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Towards a Visualization Framework for Service Selection in Cloud e-Marketplaces

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Abstract-In spite of the success of many commercial cloud service e-marketplaces the search results from these platforms are usually presented as an unordered list of icons representing the services that best fit users' keyword-based queries. The drawback of such presentation mechanisms is that users are not able to immediately discriminate among the cloud services for easy decision making. A number of cloud service selection frameworks have been proposed; however, some of these frameworks do not enable users make comparisons among services. In this paper, we introduce a visualization framework for cloud service selection. Our framework takes into cognizance the set of cloud services that matches a user's request and based on QoS attributes, users can interact with the results via bubble graph visualization to compare and contrast the search results to ascertain the best alternative. The bubble graph enables the exploration of services in a unified view of the QoS space, exhibiting both high object coherence and correlation. Result from our experiments shows that our framework simplifies decision making as users can identify services that best fit their requirements quicker and easier compared to tabular formats.

Keywords-cloud service selection, e-marketplace, bubble graph, visualization

I. INTRODUCTION

Advancements in service orientation and virtualization technologies are enabling the popularity and wide adoption of cloud-based services. As more providers participate in cloud ecosystems, there is a high increase in the number of cloud services that are available and traded via cloud service e-marketplaces. The over-abundance of functionally equivalent cloud services usually leave the users in a dilemma of which service to choose, a situation that can be referred to as service choice overload.

In spite of the success of many commercial cloud service e-marketplaces (e.g., Saasmax.com, appexchange.com, oraclemarketplace.com), the search results from these platforms are usually presented as an unordered list of icons representing the services that best fit users' keyword-based queries. The drawback of such presentation mechanisms is that users are not able to immediately discriminate among the cloud services presented in a manner that allows for comparison and easy decision making. Users are required to explore each service one after the order to gain more insights about the quality of service (QoS) attributes to guide their decisions. The additional complexity on the part of the users impacts negatively on user experience. In view of the rate of shopping cart abandonment, dissatisfaction and frustrations experienced by users on many e-commerce sites, the Matthew Adigun University of Zululand, South Africa m.adigun@pan.uzulu.za

complexity involved in the search for items is one key aspect that relate to user experience in online shopping [1].

Meanwhile, search results showing the ranking of cloud services can be presented in form of textual list, in a table or the use of more sophisticated information visualization techniques. The later, compared to the others, employs techniques that leverages on human's visual processing ability to process elements in a pictorial form faster, and derive greater insight and comprehension than from mere text [2, 3].

A number of cloud service selection frameworks have been proposed (e.g. [4]–[8]); however, some of these frameworks presents service rankings in textual format, either in a list or tables, which does not fully describe the implicit trade-off factors inherent in the search results. Such presentations are ineffective in supporting decision making in an online e-marketplace environment and can increase cognitive load of users [9, 10]. Others have used information visualization approaches like radar or kiviat charts that will not suffice to express the rankings of a large number of cloud services. Also, such information visualization approaches exhibit low object coherence and object correlation [11], referring to how compactly and distinctly the visual encodings represents the services and their relationships to facilitate easy decision making.

In this paper, we introduce a visualization framework for cloud service selection in the context of cloud service emarketplace. Our framework takes into cognizance the set of cloud services that matches a user's request and based on QoS attributes, users can interact with the results via bubble graph visualization to compare and contrast the search results to ascertain the best alternative. The bubble graph enables the exploration of services in a unified view of the QoS space, exhibiting both high object coherence and correlation, thereby simplifying decision making for users to identify services that best fits their requirements.

The remainder of this paper is as follows: Section 2 contains the description of relevant concepts underpinning our proposed framework. In Section 3, a review of related work was discussed, while our proposed visualization framework was presented in Section 4. The evaluation of the framework is contained in Section 5; the implication of the results is discussed in Section 6. This paper concludes in Section 7 with an outline of further work.

