA), analytical hierarchy process (AHP) methods, and TOPSIS. Based on case studies from Iranian banking industry, we empirically test the proposed framework and show it is superior to existing methods. We demonstrate that the fuzzy logic approach provides a robust analysis for vendor selection by appropriately trading off the perceived risks and benefits. It offers a comprehensive MCDM tool that can help practitioners prioritize vendor rankings and make optimal IS outsourcing decisions.

1. Introduction

As an effort to reduce cost, increase productivity, and gain competitive advantages in the global competition, there is a growing trend of IS outsourcing in organizations [10,11,17,23]. Many types of IT products or services can be outsourced, such as software development, data center operation, help desk, network management, disaster recovery, and web hosting. For example, cloud computing service is an emerging model of IT outsourcing. The scope of IS outsourcing ranges from incremental outsourcing of internal services to large-scale outsourcing of organizational IT functions. As the degree the client firm transfers an organization's IS functions to external vendors, the outsourcing risks increase.

When companies choose to acquire IT services externally, they lose control over outsourced activities and rely on the provider's capabilities as a basis for conducting businesses. Therefore, selecting an appropriate IT service provider becomes a critical step to minimize outsourcing risks. Although it is projected that the average U.S. firm's annual saving in IT expenses is $4 billion by outsourcing, half of all outsourcing agreements failed [19]. Very often vendors are unable to meet expected service levels and deliver expected cost savings. Lack of thorough analyses in selecting and managing relationship with service providers is one important reason for outsourcing failure [20,21].

IT service providers differ greatly in the services they offer, how they charge for services, and the service guarantees they can make and are willing to make. The most common process for selecting service providers involves a request for proposal (RFP) from a set of potentially qualified vendors. An RFP asks prospective providers for financial, technical, and operational information relevant to their service capabilities. Client firms further gather information from industry analysts, from other companies that have used providers' services, and from visits to provider sites. Many companies employ elaborated scoring mechanisms to combine both qualitative (e.g., subjective judgment of outsourcing risks) and quantitative (e.g., estimated cost savings and tangible benefits) information gathered from all sources into an integrated measure. However, final selection always comes down to the judgment of management.

There are several key challenges. First, outsourcing decisions are complex, consisting of both quantitative measurement and qualitative evaluation. How to effectively consolidate various assessments into one unified recommendation is a challenging task. Second, outsourcing decisions are often made under uncertainty and incomplete information. Lack of comprehensive decision models and tools to help managers systematically analyze outsourcing decisions often leads to wrong decisions, resulting in loss of core competencies and exposure to unexpected risks. To account for uncertainty and subjectivity in outsourcing vendor evaluation, we propose a new framework based on fuzzy multiple criteria decision-making theory.

Multi-criteria decision making methods such as data envelope analysis (DEA), analytical hierarchy process (AHP), and the technique for order preference by similarity to ideal solution (TOPSIS)

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have been widely used in assessing project risk [13, 15, 18]. We propose a framework that applies fuzzy logic concept to these traditional multiple criteria decision models. Since risk management is recognized as one of the critical success factors in IT outsourcing projects [4], our proposed framework provides a comprehensive analysis for vendor selection by appropriately trading off the perceived risks and benefits. We aim to integrate qualitative and quantitative decision making into one unified framework that can help practitioners prioritize vendor rankings and make optimal IS outsourcing decisions.

This paper is organized as follows. In the next section, we briefly review relevant literature in the context of IS outsourcing and vendor evaluation methods. Following the literature review, we present our research framework and use case studies from Iranian banking industry to validate our model. Using existing methods as benchmark, our results show our proposed model is a better decision tool that improves upon traditional methods. It not only derives consistent rankings among different methods, but provides recommendations better matched real world managerial decision making experience as shown in the case study.

2. Literature Review

With the increasing popularity of business process outsourcing, vendor selection has been a widely studied topic in the supply chain procurement literature [13]. Due to its inherent complexity, supplier selection is considered as a multi-criterion problem which includes both qualitative and quantitative factors. Performance, technical capability, financial stability, and quality of the supplier have been identified as principal criteria in supplier selection [7].

