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Cloud computing model selection for e-commerce enterprises using a new 2-tuple fuzzy linguistic decision-making method

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ABSTRACT

Cloud computing is truly transforming the way e-commerce firms do business. While there has been a sharp increase in the use of cloud computing in e-commerce, the benefits of cloud service models have yet to be explored, particularly for small-to-medium-sized businesses. A strong e-commerce offering depends on a reliable and secure online store, therefore it is important for decision makers to adopt the optimal cloud computing service model such as software-as-a-service (SaaS), platform-as-a-service (PaaS), or infrastructure-as-a-service (IaaS), which is a multi-criteria decision-making problem (MCDM). To address this MCDM problem, we propose a novel 2-tuple fuzzy linguistic multi-criteria group decision-making method based on the technique for order preference by similarity to ideal solution (TOPSIS) and rely upon a technology-organization-environment (TOE) framework to determine a set of appropriate criteria. The proposed methodology is applied to a small-to-medium-sized company to facilitate assessing the factors associated with cloud-based e-commerce and making the decision. The result analysis indicates that SaaS is the best choice for small and medium-sized e-commerce businesses considering criteria such as complexity, reliability, security and privacy, organization readiness and firm size, while the selection of PaaS or IaaS can be reinforced considering their compatibility and scalability.

1. Introduction

E-commerce is a rapidly changing environment. Competition, advancements in cloud computing, social media, and a variety of other factors are all contributing to a turbulent business landscape (Lackermair, 2011). To survive, e-commerce firms are under considerable pressure to increase their productivity and profitability and, as a result, many e-commerce managers are looking to technology to sustain and improve their competitive advantage.

E-commerce spans many functions, including marketing, human resources, inventory, finance, sales, operations, and supply chains. In addition, e-commerce businesses deal with both unstructured and structured data. In the e-commerce context, structured data is demographic data, such as a customer's name and address, while unstructured data primarily stems from social networking services, such as reviews and rankings, posts, videos, likes, links, and tweets. Today, the ability for e-commerce firms to use big data in their operational and decision-making processes is crucial for gaining and maintaining a competitive advantage (Davenport, 2013). In addition, using big data analytics to segment markets can lead to new products, business model innovations, greater transparency, improvements to infrastructure, decision-making, and performance – all of which create business value (Akter & Wamba, 2016).

However, in dealing with the structured and unstructured data of e-commerce, the challenge is generating insights that are significant enough to convert prospects into customers (Akter & Wamba, 2016). Effectively processing and analyzing big data requires substantial computational infrastructure (Hashem et al., 2015), but the shared resources associated with cloud computing can offer businesses fundamental support (Yang, Huang, Li, Liu, & Hu, 2017). Services, such as cloud storage, cloud networking, and analysis software in the cloud, now have the potential to provide solutions that allow e-commerce firms to become more efficient, more productive, and more competitive. E-commerce in the cloud is becoming renowned as the primary way for e-commerce firms to transform all facets of their operations and services (Qing, 2012). Yet, many have concerns about the quality of service, transparency, security, and the cost of cloud computing, and these concerns are inhibiting its uptake (Lackermair, 2011; Liu, 2011;

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Treesinthuros, 2012).

Cloud computing provides opportunities for businesses to increase their productivity and reduce their operations and maintenance costs while providing products to their customers (Qing, 2012). A thorough study of the factors that lead businesses to adopt, or reject, cloud-based e-commerce solutions is needed. To select the right e-commerce solution, managers need to be able to understand the strengths and weaknesses of the range of available cloud computing models. According to the National Institute of Standards and Technology (NIST), the current cloud service models are infrastructure-as-a-service (IaaS), platform-as-a-service (PaaS), and software-as-a-service (SaaS) (Mell & Grance, 2011). Each model describes which cloud services are made available to clients. For instance, an e-commerce firm might use an IaaS model to purchase computer infrastructure as an on-demand service, such as servers, storage, networks, and operating systems. PaaS provides clients with a pre-built application platform that can be used as needed rather than investing in their own underlying infrastructure. Alternatively, PaaS might be used to quickly launch an e-commerce site without worrying about server configurations or software updates. In practice, however, there are many uncertainties concerning the use of cloud-based resources for e-commerce (Wang, 2012). Reliability and security are key considerations for online stores (Treesinthuros, 2012), and it is important for managers and decision makers to map the pros and cons of various cloud-based models to their own specific technology requirements and financial constraints.

Cloud services vary greatly in terms of specifications, performance, pricing, reliability, and security, making it challenging for firms to select the vendor and services that best suit their needs (Hussain, Hussain, Hussain, Damiani, & Chang, 2017). This situation represents a multiple criteria decision-making (MCDM) problem, which means making a decision of preference from a set of available alternatives that is characterized by multiple and conflicting criteria. MCDM problems can be solved using various techniques with strengths and weaknesses and choosing the right one can be challenging. Nowadays, real world decisions are more and more complex in organizations. Therefore, it drives decision processes towards two important strands:

i Decisions made by groups, not individuals. This is referred to as group decision-making. Multi-criteria group decision-making (MCGDM) is a combination of the MCDM and group decision-making approaches, providing an effective way for final decisions to be made in a group setting (Ma, Lu, & Zhang, 2010).
ii Managing uncertainty under such a complexity by means of models that facilitate the elicitation and comprehension of the decision process and results (Rodriguez & Martinez, 2013).

Human beings deal with qualitative information often expressed by natural or artificial language in their daily tasks that imply reasoning and decision-making processes. Hence computing with words (CW) is a common methodology for linguistic decision-making (Martinez, Ruan, & Herrera, 2010). Different models and proposals have been developed to carry out such processes. However, the use of CW in group decision-making is challenging due to the type of linguistic modelling and the linguistic computational model used in the decision process. One of the most well-known and broadly used methods for CW in decision-making was proposed by Herrera and Martinez (2000), the so-called 2-tuple linguistic modeling. It does not suffer information loss during the CW processes and provides accurate linguistic results across all the decision processes. The 2-tuple model linguistic model has proven to be appropriate for dealing with linguistic term sets that are uniformly and symmetrically distributed (Li, Dong, Herrera, Herrera-Viedma, & Martínez, 2017; Rodriguez & Martinez, 2013; Ruan et al., 2010). Previous research shows that the 2-tuple semantic has been successfully used in a wide range of applications (Li et al., 2017; Rodriguez & Martinez, 2013). Therefore, in this study, the fuzzy linguistic 2-tuple model is used due to its fuzzy representation, flexibility, understandability, and accuracy in decision-making (Martinez & Herrera, 2012; Rodriguez & Martinez, 2013).

Hence, the purpose of this study is to analyze an e-commerce manager's decision-making process and its determinants, in adopting SaaS, PaaS, and/or IaaS as a public cloud computing model. Following this main aim, our research question is "what are the impacts of technological, organizational, and environmental factors on the adoption of cloud-based e-commerce?" This paper extends the study by Sohaib and Naderpour (2017) by applying a new 2-tuple fuzzy linguistic MCGDM TOPSIS method within the CW paradigm for an e-commerce company to guide the decision-making process. Our analysis of the results, following the Technology-Organization-Environment (TOE) framework, reveals insights for e-commerce managers to choose the best cloud computing service model for their needs.

The rest of this paper is organized as follows. The next section provides the theoretical background related to this paper. Section 3 presents the novel 2-tuple fuzzy linguistic TOPSIS model. The research methodology is presented in Section 4, followed by the case study in Section 5 and our analysis and the results in Section 6. Section 7 concludes the paper and provides some future research directions.

2. Theoretical background

This section provides some background and related studies on e-commerce, cloud computing, the TOE framework, and MCDM.

2.1. E-commerce

Buying and selling products and services over the Internet, i.e., e-commerce, has transformed the face of business from a people-driven endeavor into a technological landscape. Multinational corporations around the globe use different e-commerce models. These models include business to business (B2B), business to consumer (B2C), and consumer-to-consumer (C2C). Online businesses now depend on how much and how well they can exploit technology. Today e-commerce must deal with big data due to the use of social media and new technologies. Therefore, the success of e-commerce companies also depends on their e-commerce platform. As a result, the field of e-commerce has adopted technology-assisted applications to support a variety of business functions, such as business intelligence, product recommendation, and fraud detection (Ngai, Xiu, & Chau, 2009). However, analyzing data and taking advantage of feature extraction is not possible with generic data (Sarwar, Karypis, Konstan, & Riedl, 2000). Thus, the decision facing many e-commerce firms today is whether or not to move to a cloud-based e-commerce service and, if so, which one to choose.