II. BACKGROUND

A. Cloud service e-marketplace

Cloud service e-marketplaces are online internet platforms for trading cloud-based services, by providing mechanisms for enabling service composition, service discovery, service selection, service deployment, service monitoring, and payment resolutions in a single one-stop shop infrastructure [12, 13]. The e-marketplace provides a unified view of all available offerings and becomes a single point of access to offerings available in the cloud ecosystem. Similar to amazon.com, service providers enlist their offerings, while users can find, purchase and use these services [12-14]. Examples of cloud service e-marketplace include: Windows Azure Marketplace (azuremarketplace.microsoft.com), Amazon Web Service Marketplace (aws.amazon.com), Google Apps (apps.google.com/marketplace), AppExchange (appexchange.com), SuiteApp (suiteapp.com), and Zoho (zoho.com). In these e-marketplaces, the search results to keyword-based search query are an array of icons listed in no particular order and no obvious mechanism for comparing results. For example, a search with the keyword 'CRM' on appexchange.com returned a total of 173 results¹, and novice CRM users would have to painstakingly explore each service returned to identify the services that meet their requirements.

B. Information Visualization

Information visualization is concerned with the use of visualization methods to assisting users make more sense of data and use large volume or complex dataset with minimal efforts [3, 15]. Complex dataset are better communicated using symbolic forms, such as graphical representations, for the purpose of analysis, exploration and discovery [16]. The overarching goal of information visualization is to communicate information in an interactively graphical or spatial manner to aid understandability [3, 16].

Integrating information visualization as part of a cloud service selection framework is more beneficial in decision making environment compared to traditional textual or icon listings in that users can understand and relate with the services based on their QoS attributes in lesser time [17]. Thus, users can have insight into the QoS ranking results and compare services easily.

Generally, the information visualization reference model consists of four main modules [10, 15, 16]. It includes: Dataset, Representation (or visual mapping), Organization, and Interaction.

1) Dataset

Dataset is the underlying data format that characterized the objects to be visualized. According to [18], there are seven data types that have been identified in the context of Information visualization, these are : 1-Dimensional datatype – also referred to as linear data types; 2-Dimensional datatype – also referred to as planer or map data 3-Dimenional datatype – representing most real-world objects; Temporal datatype – includes data that have time lines denoting start and finish time; Tree data type – refers to hierarchies comprising a collections of items; Network data type – which is a generalization of tree data type; and Multidimensional data – correspond to most relational data. A list of cloud services are best represented as a multi-dimensional dataset comprising multiplicity of objects (services) and dimensions (QoS attributes).

2) Representation

Representation (or visual mapping) refers to how to transform symbolic representations characteristic of the objects in a dataset and their relationship, into a graphical form using visual encoding mechanisms such as object's size, shape, color, orientation (or position), and dimensionality (text, 2D, or 3D) [10, 19]. Representation must take into consideration data type, data dimensions, and the user's perceptual and cognitive abilities [15]. The dimension of the dataset refers to the number of attributes that characterize the dataset. Some of the cognitive and perceptual factors to be considered includes the user's perception of values and if the visual encoding exhibits object or attribute visibility [15].

The multiplicity of objects and dimensions of multidimensional dataset raises the issues of coherence and correlation as it pertains to objects and their dimensions [11]. A visual mapping is said to exhibit object coherence (or visibility) when the object is encoded as a single and compact graphical entity (e.g. a point or bubble as in bubble graphs) and the user can see all the attributes of the objects all at once. The converse of object coherence is when an object is represented by multiple separate visual entities (e.g. several points as in parallel coordinate plots or radial charts). Meanwhile, dimension coherence (or attribute visibility) refers to a visual mapping in which the attribute values of the objects are distributed across each dimension, such that users can quickly see the relationship among the values of the attributes for each object [11].

On the other hand, a visual mapping satisfies object correlation when the user can immediately see the similarities among objects considering all the values of their attributes. Dimension correlation refers to a representation that allows user to easily note the relationships among the dimensions of all objects in the dataset.