Theoretically, vendor selection can be modeled as a discrete multi-criteria decision making (MCDM) problem. Popular techniques for MCDM include multi-attribute decision making and multi-objective optimization. Statistical/probabilistic models and intelligent approaches such as clustering and expert systems are also used [22]. Primary concern involved in such decision problems is to rank alternatives in order of importance and choose the most preferred alternative for the final decision.

Several quantitative methods have been used to select appropriate outsourcing vendors. Data envelop analysis (DEA) is a frequently used, multi-criteria decision tool built upon the concept of the efficiency of a decision alternative [28, 26, 5]. However, one critical limitation of this method is that it only provides classification into two groups: efficient and inefficient. All outcomes on the efficient frontier are equally good in the Pareto sense. It does not perform ranking of alternatives.

To overcome this limitation, a DEA-AHP method is proposed [25]. The DEA-AHP is a two-stage model to rank organizational units where each unit has multiple inputs and outputs. In the first stage, the DEA is run for each pair of units separately. In the second stage, the pair-wise evaluation matrix generated in the first stage is used to rank the units via AHP method. The AHP utilizes pair-wise comparison between criteria to rank decision alternatives. The eigenvector of the maximal eigenvalue of the pair-wise comparison matrix is used for ranking. Therefore, the multi-criteria aspect is taken into account by DEA method and the ranking is performed by AHP.

In comparison with the original AHP where data for the pair-wise comparison matrix is subjective, data in the DEA-AHP is objective and is based on the DEA runs for all pairs of evaluation alternatives. Therefore, this method has the potential to quantify decision making based on objective measurements of the input model. However, initial data in the DEA model may be subjective in nature, making it a key challenge to convert initial subjective judgment into an objective measure used in DEA analysis. In order to more appropriately account for the initial subjectivity of data input, we propose a Fuzzy DEA-AHP model.

Fuzzy set theory has been used to model systems that are hard to be defined precisely. It incorporates imprecision and subjectivity of human decision making into the model formulation and solution process. Since Zadeh [29] first proposed fuzzy set theory and Bellman and Zadeh [8] described the decision-making method in fuzzy environments, an increasing number of studies have dealt with uncertain fuzzy problems by applying fuzzy set theory. For instance, the fuzzy AHP method can efficiently handle the fuzziness of the data involved in the decision making [15]. The fuzzy logic and results of the fuzzy approach are better than traditional statistic approach due to its ability to capture difference and ambiguity in view of linguistic variables by different evaluators. This is especially important in assessing vendor risks because assessors' risk attitude may be quite different from each other. Therefore, our proposed Fuzzy DEA-AHP method has the potential to improve upon existing DEA-AHP approach.

Due to the inherent complexity involved in the multi-criteria decision problems of strategic vendor selection, some hybrid models have been proposed in the literature. For example, the analytic network process (ANP) technique was incorporated into

TOPSIS to rank competing products from different vendors [24]. In [17, 22], a new model was proposed to integrate improved fuzzy AHP with TOPSIS algorithm to support project selection decisions. We use Fuzzy TOPSIS as a benchmark to compare rankings derived from the Fuzzy DEA-AHP method. We are able to show the consistency and robustness of the evaluation results by applying Fuzzy approach to these existing MCDM models.

3. Research Framework

The vendor selection problem can be characterized by two aspects. The first step is to determine the number of available vendors and characterize their benefits and risks. The second step is to rank vendors among the existing alternatives. We assume there are a predetermined number of preferred vendors for our consideration. In our case study of the five Iranian commercial banks, three most preferred vendors are selected because it is the real decision problem faced by the case companies. Our focus is therefore in the second step where these vendors are compared based on several criteria related to outsourcing risks and benefits.