2.2. Cloud computing

Cloud computing is a widely-accepted new technology in parallel computing that provides a range of services to consumers, such as ubiquitous computing, dynamic and elastic scaling, on-demand computing resources access, metered resource usage, and virtualized resources that can be provisioned and released without effort (Hussain, Hussain, & Hussain, 2016; Ramezani, Lu, Taheri, & Zomaya, 2017). Cloud computing assists users by offering convenient and on-demand access to a range of computer resources from computing infrastructure (i.e., IaaS) to computing platforms (i.e., PaaS) and to applications that run in the cloud (i.e., SaaS). IaaS offers network infrastructure, processing power, storage, hardware and software firewalls, virtual private network hardware and software (Shroff, 2010). PaaS combines both hardware and software to build, enhance, and execute software applications as an all-in-one service. Developers can design, automatically test and deploy, host, and maintain their applications within a single environment, saving a significant amount of time and effort (Rosenberg & Mateos, 2010). SaaS provides access to applications that have already been developed through a thin client or web browser. Consumers do not need to update the applications or manage the development platform and underlying infrastructure. SaaS applications are less vulnerable to cyberthreats, have longer life cycles, are more economical, and consume less power (Mell & Grance, 2009; Rhoton, 2013; Shroff, 2010).

Enterprises that use cloud services, and particularly small-to-medium-sized enterprises (SMEs), are better able to manage their resources wisely, efficiently, cost-effectively, and can redirect their investments in capital expenses to operational purposes to increase performance (Akter & Wamba, 2016; Lackermair, 2011). However, despite the many benefits of cloud computing, consumers may struggle with information overload and the multitude of criteria that influence their purchasing decisions when choosing a specific cloud service. As such, Zhang, Zhou, Wang, and Chen (2016) proposed a fuzzy MCDM method to assist consumers with cloud-based e-commerce purchasing decisions; however, their study only focuses on the end-user perspective and ignores the factors that are crucial when adapting an enterprise to a cloud environment. Misra and Mondal (2011) proposed two types of business models – one for new firms and another for existing firms with IT infrastructure already in place. They find that due to the wide range of services, convenience, and pay-as-you-go models, cloud computing is the best option for startups as compared to existing firms. Several researchers have proposed models for resource allocation in a cloud environment to improve organization performance and effectiveness, and each study reveals different environmental, technological, organizational, and industry-specific factors that may impact the adoption of cloud computing in an enterprise, particularly in SMEs (Buyya, Yeo, Venugopal, Broberg, & Brandic, 2009; Grossman, Gu, Sabala, & Zhang, 2009; Hussain, Hussain, Hussain, & Chang, 2016).

Based on our review of the literature, it is clear that using an MCDM framework that considers technological, organizational, and environmental factors is important to ensure that SMEs are able to make the optimal purchasing decision when selecting a cloud computing service.

2.3. The technology-organization-environment framework

For the purpose of our analysis, we adopted the technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990), which assumes that a generic set of factors can predict the possibility of cloud-based e-commerce adoption. The theory suggests that adoption is influenced by technology development, organizational conditions, and the industry of the business.

2.3.1. The technological context

Technology, in the context of the TOE framework, refers to both the internal and external technologies that are appropriate for an organization. Adopting a new technology can be a highly complex undertaking for a business, but if the technology is highly compatible with the business's needs and is managed properly, it can provide solid business growth (Walterbusch, Martens, & Teuteberg, 2013). Decisions to adopt cloud technology are determined by innovations that fit with the existing technology landscape (Tornatzky & Fleischer, 1990). The most common factors in the decision to adopt new technologies are relative advantage, complexity, compatibility, accessibility, reliability, security and privacy, and scalability (Alkhater, Walters, & Wills, 2014; Borgman, Bahli, Heier, & Schewski, 2013; Ramdani, Kawalek, & Lorenzo, 2009). Table 1 describes each factor.

2.3.2. The organizational context

Organization, in the TOE framework, refers to the characteristics and resources of an organization. Organizational readiness is good for business and can promote forward development if legitimately overseen by individuals within the business. The size of an organization also plays a role in its advancement; it should neither be too high nor too low. The organizational factors affecting cloud computing purchasing decisions explored in this study include organizational readiness, firm size, and top management support (Alkhater et al., 2014; Hemlata, Hema, & Ramaswamy, 2015). Table 2 describes these factors in more detail.

2.3.3. The environmental context

Environment relates to how "a firm conducts its business – its industry, competitors, access to resources supplied by others, and dealings with the government" (Borgman et al., 2013; Tornatzky & Fleischer, 1990). Effective communications with vendors, partners, and competitors must be optimally managed to ensure management is not affected and to maintain environmental sustainability (Tsai, Wang, & Lu, 2011). Competitive pressure, cost and trading partner pressure, and the governing regulatory environment are the factors examined in this study (Alkhater et al., 2014; Hemlata et al., 2015). Table 3 explains each factor.

2.4. Fuzzy linguistic multi-criteria group decision-making

MCDM denotes decision-making in the presence of multiple and conflicting criteria with both quantitative and qualitative factors. A typical MCDM problem based on m alternatives $(A_1, A_2, \cdots, A_m)$and n criteria $(C_1, C_2, \cdots, C_n)$ is presented as:

$$X = [x_{ij}]_{m*n},\ W = [w_j]_n \tag{1}$$

where X is the decision matrix, x_{ij} is the performance of the ith alternative with respect to the jth criterion, W is the weight vector, and w_j is the weight of the jth criterion.

In real-world problems, decisions are often made under vague, imprecise and uncertain information, increasing their complexity. Commonly, the uncertainty is not probabilistic in nature. An appropriate tool to overcome these difficulties is the fuzzy linguistic approach that enhances the trustworthiness and flexibility of classical decision models (Martínez, Ruan, Herrera, Herrera-Viedma, & Wang, 2009).

2.4.1. Fuzzy linguistic approach in decision making

In many real-world situations, humans are successful in qualitative assessment; however, their quantitative assessment abilities are very limited. In addition, humans are more prone to bias when forced to provide numerical estimates because numerical estimates require more mental effort than less precise verbal statements (Kahraman, Ruan, & Doğan, 2003). Therefore, the use of a linguistic approach seems necessary. Computing with words methodology deals with natural language, hence, linguistic inputs and outputs are easy for human beings to understand (Li et al., 2017). The fuzzy linguistic model, based on fuzzy set theory, is a well-known and applicable linguistic approach (Martínez et al., 2009). A fuzzy linguistic model translates verbal expressions into numerical ones, thereby dealing with imprecise expressions of a criterion's importance quantitatively. Thus, several multi-attribute methods have been developed that are based on fuzzy linguistic variables (Ma et al., 2010; Martínez et al., 2009; Pedrycz, Ekel, & Parreiras, 2011; Wang and Chen, 2008; Yatsalo, Korobov, & Martínez, 2017).

A linguistic variable takes words or sentences in a natural or artificial language as its values. Therefore, it is characterized by (X, T, U, M) where X is the name of the linguistic variable, T is the set of linguistic values that X can take, U is the actual physical domain in which the linguistic variable X takes its quantitative (crisp) values, and M is a semantic rule that relates each linguistic value in T with a fuzzy set in U (Naderpour, Lu, & Zhang, 2014).

The semantics of the terms are represented by fuzzy numbers defined in the interval $[0, 1]$, described by membership functions. Such functions can be defined in different ways; in our proposal we assume that the parametric (trapezoidal/triangular) functions are good enough to capture the vagueness of those linguistic assessments (Delgado, Vila, & Voxman, 1998). Fig. 1 represents the linguistic terms of the term set, $S = \{N, VL, L, M, H, VH, A\}$, by using their triangular membership functions.

Table 1
Definitions of technological factors.