A visual mapping of cloud services for selection purposes should capture services (objects) as single coherent entities so as to enable the exploration of the relationship among alternatives, not just across their attributes. Users should be able to immediately see the difference between service A and service B. Fig. 1 contains an overview of some representations suitable for the variety data type as itemized by [18].

3) Organization

Organization refers to the interface schemes that define the manner in which these visual mappings are laid out on a screen to enable user's exploration and interaction [10, 15, 16]. Generally, the interface schemes facilitate sensemaking, as it impacts on user's interpretation and perception of the information presented [10]. The layout of the information on the screen affects the type of tasks that can be performed by users. There are three main schemes for

¹Search performed on Appexchange.com on February 11, 2017.

organizing visual mappings, which are: Zooming, Overview + Details and Focus + Context [10, 15]. Zooming refers to the interface's ability to provide broader overview or more detailed view by increasing or decreasing the levels of details the user can view per time. Overview + Detail (O+D) scheme allows both the contextual and detailed views to be displayed simultaneously in separate spatial locations on the screen. Focus + Context (F+C) schemes seamlessly combine focus and context information on the same space.

DATATYPE	REPRESENTATION TYPES			
1-Dimensional	Textual Lists			
2-Dimensional	 ■ Choropleth ■ Self-organizing Maps ■ Cartogram 	 Dot distribution map Proportional symbol map 		
3-Dimensional	 Surface and volume rendering 	3D Computer models		
Temporal	■ Timeline ■ Time series ■ Gantt Chart	■ ThemeRiver ■ Arc diagram ■ Rose diagram (or Polar Area)		
Multi- Dimension al	 Tables Pie chart Histogram Tag cloud Unordered bubble chart (or Bubble cloud) Bar chart 	 Bubble chart Line chart Heat map Radar/spider chart Parallel coordinates plot 		
Tree	 General tree visualization Dendrogram Radial tree 	 Hyperbolic tree Tree map Sunburst 		
Network	 Dependency graph/Circular hierarchy Node-link diagram 	■ Matrix ■ Tube map		

Figure 1. Dataset types and corresponding Visualization [20]

4) Interactivity

Interactivity refers to the mechanisms through which users make sense of the information space by navigating, exploring, organizing or rearranging the information [10, 16]. Effective exploration of the information space is determined by the method of interaction employed, the type of tasks those methods can support and the rate of response to the interaction [10, 15]. Also, different interactions perform differently, and are a best suited for different tasks. The way in which users interact with the interface can include the use of menus (drop-down, pop-up), scrolling, flipping (replacing one discreet view with the next), and direct manipulation by mouse over, single click, double click directly on the visual elements in order to initiate a response or the use of dynamic queries for advance filtering task [10, 16, 21]. Shneiderman [18] has proposed seven tasks that the interaction used in information visualization should support, these are: Overview, Zoom, Filter, Details-on-demand, Relate, History and Extract

III. RELATED WORK

CloudAdvisor [6] enables interactive exploration of various cloud configurations and recommends optimal configurations in line with users' workload and preferences by using comparison tables. CloudRecommender [7] is a declarative approach for selecting Cloud-based infrastructure services. Users interact with CloudRecommender via an intuitive widget-based interface to browse recommendation results. Kwon et al. [8] presents IaaS selection model based on Fuzzy-AHP, to enable users' select suitable service provider that aligns with the goals of the company.

Gui et al. [4] proposed a framework for cloud service selection that incorporates line graphs and radial charts to show relationship among recommended services in line with user requirements. SMICloud [5] is a cloud ranking framework that uses kiviat charts to show the ranking of cloud services with respect to user's QoS preferences. The use of kiviat charts are only as effective as the number of services being compared, and perform better with fewer services. Apart from being able to represent a considerable number of services, a visualization format for cloud service selection should exhibit low object coherence and low object correlation.