The assessment procedure of this study consists of several steps as shown in Figure 1. First, we identify ten most important IS outsourcing risks based on two factors, probability and magnitude of loss by using 5-points Likert scale in a questionnaire. Second, the measurement of performance corresponding to each risk and benefit is conducted under Fuzzy set theory. Finally, to achieve the final ranking results, we apply the multi-criteria models DEA-AHP and TOPSIS. We implemented the application in Microsoft Excel.

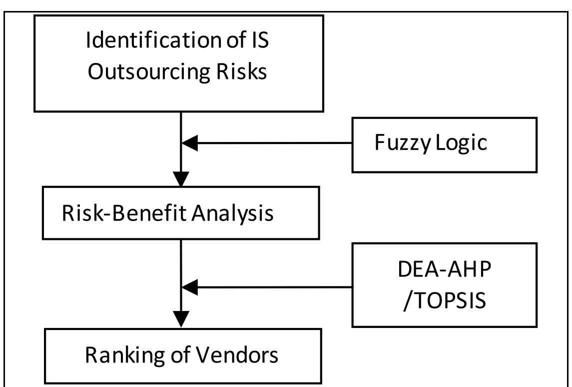

Figure 1. The General Research Framework

We will provide detailed description of each step in the following subsections. we elaborate our research framework, present our decision models, and use a case study in the Iranian commercial banks to illustrate the integrated evaluation approach. Note that, like any MCDM techniques, the method we proposed is very general. It can be applied to more than three vendors and more than ten risk factors.

3.1. Identification of Risks

In the information intensive industries such as banks, IT is considered key drivers for firm growth, advancement, and progress. A study of IS outsourcing in the U.S. banking industry found that IS outsourcing in banks was strongly influenced by production cost advantages offered by vendors [3]. While cost is usually the deciding factor, other benefits such as quality and availability should be considered simultaneously. In addition to the obvious benefits, risks involved in outsourcing are often forgotten. These risks, however, must be understood in order to make informed decisions which may be of crucial importance for the success of IS outsourcing projects [12, 6, 1].

Banks vary in size, profitability, IT scale, and scope of operations. Banks may acquire services from a variety of sources such as parent banks, service bureaus, cooperative joint ventures, and facilities management [2]. These alternative arrangements vary in the degree of internal control banks have over the IS services. Since the banking industry intensively rely on information technology and represents one of the growing concerns of the IS outsourcing, understanding the IS outsourcing risks has important practical implications.

We focus on our data collection in Iranian commercial banks and the vendors were three major IT companies in Iran. They provide IT services such as ERP to many companies and have good reputation. All of them are in Tehran and had some experience to work with financial institutes.

In practice, risk is not the sole criterion for selecting vendors. However, in the banking industry, risk is the most important factor to consider in vendor selection. Specifically, in our case study, Iranian financial institutes get a lot of supports from the government. So cost saving is not a major concern in vendor selection. Bank managers asked us to assess the vendors based on the risk and benefit tradeoff. In addition, we view some vendor selection criteria as risk factors. For example, low quality is interpreted as a risk.

There are different methods for finding risks such as Brainstorming, Delphi Technique, Interviewing and Checklist. Qualitative risk analysis focuses on a subjective analysis of risks based upon a project stakeholder's experience or judgment. This study adopts a survey research design as the primary method for collecting original data related to risk evaluation. In order to identify the most important risk factors specific to the target organizations in the banking industry, we designed a preliminary survey to ask total of 20 experts who are actively involved in recent outsourcing decisions from five Iranian commercial banks.

Because we concern the risks of IS outsourcing and the vendor relationship, we reviewed literature and identified frequently considered risk factors for IS outsourcing. We asked experts to review the risk factors and add any risk factors that were not in the list. Finally, we had incorporated 26 risks in our final survey. As in standard risk management practice, risk is measured along two dimensions: likelihood and impact. The likelihood refers to the probability of an IS outsourcing failure. The impact is concerned about the negative consequence of the IS outsourcing failure. That is, the magnitude of loss.