Factor	Definition
Relative advantage	"The degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003). An advantage of cloud computing for a business is the ability to establish new services without managing or owning computer resources. Some of cloud computing's relative advantages for e-commerce are scalability, a pay-as-you-go business model, and increased efficiency (Safari, Safari, Hasanzadeh, & Ghatari, 2015). E-commerce firms should assess the relative advantages of cloud computing, such as cost optimisation
Complexity	The perceived degree of difficulty of understanding and using a system (Sohaib & Naderpour, 2017). For example, if the differenet aspects of the cloud computing are hidden from the client, this will create higher uncertainty related to successful adoption
Compatibility	"The degree to which an innovation is perceived as being consistent with the existing value, past experiences, and the needs of receivers" (Sohaib & Naderpour, 2017). For example, cloud technologies are aligned with different computing platforms, and that the organization will be able to benefit from cloud computing
Security & privacy	Security refers to the level of security procedures in place to protect the system from unauthorized access. Privacy refers to the confidentiality of user information. When selecting a cloud provider, decisions are very often influenced by a company's security and privacy requirements (Alkhater et al., 2014; Repschläger, Wind, Zarnekow, & Turowski, 2013). Businesses have to be sure that data and applications held in the cloud are adequately protected against unauthorized access
Reliability	The ability of the cloud service to keep functioning with a particular level of performance over time. This means that the customer can trust that the cloud service will be available when needed. Providers typically guarantee availability in the form of a service level agreement (Repschläger et al., 2013)
Scalability	The ability of cloud computing to manage increasing amounts of resources. Due to the extensive usage of mobile applications, on-demand services, and transactions, workloads can rise significantly and require scalable IT structures (Repschläger et al., 2013)

Table 2
Definitions of organizational factors.

Factor	Definition
Organizational readiness	"Managers' perception and evaluation of the degree to which they believe that their organization has the awareness, resources, commitment, and governance to adopt an IT [system]" (Hemlata et al., 2015). This involves IT infrastructure and the human resources (and skills) required to adopt cloud computing
Firm size	Firm size is accepted as an important facilitator for the adoption of technology innovations (Tornatzky & Fleischer, 1990). However, investments in cloud computing for SMEs vs. large firms differ significantly (Borgman et al., 2013)
Top management support	This factor contributes to the adoption of innovations by creating a productive environment and by providing resources (Borgman et al., 2013). Top management support for the cloud computing transformation is important

Table 3
Definitions of enviromental factors.

Factor	Definition
Competitive pressure	The degree of pressure that an organization faces from competitors. More competition means more adoption of innovation
Trading partner pressure	The pressure from trading partners to implement and adopt a technology (Hemlata et al., 2015). E-commerce requires network externalities with trading partners, such as consumers, dealers, suppliers, and vendors, to ensure electronic interactions and transactions along the value chain
Government regulatory environment	Cloud computing adoption is affected by government legislation (Safari et al., 2015). For example, a lack of government regulations or standards to support business in the event of a data breach might obstruct adoption decisions

The use of linguistic information in decision-making implies processes of CW (Martinez et al., 2010). Different models and proposals have been developed to carry out such processes. In our proposal, the fuzzy linguistic 2-tuple model introduced by Herrera and Martinez (2000) is used because of its fuzzy representation, flexibility, understandability and accuracy (Martinez & Herrera, 2012; Rodriguez & Martinez, 2013). This 2-tuple linguistic representation model represents a precise and simple method that does not suffer information loss during the CW processes and provides linguistic results throughout the whole decision process. The linguistic model introduces a new parameter, $\alpha_i \in [-0.5, 0.5)$, called *symbolic translation*, that indicates the translation of the fuzzy membership function with respect to the closest term:

$$\alpha = \begin{cases} [-0.5, 0.5) & if \quad s_i \in \{s_2, s_3, \cdots, s_{t-1}\} \\ [0, 0.5) & if \quad s_i = s_1 \\ [-0.5, 0) & if \quad s_i = s_t \end{cases} \tag{2}$$

Linguistic results obtained from CW processes are fuzzy values that often do not exactly match any linguistic terms in the term set, S, their

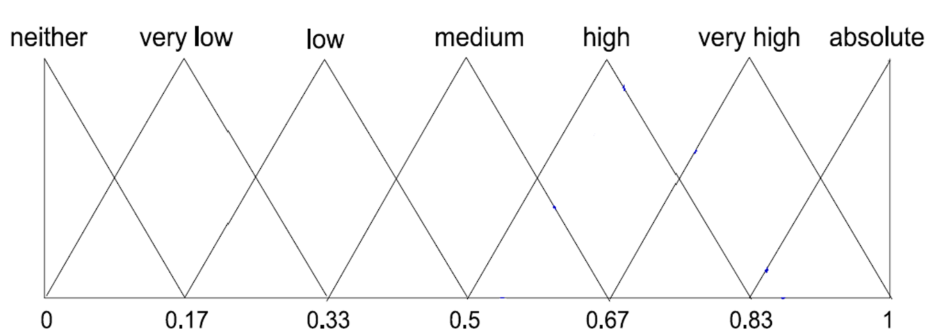

Fig. 1. The linguistic variables and membership functions (Rodríguez et al., 2013).

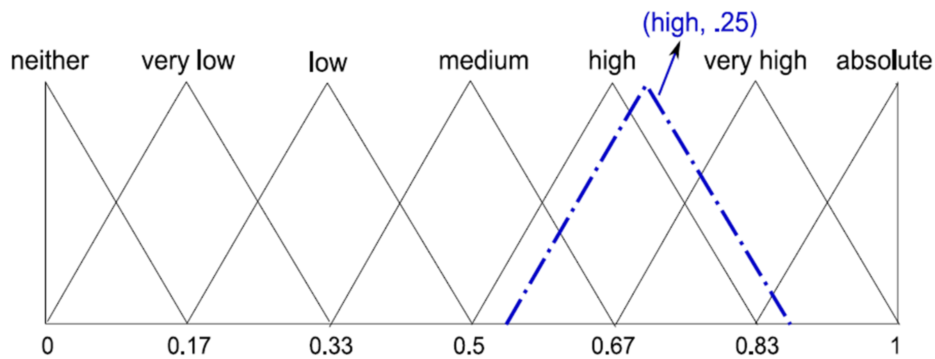

Fig. 2. A 2-tuple linguistic representation (Rodríguez et al., 2013).

linguistic representation can be easily constructed by means of linguistic 2-tuples (s_i, α_i), $s_i \in S$, and $\alpha_i \in [-0.5, 0.5)$. Fig. 2 illustrates a 2-tuple linguistic representation.

This representation model defines a set of functions to facilitate the CW processes by transforming the linguistic 2-tuples into numerical values (Herrera & Martinez, 2000; Martinez & Herrera, 2012):

Definition 1:. Let β be the result of a symbolic aggregation of the indices of a set of labels assessed in a linguistic term set S. $\beta \in [1, t]$, with t being the cardinality of S. Let $i = round(\beta)$ and $\alpha = \beta - i$ be two values such that $i \in [1, t]$ and $\alpha \in [-0.5, 0.5)$: α is a symbolic translation.

Definition 2:. Let $S = \{s_1, s_2, \cdots, s_t\}$ be a linguistic term set and let $\beta \in [1, t]$ be a value supporting the result of a symbolic aggregation operation. The 2-tuple that expresses the equivalent information is obtained with the following function:

$$\Delta_S: [1, t] \to S * [-0.5, 0.5) \tag{3}$$

$$\Delta_S(\beta) = \begin{cases} s_i, \ i = round(\beta) \\ \alpha = \beta - i, \ \alpha \in [-0.5, 0.5) \end{cases} \tag{4}$$

where *round* is the usual rounding operation, s_i has the closest index label to β, and α is the value of the symbolic translation.

Proposition 1:. *Let* $S = \{s_1, s_2, \cdots, s_t\}$ *be a linguistic term set and* (s_i, α_i) *be a 2-tuple. There is always a function* Δ_S^{-1} *that returns a 2-tuple equivalent to the numerical value* $\beta \in [0, t] \subset R$:

$$\Delta_S^{-1}: S * [-0.5, 0.5) \to [0, t] \tag{5}$$

$$\Delta_S^{-1}(s_i, \alpha_i) = i + \alpha = \beta \tag{6}$$

It can be concluded that converting a linguistic term into a linguistic 2-tuple consists of adding a value 0 as symbolic translation, i.e., $s_i \in S \Rightarrow (s_i, 0)$.

Definition 3:. Let (s_k, α_k) and (s_l, α_l) be two 2-tuples. If $k < l$, then (s_k, α_k) is smaller than (s_l, α_l). If $k = l$, then: (a) if $\alpha_k = \alpha_l$, then (s_k, α_k) and (s_l, α_l) represent the same information; (b) if $\alpha_k < \alpha_l$, then (s_k, α_k) is smaller than (s_l, α_l); and (c) if $\alpha_k > \alpha_l$, then (s_k, α_k) is bigger than (s_l, α_l).