IV. THE PROPOSED VISUALIZATION FRAMEWORK

We propose a visualization framework for service selection as a mechanism for effective presentation and comparison of search results in cloud service e-marketplace. The framework uses bubble graph visualization to depict relationships among ranked cloud services with respect to user requirements. The framework is an instantiation of the information visualization reference model and includes the following modules: dataset, representation (visual mapping), presentation scheme and the interaction mode (see Fig. 2).

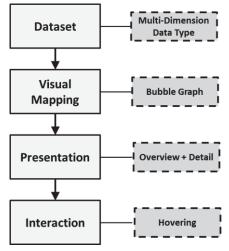


Figure 2. Proposed Visualization Framework

The list of services is a multi-dimensional dataset with as many as four QoS dimensions that describes the services. The multi-dimensional dataset are visually encoded in bubble graph visualization, showing the services in a fourdimensional QoS space. The overall interface is designed using Overview+Detail scheme. Finally, the users can interact with the visualization by hovering on each bubble (service) to uncover more details. Next, we describe each module in details.

A. Dataset

The multi-dimensional dataset comprising a collection of cloud services in a ranked order can be presented in a table format (see Table I), such that each column correspond to cloud service QoS attributes while each row refers to each services in the list. However, table representations are limited in expressing the relationships among the rankings, particularly if there are many services in the ranked list and many QoS attributes to consider. The user will have to explore each service attribute by attribute in order to identify a more suitable service, which is more cognitively demanding.

B. Representation

The multi-dimensional datatype containing the values for all of the relevant QoS attributes (e.g. see Table I). The services represented in each in each row are visually encoded using a bubble graph. A bubble encompasses a combination of encoding mechanisms, which includes size, color, and position (or orientation), into a single coherent entity that exhibits high object coherence and correlation. The bubble graph (see Fig. 3) can be used to visualize up to four QoS dimensions simultaneously each dimension represented by size, color and position (x and y coordinates). More details are presented in Section V.

The advantage of a bubble encoding is that users can easily see all attributes defining a service, and also make sense of that service's attributes compared to other services in the QoS information space via a single interface.

C. Presentation

The information visualization to support cloud service exploration and selection must be such that it lays out both the broader and more detail views on the display screen. F+C presentation style is reported inappropriate for decision making environment because of its distorted view, as it may lead to wrong interpretations [22]. Other studies reported higher user satisfaction [10] and faster task completion time [23] of O+D styles over zoom-based presentation styles. For this, O+D is considered, since the volume of information displayed must be such that it does not add to the cognitive load of users, which can impact negatively on user satisfaction [10]. The bubble graph presents an overview of the decision elements, while details are shown on demand.

D. Interaction

Interactivity refers to the ability of users to engage the visualization of search results in real time, making changes to visualization and viewing immediate responses in the visualization [16]. Based on Shneiderman's Task by Datatype Taxonomy [18], two interaction tasks were identified, which are: to gain a general overview of the

ranking results (overview); and to view details of a particular selection as desired, by either a mouse click or hovering (Details-on-demand). In this paper, the interaction method considered is hovering. Furthermore, by hovering over a bubble, users can view additional information about the service, while a click displays all the details about that service in a side menu for deeper exploration. Dynamic exploration enabled by hovering to access details of each service is a direct interaction in which users view details of each service almost immediately [2].

We implemented our framework using Google Charts API. Google charts provide customizable JavaScript classes for visualizing data on web pages. The Google Chart JavaScript libraries expose a variety of charts types including tables, line charts, tree maps, scatterplot, bubble graph etc. The charts are rendered in HTML5/SVG technology that works across browser types. The charts are populated from data sources such as a database or directly from a web page.

V. EVALUATION AND RESULTS

To ascertain the effectiveness of our framework, we performed a controlled user study designed to evaluate the user experience of the bubble graph visualization for exploring and selecting cloud services compared to the traditional tabular format. The use of visualization techniques is expected to reduce the cognitive load of the user by aiding the completion of user tasks accurately, satisfactorily and time efficiently. The use of a controlled experiment is well suited for answering how one visualization format technique compares to another [24]. In this experiment, a "head-to-head" comparison was carried out on both visualization formats [24]. The effectiveness of the visualizations were measured based on time it takes to complete tasks, and qualitative assessment based on user's feedback.