To find the most important risks, we adopted the method by [6]. We asked experts to rate each risk according to a five-point Likert scale based on magnitude of loss and probability of occurrence. The most important risks were those average scores for both likelihood and impact were between 4 and 5 (i.e., those frequent and significant risks). The final top 10 risks are presented in Table 1.

Table 1. Identified Top 10 Risk Factors

No.	Risk Factors
1	Breach of contract by the vendor
2	Lack of experience and expertise of the supplier with the outsourced activities
3	Cultural differences between client and supplier
4	Lack of experience and experience with project management
5	Costly contractual amendments
6	Disputes and litigation
7	Supplier financial stability
8	Security/privacy breech
9	Inflexible contracts
10	Lack of innovation from supplier

We see that the top 10 risk factors are related to technical expertise and financial strength of the vendor, as well as the service contract. Despite the fact that the identified risk factors are more specific to the target organizations based on their outsourcing experiences, in general these risk aspects are consistent with findings in the literature. For example, in the context of supplier selection, Ellram [12] proposed three principal criteria: the financial state, organizational culture and strategy, and the technological state of the supplier. These considerations are also reflected by our survey results (e.g., items 7, 3, and 2, respectively).

3.2. Fuzzy Logic Approach for Risk-Benefit Assessment

Vendor selection requires a careful examination of various attributes. In this study, we use a risk-benefit analysis to assess vendors. We have identified 10 risk factors in previous section. The benefit is evaluated by two aspects: tangible and intangible. Tangible benefit includes direct cost savings through outsourcing, and intangible benefits may include service quality improvement, customer satisfaction, brand recognition, and so on. In this study, we measure tangible benefits by dollar amounts and the intangible benefits by a subjective rating using a five-point Likert scale.

Traditional survey method requires the evaluators to make the choices among “very low”, “low”, “medium”, “high”, and “very high” based on a 5-point Likert scale. It does not account for the difference and ambiguity among evaluators. For example, two evaluators may perceive “high” risk very differently due to their own risk attitude. Since every respondent perceives differently toward every attribute, the subsequent valuation of the linguistic variable certainly varies among individuals. When respondents convert their preferences to scores in the 5-point Likert scale survey, the conversion may not accurately measure the real preferences. In addition, ‘‘Not very clear’’, ‘‘probably so’’, and ‘‘very likely’’ are terms of expression that have been frequently heard in vendor evaluation. This study deals with the fuzzy subjective judgment of the evaluators during vendor risk-benefit assessment by incorporating fuzzy decision-making theory.

We apply Fuzzy set theory to capture the decision makers’ preference structure by allowing ambiguity of concepts. In the fuzzy environment, evaluation is conducted by allowing uncertainty associated with an individual’s subjective judgment, expressed as membership function of the fuzzy set representation in which fuzzy numbers represent a decision maker’s subjective judgment.

Following Zadeh [29], the linguistic variable that measures a risk factor may be expressed as a triangular fuzzy membership function (L, M, U) within the scale range of 0 to 100. The evaluator can subjectively assume their personal range of the linguistic variable by assigning a real number for the lower bound L, upper bound U and mean value M from a triangle distribution. For example, an evaluator may assign L=0, M=30, U=60 to represent his/her subjective evaluation of very low risk.

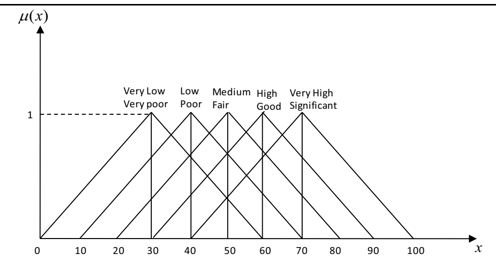

Figure 2. Triangle Membership Function of Fuzzy Set Representation

As shown in Figure 2, the linguistic variable is measured by categorical evaluation using the 5-point Likert scale. The triangle membership function is used. We establish the correspondence between the Likert scale and the Fuzzy set in Table 2.