Definition 4:. A 2-tuple negation operator is defined as

$$neg(s_i, \alpha_i) = \Delta_S((t + 1) - (\Delta_S^{-1}(s_i, \alpha_i))) \tag{7}$$

where t is the cardinality of $S = \{s_1, s_2, \cdots, s_t\}$.

Different aggregation operators have been defined for the linguistic 2-tuple model (Martinez & Herrera, 2012), such as the arithmetic mean:

Definition 5:. The 2-tuple arithmetic mean of a set of 2-tuples, i.e., $x = \{(s_1, \alpha_1), (s_2, \alpha_2), \cdots, (s_n, \alpha_n)\}$ is defined as

$$(\bar{r}, \bar{\alpha}) = \Delta_S\left(\frac{1}{n}\sum_{j=1}^{n}\Delta_S^{-1}(s_j, \alpha_j)\right) \tag{8}$$

where $\bar{r} \in S$ and $\bar{\alpha} \in [-0.5, 0.5)$.

In regards to the different distance and similarity proposals for linguistic information, in our proposal we have followed the idea introduced by Dutta, Guha, and Mesiar (2015) keeping the meaning of the linguistic result after the operation.

Definition 6:. Let $S = \{s_1, s_2, \cdots, s_t\}$ be a linguistic term set as before and consider the new linguistic term set $S' = \{l_1, l_2, \cdots, l_{t'}\}$ whose term l_i represents the linguistic evaluation of the similarity between any two linguistic terms s_p and s_r from S such that $|p - r| = t' - i$. The linguistic similarity degree between any two linguistic 2-tuples is then given as:

$$sim^{2t}((s_p, \alpha_p), (s_r, \alpha_r)) = \Delta_{S'}\left(t' - \frac{|\Delta_S^{-1}(s_p, \alpha_p) - \Delta_S^{-1}(s_r, \alpha_r)|\ \hat{A}\cdot(t' - 1)}{t - 1}\right) \tag{9}$$

We propose $S' = \{l_1$: *totally dissimilar*, l_2: *almost totally dissimilar*, l_3: *a bit dissimilar*, l_4: *neither dissimilar nor similar*, l_5: *a bit similar*, l_6: *almost similar*, l_7: *completely similar*$\}$.

Hence the similarity results will be linguistic and easy to understand. For instance, let us assume $S = \{$*very low*, *low*, *medium*, *high*, *very high*$\}$:

$sim^{2t}((high, 0), (Medium, 0.5)) = (almost\ \ similar, 0.25)$

Definition 7:. Let $S = \{s_1, s_2, \cdots, s_t\}$ be a linguistic term set as before and consider a new linguistic term set $S'' = \{r_1, r_2, \cdots, r_{t''}\}$ whose term r_i represents the linguistic evaluation of the distance between any two linguistic terms s_p and s_r from S such that $|p - r| = (t'' + 1) - i$. The linguistic distance between any two linguistic 2-tuples is then given as:

$$d^{2t}((s_p, \alpha_p), (s_r, \alpha_r)) = \Delta_{S''}\left((t''+1) - (t'' - \frac{|\Delta_S^{-1}(s_p, \alpha_p) - \Delta_S^{-1}(s_r, \alpha_r)|\ \hat{A}\cdot(t'' - 1)}{t - 1})\right) \tag{10}$$

We propose $S'' = \{r_1$: *equal*, r_2: *almostequal*, r_3: *abitclose*, r_4: *neitherclosenorfar*, r_5: *abitfar*, r_6: *far*, r_7:*faraway*$\}$. Following the previous example for the similarity, the distance values will be:

$d^{2t}((high, 0), (Medium, 0.5)) = (almost\ \ equal, -0.25)$

2.4.2. Fuzzy linguistic decision-making methods

To solve real-world multi-attribute decision problems, many methods have been developed over time. In one classification, these methods can be categorized by the type of information received by decision makers. If there is no information, the dominance method can be used. If the information is either pessimistic or optimistic, the maximin or maximax method is applicable. If information on the attributes is given, a sub-category is used to further group the methods. If the information is a standard level for each attribute, conjunctive and disjunctive methods can be used. If the attribute weights are assessed by ordinal or cardinal scales, the methods used include simple additive weighting (SAW), a technique for order preference by similarity to ideal solution (TOPSIS), an analytic hierarchy process (AHP), the elimination and choice expressing reality method, etc. (Lu, Zhang, Ruan, & Wu, 2007). Despite having many MCDM techniques, the TOPSIS method sounds logical and represents the rationale of individual choice; simultaneously considering both the ideal and the anti-ideal solutions; and employs a systematic, explicit and easily programmable computation procedure (Kim, Park, & Yoon, 1997; Shih, Shyur, & Lee, 2007). Unlike pairwise comparison methods, it also allows for both criteria and alternatives (as can be seen in our proposal). Aside from the recorded advantages and the domain popularity of the method, we have selected TOPSIS as the cornerstone of our procedural framework because of the availability of extensions in the fuzzy environment that will be improved in our proposal, effectively facilitating the ranking of the alternatives.

The TOPSIS technique is based on the idea that the best alternative is the closest to the positive ideal solution and the farthest from the negative ideal solution, and follows the following steps (Hwang & Yoon, 1981):

- Construct a normalized decision matrix $D_{norm} = [r_{ij}]_{m*n}$, where r_{ij} of the ith alternative with respect to the jth criteria is given as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x^2_{ij}}} \quad i = 1, 2, \cdots, m \quad j = 1, 2, \cdots, n \tag{11}$$

- Construct a weighted normalized decision matrix $V = [v_{ij}]_{m*n}$, where v_{ij} of the ith alternative with respect to the jth criteria is calculated as:

$$v_{ij} = r_{ij} * w_j \quad \sum_{i=1}^{n} w_j = 1 \quad i = 1, 2, \cdots, m \quad j = 1, 2, \cdots, n \tag{12}$$

- Determine the positive ideal solution V^+ and the negative ideal solution V^- as follows:

$$\mathrm{V}^+ = \{(max v_{ij} | j \in J), (\min v_{ij} | j \in \hat{J})\} = \{v^+_1, v^+_2, \cdots, v^+_n\} \tag{13}$$

$$\mathrm{V}^- = \{(min v_{ij} | j \in J), (\max v_{ij} | j \in \hat{J})\} = \{v^-_1, v^-_2, \cdots, v^-_n\} \tag{14}$$

where J is associated with the benefit attributes and $\acute{J}$ is associated with negative attributes.

- Calculate the Euclidean distance of each alternative from V^+ and V^- as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_j^+ - v_{ij})^2} \quad i = 1, 2, \cdots, m \tag{15}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_j^- - v_{ij})^2} \quad i = 1, 2, \cdots, m \tag{16}$$

- Calculate the closeness of each alternative from the ideal solution as follows:

$$C_i = \frac{D_i^-}{(D_i^+ + D_i^-)} \quad i = 1, 2, \cdots, m \tag{17}$$

- Order the preferences according to rank and choose the best alternatives in terms of the value of C_i in descending order. The highest value of C_i is the closest alternative to the ideal solution and is ranked as the best option.

If the decision matrix includes linguistic values $X = \{x_{ij}, i = 1, 2, \cdots, m, \quad j = 1, \cdots, n\}$ for the alternatives with respect to the criteria, a fuzzy linguistic rating x_{ij} preserves the property belonging to the ranges of normalized fuzzy numbers [0, 1]; thus, there is no need for normalization and $[v_{ij}]_{m*n} = x_{ij} * w_j$, $i = 1, 2, \cdots, m; j = 1, 2, \cdots, n$ represents the weighted normalized fuzzy-decision matrix. In this case, the fuzzy positive ideal and fuzzy negative ideal solutions are:

$$V^+ = \{v_1{}^+, v_2{}^+, \cdots, v_n{}^+\} \tag{18}$$

$$V^- = \{v_1{}^-, v_2{}^-, \cdots, v_n{}^-\} \tag{19}$$

where$v_j{}^+, j = 1, 2, \cdots, n$ is $(1, 1, 1)$ and $v_j{}^-, j = 1, 2, \cdots, n$ is $(0, 0, 0)$if the linguistic variables have triangular membership functions. Then, the distance of each alternative from V^+ and V^- becomes:

$$D_j^+ = \sum_{j=1}^{n} d(v_{ij}, v_j{}^+) \quad i = 1, 2, \cdots, m \tag{20}$$

$$D_j^- = \sum_{j=1}^{n} d(v_{ij}, v_j{}^-) \quad i = 1, 2, \cdots, m \tag{21}$$

where $d(a, b)$ represents the distance between two fuzzy numbers a and b. For example, if $a = (a_1, a_2, a_3)$ and $b = (b_1, b_2, b_3)$ are two triangular fuzzy numbers, the distance is:

$$d(a, b) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \tag{22}$$

Then, the alternative with maximum value forC_j can be selected using Eq. (17).