A. Experiment Design and Protocol

The independent variable of the study is the visualization format and it has two levels: Bubble Graph Visualization and Tabular Visualization. The dependent variables are the speed of task completion, and User Satisfaction in performing defined tasks with the two visualization formats. Task completion time was achieved by tracking of the overall completion time in seconds, and the aggregated user satisfaction scores from participants' feedback.

The objects evaluated are the bubble graph and tabular visualizations of a list containing 20 services. Although, all QoS dimensions are important, we considered four QoS dimensions, for the purpose of this study, to represent the attributes of the services: Availability, Response Time, Reliability and Cost. Table II shows the tabular listing of 20 cloud services, their QoS attributes and corresponding bubble graph visualization is shown in Figure 3.

The legend of the bubble graph is as follows: x-axis represents availability measured in percentage, y-axis the response time of the services in milliseconds, the colors of the bubble represent the reliability, and the darker color signifies higher reliability. The cost is represented by the size of the bubble, as bigger bubbles signify higher cost. The task guidelines contain the tasks that participants are expected to complete. The tasks were based on the taxonomy of user's tasks proposed by [25]. Although, the taxonomy describes seven user tasks (locate, compare, configure, infer, determine, identify, and visualize), we selected the locate tasks for this experiment, as it represent decision making scenarios in a cloud service e-marketplace.

Locate tasks refers to finding specific information in the visualization relating to data items, dimensions, properties, values etc. [25]. The starting point of a locate task, is the participant exploring the visualization, and ends with the participants identifying the desired information [25]. Figure 7 shows the list of 16 tasks grouped into two categories (eight tasks in each category) to represent the subset of activities users undertake in a cloud service e-marketplace. The tasks were grouped according to levels of complexity ranging from locating services by both one to two QoS criteria.

ID	Availability (%)	Response Time (ms)	Reliability (%)	Cost(\$)
1	98.68	668.89	75.73	340.64
2	97.16	668.89	72.78	331.15
3	98.67	546.24	75.43	390.64
4	97.16	546.24	72.48	381.15
5	98.29	648.77	74.48	304.14
6	96.79	648.77	71.53	294.65
7	98.29	526.12	74.19	354.14
8	96.79	526.12	71.23	344.65
9	98.49	668.89	75.02	335.64
10	98.49	546.24	74.72	385.64
11	98.11	648.77	73.77	299.14
12	98.11	526.12	73.47	349.14
13	99.03	668.89	75.73	336.15
14	97.53	668.89	72.78	326.66
15	99.51	682	76.3	340.48
16	98.01	682	73.34	330.99
17	99.03	546.24	75.43	386.15
18	97.53	546.24	72.48	376.66
19	99.51	559.35	76	390.48
20	98.01	559.35	73.04	380.99

TABLE I. LIST OF 20 CLOUD SERVICES

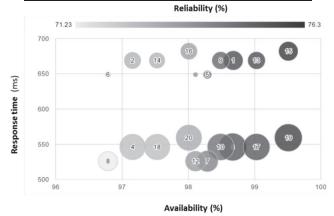


Figure 3. Bubble Graph Visualization of 20 services list in Table II

The experiment was run offline (i.e. not in a real cloud service e-marketplace context). Because the experiments

involves multiple subjects (participants) and objects (bubble graph and tabular visualization formats), it was designed as a blocked subject-object study [26].