Table 2. Conversion of Likert Scale into Fuzzy Set Representation

Likert Scale	Outsourcing Risks	Benefits		Fuzzy Set
		Tangible (T)	Intangible (I)	
1	Very Low	Up to \$25,000	Very poor	(0, 30, 60)
2	Low	\$25,001-50,000	Poor	(10,40,70)
3	Medium	\$50,001-75,000	Fair	(20,50,80)
4	High	\$75,001-100,000	Good	(30,60,90)
5	Very High	Over \$100,000	Significant	(40,70,100)

It is worth noting that other transformation functions are possible. If an evaluation does not agree with Table 2 transformation, we allow an evaluator to propose his/her own corresponding fuzzy set by assigning different (L, M, U) triangular fuzzy numbers. Therefore, every respondent perceives differently toward their evaluation of the risk factors. By allowing the evaluators to define their own risk mapping of these linguistic variables, we believe we are able to achieve more accurate evaluation and better results than the traditional method.

Let S_{ij}^k be the overall average assessment of vendor i under criterion j by the kth respondent. If the assessment "high", it will be represented as $S_{ij}^k = (LS_{ij}^k, MS_{ij}^k, US_{ij}^k) = (30, 60, 90)$. Assume there are m assessors. The overall valuation of the fuzzy judgment can be calculated according to Buckley method [9]:

$$LS_{ij} = \left(\sum_{k=1}^{m} LS_{ij}^k\right) / m,$$
$$MS_{ij} = \left(\sum_{k=1}^{m} MS_{ij}^k\right) / m,$$
$$US_{ij} = \left(\sum_{k=1}^{m} US_{ij}^k\right) / m,$$

These aggregated fuzzy numbers need to be converted into a synthetic, non-fuzzy performance value. Several available methods may serve this purpose. Mean-of-Maximum, Center-of-Area, and a-cut Method are the most common approaches. This study utilizes the Center-of-Area method due to its simplicity. The final, best non-fuzzy performance (BNP) value, or the defuzzified value is calculated as:

$$BNP_{ij} = \frac{[(US_{ij} - LS_{ij}) + (MS_{ij} - LS_{ij})]}{3} + LS_{ij}$$

In this study, 70 assessors were asked to evaluate 3 vendors according to the 10 top ranked risk factors as well as the tangible and intangible benefits. The following table shows the aggregated risk and benefit assessment scores BNP_{ij} we obtained from this study:

Table 3. Aggregate Non-Fuzzy Vendor Evaluation Based on Fuzzy Set Theory

	Vendors	A	B	C
Risks (Input)	R1	61.573	61.947	64.690
	R2	53.103	65.497	62.637
	R3	58.800	52.633	65.750
	R4	62.633	63.507	44.517
	R5	64.947	60.001	56.703
	R6	63.683	63.930	62.317
	R7	62.197	55.650	56.703
	R8	59.687	57.210	58.307
	R9	54.727	55.210	60.793
	R10	63.893	63.827	62.537
Benefits (output)	Tangible	55.057	45.650	58.893
	Intangible	58.620	40.314	60.877

3.3. DEA-AHP Method for Vendor Selection

Sinuany-Stern et al. [25] proposed an DEA-AHP method for ranking decision making alternatives (i.e., IS outsourcing vendors in our context). The method includes the following steps:

Step 1: Calculating the pair-wise relative efficiency scores between two vendors. Suppose there are n vendors. Each vendor has m inputs and s outputs. Let X_{ij} be the input i of vendor j and Y_{rj} be output r of vendor j. Denote $v_i \geq 0$ and $u_r \geq 0$ as coefficients of input and output operations. For any pair of vendors A and B, we perform the following DEA runs. The relative efficiency score for these two vendors consists of four linear program (LP) formulation of the DEA: problems AA, AB, BA, BB. The general decision problem AA can be expressed:

Problem AA:

$$E_{AA} = Max\sum_{r=1}^{s} u_r Y_{rA}$$

s.t.