Remark 1.. It is easy to observe that the results obtained by the distance function, Eq. (22) are fuzzy values, but are however not within the CW paradigm. This is due to fact that the output results are not linguistic ones and they are hard to interpret because it does not match with any semantics or syntax related to the distance interpretation. Additionally, the closeness obtained is a fuzzy value that should be ranked. The ranking of fuzzy quantities is a challenging process because they do not have a natural order. Therefore, in Section 3, we overcome these limitations regarding interpretability and ranking by redefining the distance measures in the fuzzy TOPSIS method.

2.4.3. Fuzzy group decision-making methods

Usually, real-world problems are complex. Therefore, assessing problems from multiple points of view seems necessary. In such situations, MCGDM is quite commonly used to achieve a solution from the knowledge provided by a group of experts. Formally, a group decision-making problem is defined as a decision situation in which two or more experts $E = \{e_1, e_2, \cdots, e_k\} (k \geq 2)$ express their preferences over the alternatives, X, to obtain a solution for the decision problem. The selection process involves two main phases: aggregation and exploitation. The aggregation phase combines the experts' preferences using an aggregation operator to form a collective preference matrix that represents all the preferences in the decision problem. The exploitation phase selects the best alternative(s) to solve the decision problem based on the collective preference matrix obtained in the previous phase (Rodríguez, Martínez, & Herrera, 2013).

If experts use fuzzy linguistic variables to provide their preferences over the set of alternatives, a general scheme can be used, as shown in Fig. 3. The solution scheme is formed using the following steps (Rodríguez et al., 2013):

- Choose a linguistic term set with its semantics. This establishes the linguistic descriptors that experts use to provide their preferences concerning the criteria weights and alternatives according to their knowledge and experience.
- Choose an aggregation operator for the linguistic information. A linguistic aggregation operator is chosen to aggregate the linguistic preferences provided by the experts.
- Select the best alternative(s). This consists of selecting the best

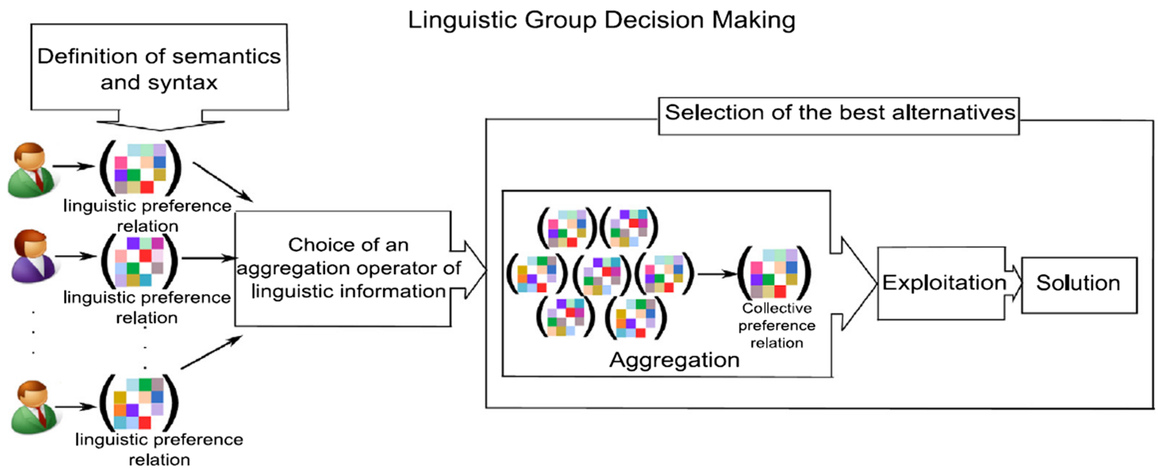

Fig. 3. The fuzzy group decision-making problem scheme (Rodríguez et al., 2013).

alternative or subset of alternatives.

In the aggregation phase, different linguistic computing models, such as those presented in Delgado, Verdegay, and Vila (1993), Degani and Bortolan (1988), and Herrera and Martinez (2000), can be used. The exploitation phase typically relies on conventional MCDM techniques.

3. A 2-tuple fuzzy linguistic group TOPSIS model

As pointed out previously, the TOPSIS method and its fuzzy extensions have been widely used in different applications (Ju & Wang, 2013; Ju, Wang, & You, 2015; Lu, You, Liu, & Li, 2016; Wei, 2010); but either they do not use linguistic domain for distances or the linguistic domain is wrong because they use the domain of the preferences as distance domain. In the first case they do not fulfil the CW requirements because outputs are not linguistic and in the latter the interpretability is wrong. Therefore, this study presents a new linguistic TOPSIS model that accommodates the use of a 2-tuple linguistic model for situations in which the weightings and criteria for each criterion are expressed as fuzzy linguistic variables, and it keeps CW requirements to obtain accurate, flexible and easy understanding linguistic results by using proper syntax and semantics for both preferences and distances.

Assume $A = \{A_1, A_2, \cdots, A_m\}$ is the set of alternatives, $C = \{C_1, C_2, \cdots, C_n\}$ is the set of criteria and $D = \{D_1, D_2, \cdots, D_k\}$ is the set of decision makers. Let $U = \{u_1, u_2, \cdots, u_p\}$be the linguistic term set for weighting the criteria, and let $S = \{s_1, s_2, \cdots, s_t\}$be a linguistic term set for evaluating the alternatives. In addition, let $S' = \{l_1, l_2, \cdots, l_{t'}\}$ and $S'' = \{r_1, r_2, \cdots, r_{t''}\}$ be the linguistic term sets for evaluating the similarity and the distance between any two linguistic terms s_p and s_r from S respectively.

Suppose $U_t = (u_j^t)^T_{1*n}$ is the weight vector, where $u_j^t \in U$ is the linguistic value preference given by the decision maker $D_t \in D$ for the criteria $C_j \in C$. In addition, suppose $X_t = (r_{ij}^t)_{m*n}$is the decision matrix, where $r_{ij}^t \in S$ is the linguistic value preference given by the decision maker $D_t \in D$ for the alternative $A_i \in A$ with respect to the criteria $C_j \in C$. It is assumed that the level of importance of each decision maker is the same. The extended version of TOPSIS consists of the following steps:

Step 1: $U_t = (u_j^t)^T_{1*n}$ is transformed into a 2-tuple linguistic decision matrix $U_t = (u_j^t, 0)^T_{1*n}$.
Step 2: The collective overall 2-tuple linguistic weight vector $U^T = (\bar{u}_j, \bar{\beta}_j)^T_{1*n}$is constructed as

$$(\bar{u}_j, \bar{\beta}_j) = \Delta_u\left(\frac{1}{k}\sum_{t=1}^{k}\Delta_u^{-1}(u_j^t, 0)\right), j = 1, 2, \cdots, n \tag{23}$$

Step 3: The normalized 2-tuple linguistic weight vector $u^N = (\bar{\bar{u}}_j, \bar{\bar{\beta}}_j)^T_{1*n}$ is constructed as

$$(\bar{\bar{u}}_j, \bar{\bar{\beta}}_j) = \Delta_u\left(\frac{(\bar{u}_j, \bar{\beta}_j)}{\max\{(\bar{u}_1, \bar{\beta}_1), \cdots, (\bar{u}_n, \bar{\beta}_n)\}}\right), j = 1, 2, \cdots, n \tag{24}$$