A total of 8 persons participated in the experiment, comprising 5 males and 3 females, ranging in age from 17 to 23 years. The participants were undergraduate students studying Computer Science. Participants were taken through a ten minutes tutorial session where the purpose and the process of the experiments were made known. Participants were given a tutorial on the use of both visualization formats to complete sample tasks and allowed to complete some preliminary tasks to ascertain their ability to perform the main tasks defined for the experiments. As soon as participants were comfortable with the process, they were presented with copies of guideline containing tasks to be completed. The tasks involved using the bubble graph and tabular visualizations, and the task performance survey instrument. The experiment administrator recorded the time it took each participant to complete each task with the aid of a stop watch. Upon completion of the tasks, a postexperiment survey was conducted in order to capture participants' impressions of both visualization formats.

Locate Services based on one Attributes

- 1. The least expensive service
- 2. The most expensive service
- 3. The most available service
- 4. The least available service
- 5. The service with the best response time
- The service with the worse response time
- 7 The most reliable service
- 8. The least reliable service

Locate Service based on two attributes

- 1. The most expensive and least available service
- 2. The most expensive and most available service
- The most expensive service with best response time
- 4. The least expensive service with best response time
- 5. The most reliable service with the worse response time
- 6. The least reliable service with the best response time
- 7. The most reliable and most available service
- 8. The least reliable and least available service

Figure 4. List of 16 'Locate' Tasks

B. Results and Analysis

1) Task Completion Time (Speed)

Overall, the use of bubble graph had faster completion time than the tabular visualization with median completion time of 10.8 seconds compared to 37.5 seconds for table visualization. The magnitude of the difference in completion time is demonstrated by U-statistics from Mann-Whitney test, with U=3709.500, z=-5.379, p =.000. Furthermore, there was also a significant difference in the speed between the tasks in both task types (U=4153.500, z=-4.519, p=.000). Figure 5 shows the median completion time for tasks in category A and category B using the bubble and table visualization types. Generally, participants completed tasks in category A faster than those in category B because tasks in category A involved exploration with just one QoS attribute while those in category B involved two QoS dimensions. Generally, the use of bubble graph was faster (md=11.7 seconds) than table (md=34.5 seconds).

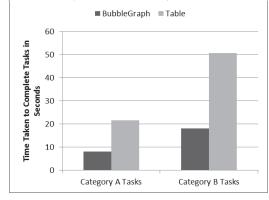


Figure 5. Median Time taken to complete the tasks for different categories

2) User Satisfaction

We elicited feedbacks from the users to ascertain perceived ease, speed and accuracy using both visualization formats for both categories of tasks involving one and two QoS attributes. For exploration based on single QoS attributes, 75% of the participants confirmed that the bubble graph was easier to use compared to 25% who said the table was easier; 63% of participants said they performed the task faster than using table (38%), while 88% reported that the use of table was more accurate that bubble graph.

Furthermore, while performing exploration using two QoS attributes, 88% of participant reported that the bubble graph was easier; 88% confirmed the bubble graph was faster, while 63% said the use of bubble graph was more accurate than the tabular visualization.

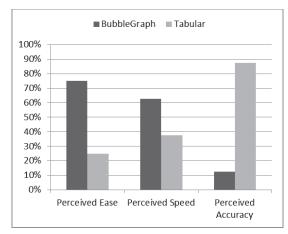


Figure 6. Perceived User satisfaction (Single QoS Attribute)

VI. DISCUSSION

Realizing the vision of a true cloud service e-marketplace in the face of the growing trend for personalized products and services requires that user satisfaction and user experience be given top priority. The overall goal of this study is to simplify cloud service selection, while optimizing user experience and satisfaction in the decision making process [3]. Just like one of the laws of e-commerce states that if users cannot find it, they cannot buy it either; integrating information visualization in the user interface (UI) design of e-marketplace provides the mechanisms for user to, in the shortest possible time and through the easiest means, find a service that meets their requirements.