$$\sum_{i=1}^{m} v_i X_{iA} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0$$

Define the slack variables corresponding to the first and the second sets of constraints as $s_2 \geq 0$ and $s_3 \geq 0$, respectively. The highest score of E_{AA} is 1, which is obtained when $s_2 = 0$ and $s_3 \geq 0$. When $E_{AA} = 1$, we say vendor A is efficient. If $E_{AA} < 1$, then $s_2 \geq 0$ and $s_3 = 0$. In this case, we say vendor A is less efficient than vendor B. In this study, evaluation of risk factors provides the input data v_i, $i = 1,\ldots,10$. Evaluation of benefit provides the output data u_r, where $r = 1,2$, and $m = 10$, $s = 2$.

Note that, as the number of inputs and outputs increases, we may have many feasible input-output values. If any pair of inputs and outputs for which one vendor performs better than the others, it receives a DEA score 1, and vice versa. That is, a vendor will receive a comparison value less than 1 in relation to another vendor if it is worse in all the possible combinations of inputs and outputs.

In order to quantify the degree of relative efficiency, we run the following cross evaluation of vendor B:

Problem BA:

$$E_{BA} = Max\sum_{r=1}^{s} u_r Y_{rB}$$

s.t.

$$\sum_{i=1}^{m} v_i X_{iB} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rB} \leq 1$$

$$\sum_{r=1}^{s} u_r Y_{rA} - E_{AA} \sum_{i=1}^{m} v_i X_{iA} = 0$$

$$u_r \geq \varepsilon, v_i \geq \varepsilon$$

Note here that in the cross evaluation, the efficiency score E_{AA} shows up in the third set of constraint. The optimal objective value E_{BA} is the optimal cross evaluation efficiency score. Symmetrically, Problems BB and AB are solved and E_{BB} and E_{AB} can be calculated. For each pair of vendors j and k, we have the entry for the pair-wise comparison matrix needed for AHP as follows:

$$a_{jk} = \frac{E_{jj} + E_{jk}}{E_{kk} + E_{kj}}$$

and

$$a_{jj} = 1.$$

Therefore, in the AHP pair-wise comparison matrix, the diagonal entry a_{jj} has a rank of 1 and the element a_{jk} reflects the evaluation of vendor j over vendor k. a_{jk} is constructed from the paired DEA results. Obviously, a_{jk}=1/ a_{kj}, consistent with the AHP method.

Note that, the pair-wise comparison matrix is $n \times n$. This matrix has not been evaluated subjectively by a decision maker yet. Rather, it is an objective evaluation. It is calculated from the DEA pair-wise runs, which provide cross evaluation, thus allowing each vendor to receive its most favorable evaluation relative to any other vendor. Table 4 shows the pair-wise comparison matrix of vendors based on DEA method.

Step 2: Calculating the pair-wise relative efficiency scores between two vendors. In the second stage, based on the pair-wise comparison matrix generated in the first stage (presented in Table 4), a single hierarchical level AHP is run to calculate the maximal eigenvalue and its corresponding eigenvector $\vec{w}$. The j th component of $\vec{w}$ reflects the relative importance given to vendor j. We assign the rank 1 to the vendor who has the maximal value of w_j, Ranks for other vendors are in a decreasing order of w_j.

Table 4. Pair-wise Comparison of Vendors			
Vendor	**A**	**B**	**C**
A	1	1.079	1
B	0.927	1	0.968
C	1	1.033	1
Total	2.927	3.112	2.968

AHP is a decision making method for prioritizing alternatives when multiple criteria and sub-criteria must be used. The AHP ranks alternatives based on the decision maker's judgment concerning the importance of the criteria and the extent to which they are met by each alternative. The pair-wise comparisons are used to determine the relative importance of one vendor with respect to another in meeting the risks and benefits criterion. Table 5 shows the final vendor ranking using one level AHP. As seen, vendor A is determined as the most preferred vendor.