Step 4: $X_t = (r_{ij}^t)_{m*n}$ is transformed into a 2-tuple linguistic decision matrix $X_t = (r_{ij}^t, 0)_{m*n}$.
Step 5: The collective overall 2-tuple linguistic decision matrix $X = (\tilde{r}_{ij}, \tilde{\alpha}_{ij})_{m*n}$is constructed as

$$(\tilde{r}_{ij}, \tilde{\alpha}_{ij}) = \Delta_S\left(\frac{1}{k}\sum_{t=1}^{k}\Delta_S^{-1}(r_{ij}^t, 0)\right), i = 1, 2, \cdots, m, j = 1, 2, \cdots, n \tag{25}$$

Step 6: The weighted decision matrix $\bar{X} = (\bar{r}_{ij}, \bar{\alpha}_{ij})_{m*n}$is constructed as

$$(\bar{r}_{ij}, \bar{\alpha}_{ij}) = \Delta_S(\Delta_u^{-1}(\bar{\bar{u}}_j, \bar{\bar{\beta}}_j).\Delta_S^{-1}(\tilde{r}_{ij}, \tilde{\alpha}_{ij})), i = 1, 2, \cdots, m, j = 1, 2, \cdots, n \tag{26}$$

Step 7: The positive ideal solution and negative ideal solution are determined by

$$(r^+, \alpha^+) = \{(r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \cdots, (r_n^+, \alpha_n^+)\} \tag{27}$$

$$(r^-, \alpha^-) = \{(r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \cdots, (r_n^-, \alpha_n^-)\} \tag{28}$$

where

$$(r_j^+, \alpha_j^+) = (\max_i\{(\bar{r}_{ij}, \bar{\alpha}_{ij})|C_j \in B\} \;\; or \;\; \min_i\{(\bar{r}_{ij}, \bar{\alpha}_{ij})|C_j \in B'\}), j = 1, 2, \cdots, n \tag{29}$$

$$(r_j^-, \alpha_j^-) = (\min_i\{(\bar{r}_{ij}, \bar{\alpha}_{ij})|C_j \in B\} \;\; or \;\; \max_i\{(\bar{r}_{ij}, \bar{\alpha}_{ij})|C_j \in B'\}), j = 1, 2, \cdots, n \tag{30}$$

and where B is the benefit criteria set and B' is the cost criteria set.

Step 8: The distances of each alternative from the positive ideal solution and the negative ideal solution are calculated with

$$(\xi_i^+, \eta_i^+) = \Delta_{S''}\left(\frac{1}{n}\sum_{j=1}^{n}\Delta_{S''}^{-1}(d^{2t}((\bar{r}_{ij}, \bar{\alpha}_{ij}), (r_j^+, \alpha_j^+)))\right) \tag{31}$$

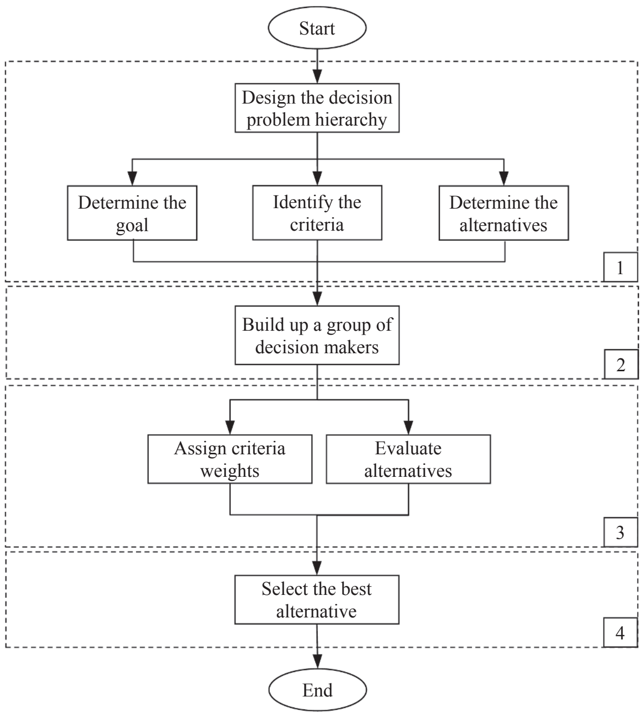

Fig. 4. The proposed methodology.

$$(\xi_i^-, \eta_i^-) = \Delta_{S''}\left(\frac{1}{n}\sum_{j=1}^{n}\Delta_{S''}^{-1}(d^{2t}((\bar{r}_{ij}, \bar{\alpha}_{ij}), (r_j^-, \alpha_j^-)))\right) \tag{32}$$

Step 9: The relative closeness degree of each alternative from the positive ideal solution is calculated with:

$$(\xi_i, \eta_i) = \Delta_{S''}\left(\left(\left(\frac{(\Delta_{S''}^{-1}(\xi_i^-, \eta_i^-) - 1)}{(\Delta_{S''}^{-1}(\xi_i^+, \eta_i^+) - 1) + (\Delta_{S''}^{-1}(\xi_i^-, \eta_i^-) - 1)}\right)\cdot t''\right) + 1\right), \quad i = 1, 2, \cdots, m \tag{33}$$

Step 10: The ranking of alternatives is determined using the relative closeness degree (ξ_i, η_i). The alternative with the highest linguistic distance is the most desirable alternative, and its interpretation is related to the distance to the anti-ideal solution.

4. The methodology

The proposed methodology for the selection problem consists of the following phases, as illustrated in Fig. 4.

4.1. Phase 1

The main goal in constructing the hierarchy of the decision problem was to adopt the best cloud computing model for e-commerce. The criteria and sub-criteria were determined based on the TOE framework; they include three criteria and 12 sub-criteria. The alternatives are the cloud computing models SaaS, PaaS, and IaaS. The hierarchical structure of the decision problem is shown in Fig. 5.

4.2. Phase 2

In this phase, we assembled a group of five managers from different functional departments in the company under study. All group members recognized the existence of a common problem (i.e., adoption of cloud computing), and were attempting to reach a collective decision. A "consensus rule" was applied to the final decision. Consensus in group decision-making means that all participants genuinely agree that the decision is acceptable (Lu et al., 2007). With the consensus rule, all members of the group feel that they have had an equal opportunity to impact and support the group decision.

Fuzzy group decision-making methods are usually based on the consensus rule, which also encompasses ranking and majority rules. The Delphi method is the most popular and representative technique for improving the group decision making process by using the consensus rule. The Delphi method (also called the Delphi technique) aims at reaching an interdisciplinary consensus about an opinion. We applied the Delphi technique using a questionnaire to build interdisciplinary consensus for the various opinions, without necessarily having people meet face to face.

4.3. Phase 3

The relative importance of the criteria was weighted and described using linguistic variables in this phase, as defined in Table 4. The membership functions of these linguistic variables are triangular fuzzy numbers for the sake of simplicity. Linguistic terms were also used to evaluate the alternatives. Seven linguistic variables are presented in Table 5 in the form of triangular fuzzy numbers. Table 6 also represents the linguistic term set for measuring the distance.

4.4. Phase 4

The required ranking was obtained by using the proposed 2-tuple group TOPSIS method in Section 3. The alternative with the maximum closeness degree to the ideal solution (or the longest distance to the anti-ideal solution) was chosen as the optimal strategy.

5. Case analysis

An effective digital strategy must include an assessment of the firm's situation. The strategic planning process stresses the importance of focusing on the future within the context of an ever-changing online environment. The strategy assessments made by the expert group were based on a set of criteria involving both qualitative and quantitative data. Quantitative data consists of fact-based information, such as examination results. Qualitative data is based on observations, surveys, etc. As a result, a situation assessment gathers the decision makers' perceptions to determine the impact of the strategy and whether it will achieve the business's goals. Often, situation assessments are conducted by a group of people, such as the decision makers in our group, with expert opinions and quality information to deal with the strategic planning process.

We evaluated a SME in the e-commerce industry. The names of the company and the experts have been withheld to maintain confidentiality. The company is an online electronics business in Sydney, Australia. When the company was ready to switch from an on-site data center to a cloud-based data center, they were looking to increase their small business's flexibility and cut the high cost of hardware. The business consists of 40 employees and is run by an independent owner. The owner and senior managers are the principal decision makers. The company follows a hierarchical organization structure, and the decisions flow from top to bottom.

An executive group, consisting of five members DM1 to DM5 from four functional departments, was invited to survey three alternatives – SaaS, PaaS, and IaaS – using the research methodology in Section 4. DM1 owns the business (leader), DM2 is responsible for marketing, DM3 manages finance, DM4 manages IT, and DM5 manages logistics. All participants have more than eight years of experience in the industry.