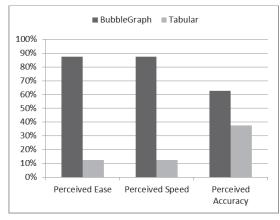


Figure 7. Perceived User satisfaction (Double QoS Attributes)

Since humans possess the ability to recognize the spatial arrangements of elements in a picture and decipher relationships among elements quickly and easily [27]. Such abilities enable humans to derive greater insight and comprehension from the content of a picture faster than mere text. This process leads to a more informed decision making by capitalizing on the well-developed human visual processing capability [27]. This study posits that applying information visualization technique for aiding cloud service selection would improve cloud service exploration, and proposed a visualization framework to allow users compare cloud services with respect to their requirements.

The factors observed and measured in our experiments were the speed at which the tasks were completed and the ease at which it was done. Generally a faster completion time and greater ease in carrying out the assigned tasks meant higher quality of user experience for a particular visualization format.

Although, the use of table can be enhanced to include the ability to perform sort, the extra activity of sorting introduces additional complexity for the user when making comparison. However, the bubble visualization requires users just gazing at the visualization (display) and with minimal interaction with the display, by hovering, can gather more insight about the various alternatives. The task completion results shows that bubble graph will drastically reduce the time it takes to find the most suitable service.

Furthermore, the use of bubble graph exhibit both high object coherence and correlation with compact visual encoding of entities showing all the attributes of the objects all at once and users can distinctly see the relationship among entities in one view.

Based on the feedback provided by the participants, the results clearly indicates that using the tabular visualization to complete the tasks took longer time, and the tabular formats could not adequately support participants while performing the required tasks. The bubble graph was the faster of the two formats evaluated particularly for more complex tasks involving two or more QoS attributes, with an average improvement over tabular formats.

There are threats to experimental evaluations which often affect the validity of the results. We carefully investigated possible threats to the validity of our results including threats to internal, conclusion, external and construct validities.

Internal validity refers to the causal relationship between the visualization types and the effectiveness in performing locate task in terms of task completion time, perceived ease, speed and accuracy of the visualization types. The threat to internal validity of our results is in the selection of the participants. Although, the participants were selected at random, they all had the required knowledge background to act competently while participating in the experiment. [26].

Threats to the conclusion validity affect the ability to arrive at the correct conclusion about relations between the treatment and the outcome of an experiment [26]. The concern is the extent to which, we can generalize based on the experiment, particularly considering the number of participants (8) and their level of experience. Could we have obtained a different result with a bigger group and more experienced subjects? Well, from the experiment the subjects who were students have similar computing background as technology officers, who would normally make such decisions for many organizations. They also showed that they had potential to make rational decisions as regards the tasks assignment, although they not be adept as real technology expert, but good enough to form a valid opininon on suitability of bubble graph and tabular visualizations. Also, for a first-rate evaluation experiment, 8 is an acceptable sample size in order to obtain a valid first impression [28].

To ensure construct validity all participants performed exactly the same tasks based on the same set of instructions thus minimizing any mono-method bias [24]. Therefore, we believe there are no serious threats to validity for our conclusions from the experimental evaluation.

VII. CONCLUSION

In this paper, we argue that user experience of cloud service e-marketplace can be enhanced by providing visualization mechanism for exploring the results of service search on cloud e-marketplace platform. This way, user can quickly discern the differences in cloud services with respect to their requirements. For cloud service e-marketplaces, search result should be innovatively presented in a way that ease understanding and reduce cognitive load of users during service selection. This allows the user to immediately understand the impact of trade-off choices when exploring the plethora of services. Users can therefore exploit such information in making satisfactory service selection decision [3]. Moreover, advances in the domain of Information Visualization (IV) employs relevant techniques to reduce human cognitive effort to view, explore, and comprehend large amounts of information at once, by presenting such complex information in intuitive ways [16]. The main contribution of this paper is the presentation of a visualization framework based on bubble graph for the exploration and comparison of cloud services in response to user query in a cloud e-marketplace context. In contrast to existing approaches (e.g. tables), bubble graph visualization is presented as viable alternative for information visualization during service selection and experimental results shows its speed and ease of use. In the near future, we intend to integrate the framework in a more holistic and integrated service selection framework for cloud service e-marketplaces.

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