Table 5. Fuzzy DEA-AHP Vendor Ranking					
Vendor	**A**	**B**	**C**	**Average**	**Rank**
A	0.342	0.347	0.337	0.342	1
B	0.316	0.321	0.326	0.321	3
C	0.342	0.332	0.337	0.337	2

3.4. TOPSIS Method for Vendor Selection

The TOPSIS method was first proposed by [14]. The underlying logic of TOPSIS is to define the ideal solution and the negative ideal solution. First, the ideal solution is formed as a composite of the best performance values exhibited in the decision matrix by any alternative for each attribute. The negative-ideal solution is the composite of the worst performance values. Second, proximity to each of these performance poles is measured in the Euclidean sense (e.g., square root of the sum of the squared distances along each axis in the attribute space). Finally, the ranking of alternatives in TOPSIS is based on 'the relative similarity to the ideal solution'.

In our context, the ideal solution is the solution that maximizes the benefit criteria and minimizes the risk criteria. Define the ideal and negative ideal solutions associated with R1-R10, tangible benefit (T), and intangible benefit (I) as V_j^* and V_j^-, j=1,...,12.

Next, calculate the distance between ideal solution and negative ideal solution for each vendor:

$$S_i^* = \sqrt{\sum_{j=1}^{12}(V_{ij} - V_j^*)^2}\,, i = A, B, C$$

$$S_{i^*}^- = \sqrt{\sum_{j=1}^{12}(V_{ij} - V_j^-)^2}\,, i = A, B, C$$

Finally, calculate the relative closeness to the ideal solution of each vendor:

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}\,, i = A, B, C\,,$$

where $0 \le C_i^* \le 1$. That is, an alternative i is closer to the ideal solution as C_i^* approaches to 1. Final vendor ranking based on closeness to the ideal solution is presented in Table 6.

Table 6. Fuzzy TOPSIS Vendor Ranking		
Alternatives	**Similarity to ideal solution**	**Rank**
A	0.987	1
B	0.002	3
C	0.166	2

Comparing Tables 5 and 6 we see that rankings based on Fuzzy DEA-AHP and Fuzzy TOPSIS are consistent. Both methods rank vendor A as the first choice, followed by vendors C and B.

4. Evaluation of the Fuzzy Logic Framework

To calibrate our proposed model, we use the DEA-AHP model and the TOPSIS method as a benchmark. The DEA-AHP method follows the same two steps described in previous section. Different from Table 3 in which *BNP* vendor evaluation scores are used as input to the DEA-AHP model and TOPSIS method, the following Table 7 shows the average itemized evaluation from all assessors without using the Fuzzy set conversion.

Using values in Table 7 as input to the DEA-AHP method, the corresponding pair-wise comparison matrix of vendors and final ranking of the vendors are presented in Tables 8 and 9, respectively.

Table 7. Aggregate Vendor Evaluation Based on Subjective Assessment				
	Vendors	A	B	C
Risks	R1	3.5	4	3.2
	R2	4	4.25	4.6
	R3	3.75	3.85	4.7
	R4	4.1	4.2	3.3
	R5	4.6	3.8	4.4
	R6	3.9	3.1	4.8
	R7	4.3	3.6	4.08
	R8	3.8	3.7	4.65
	R9	3.2	4.2	3.45
	R10	4.05	3.1	4.1
Benefits	Tangible	2.9	4.2	3.8
	Intangible	3	4.1	3.9

Table 8. Pair-wise Comparison Matrix of Vendors

Vendor	**A**	**B**	**C**
A	1	0.9802	0.9821
B	1.0202	1	1
C	1.0182	1	1
Total	3.0384	2.9802	2.9821

Table 9. DEA-AHP Vendor Ranking

Vendor	**A**	**B**	**C**	**Average**	**Rank**
A	0.329	0.329	0.335	0.329	3
B	0.336	0.336	0.335	0.336	1
C	0.335	0.336	0.335	0.335	2

Similarly, using values in Table 7 as input to the TOPSIS method, we have the following ranking:

Table 10. TOPSIS Vendor Ranking

Alternatives	**Similarity to ideal solution**	**Rank**
A	0.403	2
B	0.778	1
C	0.361	3

Although both DEA-AHP and TOPSIS (without applying Fuzzy logic) recommend vendor B as the first choice, their ranking for A and C are different. This is in contrast with the two methods based on fuzzy logic approach, which yielded consistent ranking among the three vendors. This shows the robustness of results of the proposed fuzzy logic framework.