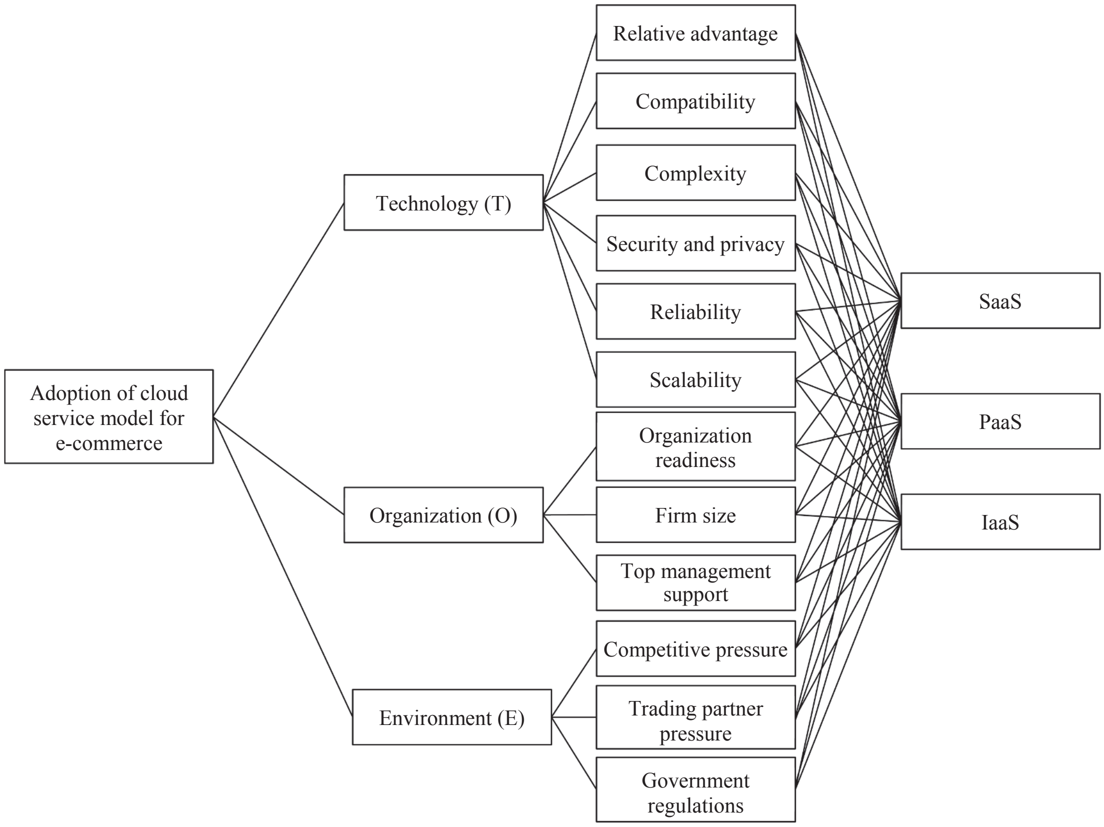

Fig. 5. The hierarchy of the decision problem.

Table 4
Linguistic terms for weighting the criteria.

Symbol	Linguistic term	Fuzzy number
u_1	Very low (VL)	(0, 0, 0.1)
u_2	Low (L)	(0, 0.1, 0.3)
u_3	Medium low (ML)	(0.1, 0.3, 0.5)
u_4	Medium (M)	(0.3, 0.5, 0.7)
u_5	Medium high (MH)	(0.5, 0.7, 0.9)
u_6	High (H)	(0.7, 0.9, 1.0)
u_7	Very high (VH)	(0.9, 1.0, 1.0)

Table 5
Linguistic terms for rating the alternatives.

Symbol	Linguistic term	Fuzzy number
s_1	Very poor (VP)	(0, 0, 1)
s_2	Poor (P)	(0, 1, 3)
s_3	Medium poor (MP)	(1, 3, 5)
s_4	Fair (F)	(3, 5, 7)
s_5	Medium good (MG)	(5, 7, 9)
s_6	Good (G)	(7, 9, 10)
s_7	Very good (VG)	(9, 10, 10)

6. Implementation

This section describes the implementation of the proposed methodology within the company.

6.1. Criteria weights

The experts' judgments about criteria weights were collected using linguistic variables as described in Table 4. The results are presented in Table 7.

Table 6
Linguistic terms for calculating the distance.

Symbol	Linguistic term	Fuzzy number
r_1	Equal (EQ)	(0, 0, 1)
r_2	Almost equal (AE)	(0, 1, 3)
r_3	A bit close (BC)	(1, 3, 5)
r_4	Neither close nor far (NC)	(3, 5, 7)
r_5	A bit far (AF)	(5, 7, 9)
r_6	Far (FA)	(7, 9, 10)
r_7	Far away (FW)	(9, 10, 10)

Table 7
Criteria weight matrix.

Criteria	Sub-criteria	DM1	DM2	DM3	DM4	DM5
Technology	Relative advantage	VH	H	H	VH	VH
	Compatibility	H	MH	M	MH	MH
	Complexity	H	H	MH	H	H
	Security and privacy	VH	VH	VH	VH	VH
	Reliability	VH	H	VH	H	VH
	Scalability	H	M	M	ML	M
Organization	Organization readiness	M	MH	H	VH	MH
	Firm size	H	H	MH	M	MH
	Top management support	H	H	MH	MH	MH
Environment	Competitive pressure	M	ML	ML	M	M
	Trading partner pressure	ML	ML	ML	L	M
	Government regulations	L	L	VL	M	MH

6.2. Alternative evaluation

An alternative evaluation decision matrix using linguistic variables was then developed, as shown in Table 8.

The proposed 2-tuple TOPSIS method was used to provide decision

Table 8
Alternative evaluation matrix.

Criteria	Sub-criteria	Alternatives	DM1	DM2	DM3	DM4	DM5
Technology	Relative advantage	SaaS	MG	MG	MG	G	G
		PaaS	G	MG	MG	VG	VG
		IaaS	VG	MG	MG	VG	VG
	Compatibility	SaaS	F	F	F	MG	MP
		PaaS	MG	MG	G	F	F
		IaaS	VG	VG	G	G	G
	Complexity	SaaS	G	G	G	MG	MG
		PaaS	MG	MG	MG	G	G
		IaaS	F	F	G	G	MG
	Security and privacy	SaaS	G	G	MG	VG	MG
		PaaS	MG	MG	G	G	G
		IaaS	VG	G	G	MG	MG
	Reliability	SaaS	VG	VG	VG	G	G
		PaaS	MG	G	MG	VG	G
		IaaS	F	F	G	MG	MG
	Scalability	SaaS	P	MP	P	P	MP
		PaaS	F	MG	MG	G	MG
		IaaS	VG	VG	VG	G	G
Organization	Organization readiness	SaaS	VG	VG	VG	G	VG
		PaaS	MP	MP	P	P	P
		IaaS	F	F	F	MP	MG
	Firm size	SaaS	VG	VG	VG	G	VG
		PaaS	F	MP	P	VP	VP
		IaaS	F	F	MP	P	P
	Top management support	SaaS	VG	VG	G	G	G
		PaaS	MP	P	VP	P	VP
		IaaS	MP	P	VP	P	P
Environment	Competitive pressure	SaaS	G	G	MG	MG	G
		PaaS	MP	MP	MP	MP	P
		IaaS	F	P	F	P	MP
	Trading partner pressure	SaaS	G	G	G	G	MG
		PaaS	F	P	MP	VP	VP
		IaaS	F	F	F	P	MP
	Government regulations	SaaS	MP	MP	P	P	VP
		PaaS	VP	VP	VP	MP	P
		IaaS	P	VP	P	VP	VP

Table 10
The aggregated 2-tuples of the decision matrix.