At the time of our survey in 2009, all five Iranian commercial banks were considering business process outsourcing of some back office IT functions both due to peer pressure in the banking industry and an effort to concentrate on their core businesses. The outsourcing projects among these banks were similar in scope and share some common characteristics. All survey respondents were involved in their respective outsourcing vendor selection. Independent of our evaluation of vendors based on survey data, each bank chose their own outsourcing vendors. We tracked the outsourcing results of these banks. So far, vendor A is the most frequently chosen outsourcing vendor.

Comparing Tables 5, 6, 9, and 10 we see that methods based on Fuzzy logic come up with different orders of vendor ranking. DEA-AHP and TOPSIS methods suggest B should be the most preferred vendor. But Fuzzy DEA-AHP and Fuzzy TOPSIS suggest A is the best. The practice of the five Iranian commercial banks confirms the recommendation based on the Fuzzy logic approach. The major driving force to the different conclusion is that, even for the same rating of the risk factor, assessors may perceive differently about the linguistic meaning of their ratings. The models based on Fuzzy logic better captures this subjectivity among evaluators. This demonstrated superiority of our proposed framework over the existing MCDM models.

5. Conclusion

Standardization and technology advances permit specialization in the value chain. Services traditionally provided by internal IT departments can be acquired externally from service providers over the Internet. However, enterprises often enter outsourcing deals without carefully evaluating IS outsourcing risks and benefits. This study proposes a hybrid model to evaluate multi-aspects of vendor selection problem by integrating several decision models into one unified decision framework. We use a real world case study of Iranian commercial banks to illustrate the validity of incorporating fuzzy logic into existing DEA-AHP and TOPSIS methods. Results show the superiority of our proposed framework over these existing approaches, as our ranking is more consistent with the final outsourcing vendor selection results.

Theoretical contribution of this paper is a new approach for outsourcing vendor selection based on a fuzzy multi-criterion decision framework. This framework can overcome the weakness in existing multi-criterion decision models by better taking into account the heterogeneity of assessor subjectivities in the qualitative assessment process. To the best of our knowledge, no prior work has combined Fuzzy theory into DEA-AHP and TOPSIS decision making models in the IS outsourcing risk assessment context.

The practical significance is that it provides an effective decision tool for managers to better capture subjectivity among evaluators. Because assessors may perceive differently about the linguistic meaning of their ratings even for the same rating of the risk factor, traditional methods without taking into account this subjectivity will lead to evaluation bias during the data aggregation process. The proposed framework effectively integrates various considerations from different assessors to come up with a more consistent evaluation.

A thorough evaluation and comparison among vendors is the key to minimize IS outsourcing risks. This study provides a theoretical foundation for selecting IT service providers that matched real world experience. Our proposed framework does improve consistency in terms of ranking between different methods provides a better match with the real world experience.

Although this study presents an application of the developed method in the banking industry, the new method is not limited to any industry specific IS outsourcing projects. In fact, it can be used for risk assessment of vendors in the general context of IS outsourcing and IT service provider selection.

Future work may collect data in other industries and consider IS outsourcing risks with different scopes and degrees of vendor control. In addition, future study may compare other existing quantitative methods that are used in IS outsourcing vendor evaluation. Although incorporating fuzzy set theory into the existing multi-criteria decision models has certain benefits over existing models, such as better account for uncertainty and subjectivity in outsourcing vendor evaluation, further validation of the proposed framework is necessary and is an interesting direction for future research.

6.References

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