Criteria	Sub-criteria	Alternatives	Mean
Technology	Relative advantage	SaaS	$(s_5, 0.4)$
		PaaS	$(s_6, 0)$
		IaaS	$(s_6, 0.2)$
	Compatibility	SaaS	$(s_4, 0)$
		PaaS	$(s_5, -0.2)$
		IaaS	$(s_6, 0.4)$
	Complexity	SaaS	$(s_6, -0.4)$
		PaaS	$(s_5, 0.4)$
		IaaS	$(s_5, 0)$
	Security and privacy	SaaS	$(s_6, -0.2)$
		PaaS	$(s_6, -0.4)$
		IaaS	$(s_6, -0.2)$
	Reliability	SaaS	$(s_7, -0.4)$
		PaaS	$(s_6, -0.2)$
		IaaS	$(s_5, -0.2)$
	Scalability	SaaS	$(s_2, 0.4)$
		PaaS	$(s_5, 0)$
		IaaS	$(s_7, -0.4)$
Organization	Organization readiness	SaaS	$(s_7, -0.2)$
		PaaS	$(s_2, 0.4)$
		IaaS	$(s_4,0)$
	Firm size	SaaS	$(s_7, -0.2)$
		PaaS	$(s_2, 0.2)$
		IaaS	$(s_3, 0)$
	Top management support	SaaS	$(s_6, 0.4)$
		PaaS	$(s_2, -0.2)$
		IaaS	$(s_2, 0)$
Environment	Competitive pressure	SaaS	$(s_6, -0.4)$
		PaaS	$(s_3, -0.2)$
		IaaS	$(s_3, 0)$
	Trading partner pressure	SaaS	$(s_6, -0.2)$
		PaaS	$(s_2, 0.2)$
		IaaS	$(s_3, 0.4)$
	Government regulations	SaaS	$(s_2, 0.2)$
		PaaS	$(s_2, -0.4)$
		IaaS	$(s_1, 0.4)$

support for this problem as outlined in Phase 4 of the methodology. The 2-tuple arithmetic mean was used to aggregate the 2-tuples of the weighting to obtain collective values. Table 9 provides the corresponding 2-tuple linguistic values with their averages in the last column.

As can be seen in Table 9, 'security and privacy' with a 2-tuple of $(u_7, 0)$ was the most important criteria according to our experts, with an importance ranking of Very High, followed closely by 'Relative advantage' and 'reliability', each with the same 2-tuple of $(u_7, -0.4)$. Likewise, we constructed the 2-tuples for the evaluation matrix and their averages. The final results are provided in Table 10.

6.3. Results

The positive ideal and negative ideal solutions were determined; giving consideration to the fact that complexity is the only cost criteria, while all the other criteria are benefits. The distance of the alternatives to the ideal solutions was then calculated. Finally, the relative closeness degree of each alternative was determined. The results appear in Table 11. The final results suggest that SaaS is the best adoption model for the e-commerce SME as it has a "Far" distance from anti-ideal solution. As can be seen, the difference between closeness degrees of alternatives is considerable and there is no need to perform any sensitivity analysis.

The results of this case study show that SaaS cloud computing is a

Table 9
The corresponding 2-tuples of weights and their arithmetic means.

Criteria	Sub-criteria	DM1	DM2	DM3	DM4	DM5	Mean
Technology	Relative advantage	$(u_7, 0)$	$(u_6, 0)$	$(u_6, 0)$	$(u_7, 0)$	$(u_7, 0)$	$(u_7, -0.4)$
	Compatibility	$(u_6, 0)$	$(u_5, 0)$	$(u_4, 0)$	$(u_5, 0)$	$(u_5, 0)$	$(u_5, 0)$
	Complexity	$(u_6, 0)$	$(u_6, 0)$	$(u_5, 0)$	$(u_6, 0)$	$(u_6, 0)$	$(u_6, -0.2)$
	Security and privacy	$(u_7, 0)$	$(u_7, 0)$	$(u_7, 0)$	$(u_7, 0)$	$(u_7, 0)$	$(u_7, 0)$
	Reliability	$(u_7, 0)$	$(u_6, 0)$	$(u_7, 0)$	$(u_6, 0)$	$(u_7, 0)$	$(u_7, -0.4)$
	Scalability	$(u_6, 0)$	$(u_4, 0)$	$(u_4, 0)$	$(u_3, 0)$	$(u_4, 0)$	$(u_4, 0.2)$
Organization	Organization readiness	$(u_4, 0)$	$(u_5, 0)$	$(u_6, 0)$	$(u_7, 0)$	$(u_5, 0)$	$(u_5, 0.4)$
	Firm size	$(u_6, 0)$	$(u_6, 0)$	$(u_5, 0)$	$(u_4, 0)$	$(u_5, 0)$	$(u_5, 0.2)$
	Top management support	$(u_6, 0)$	$(u_6, 0)$	$(u_5, 0)$	$(u_5, 0)$	$(u_5, 0)$	$(u_5, 0.4)$
Environment	Competitive pressure	$(u_4, 0)$	$(u_3, 0)$	$(u_3, 0)$	$(u_4, 0)$	$(u_4, 0)$	$(u_4, -0.4)$
	Trading partner pressure	$(u_3, 0)$	$(u_3, 0)$	$(u_3, 0)$	$(u_2, 0)$	$(u_4, 0)$	$(u_3, 0)$
	Government regulations	$(u_2, 0)$	$(u_2, 0)$	$(u_1, 0)$	$(u_4, 0)$	$(u_5, 0)$	$(u_3, -0.2)$

Table 11
Alternatives and their closeness degrees.

Alternative	Closeness degree to negative ideal solution	Linguistic term
SaaS	(r_6, 0.2)	Far
PaaS	(r_2, 0.3)	Almost equal
IaaS	(r_4, −0.2)	Neither close nor far

considerably inexpensive alternative to maintaining enterprise system and data in-house for e-commerce SMEs. In addition, the findings show that while the technological analysis of cloud computing migration is essential, the organizational and environmental aspects should also be considered.

The SaaS potentially reduce many support-related issues since there would be no demand for access to a range of computer resources, from computing infrastructure (i.e., IaaS) to computing platforms (i.e., PaaS). Further economical benefits differ in other factors – software fit to the business need, possible vendor's support to SME throughout the product lifecycle, contribution in co-creation of values to the client business (Seethamraju, 2015). Moreover, SaaS applications provide network based access to the applications that are managed centrally while sharing a single instance of an application in multi-tenant architecture that assists the SME in managing the updates and installing patches (Danaiata & Hurbean, 2010). The findings show that the relative advantage, complexity, reliability, security and privacy in a technological context, organization readiness, firm size and top management support in an organizational context, and competitive pressure in environmental context are significant factors in cloud computing adoption for SMES. However, the top five prioritized factors for adopting SaaS cloud computing are complexity, reliability, security and privacy, organization readiness and firm size. These results are reinforced by the fact that the decision-makers are reluctant to adopt PaaS or IaaS into their business operations considering compatibility and scalability.

7. Conclusions and future work

Global competition is placing huge pressure on e-commerce firms to enhance productivity and increase profitability. To survive in this rapidly changing environment, e-commerce firms have to adopt the latest technologies, such as cloud computing, to improve their offerings and sustain a competitive advantage. However, the selection of cloud-based e-commerce is a typical MCDM problem. To address this MCDM problem, the paper develops a novel 2-tuple fuzzy linguistic group TOPSIS model that deals with the imprecise judgments of decision makers, avoids the risk of losing information and facilitates the understanding of the results. The paper then relies on the TOE framework to represent a set of appropriate criteria for the decision-making problem. The proposed methodology is implemented in a small-to-medium-sized e-commerce business, and the results suggest that SaaS is the best choice.

This study has significant implications. First, this study has revealed the decision-making process of adopting public clouds for small-to-medium sized businesses. The decision-makers can improve the competence of decision-making based on the technical features, the management requirements of the organizations, and the business value. Second, our decision-making framework shows that cloud service providers want to improve the cloud service from technical, business, and management factors to meet the requirements of decision-makers in e-commerce firms. Despite there being many factors, the significant effect of TOE factors on the three modes of decision-making on public computing adoption (IaaS, PaaS, and SaaS) is still debatable. Moreover, the main contribution of our proposed approach lies in modifying the TOPSIS method to solve multi-criteria group decision-making problems, with the use of 2-tuple linguistic variables. The proposed 2-tuple linguistic model TOPSIS is useful for any MCDM problem, and the criteria provided via the TOE framework are also helpful in many other fields, such as e-government and e-health.

Future studies could include the use of complex linguistic expressions (Rodríguez, Labella, & Martínez, 2016) within the linguistic TOPSIS framework to improve and facilitate preference elicitation under uncertainty for these types of problems. In addition, the use of the ordered weighted average (OWA) operator developed by Yager (1988) and its extensions could be considered.

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