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# Identification of Effective Factors on the Use of "Query Suggestions" through Fuzzy Delphi Method

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**Abstract**

**Purpose**: Query suggestions are contributive in formulating queries and improving search results on the Web. This tool is used in most search and retrieval systems like the search engines, databases, personal search tools and so on. The factors affecting the use of query suggestions by the users from the perspective of experts are identified.

**Methodology**: First, a number of factors are identified through the documentary methodology, and next the significance of each factor is determined through the fuzzy Delphi method here.

**Findings**: A total of 48 factor is extracted from the available literature view and is classified into 13 categories of demographic characteristics, search experience, domain knowledge and expertise, linguistic features, user's query, creativity creation, psychological and cognitional, source of creation of query suggestions, contextual factors, semantic features of query suggestions, structural characteristics of query suggestions, increasing the user's performance and ease of use. To assess the importance of these factors eight factors are eliminated and 40 factors are identified as the final factors affecting the use of query suggestions through Fuzzy Delphi method.

**Research limitations/implications:**The results of this research can be used to present a structural-interpretation model in which the most important factor is identified through the view of the experts.

**Originality/Value**: The results obtained in this study will assist researchers and designers of search tools to apply the knowledge gained from effective factors in providing algorithms for query suggestions in their search tools. The factors extracted in this study are fundamental and basic which researchers can use when examining the performance and status of the query suggestion of each search tool.

**Keywords**: query suggestions, query formulation, information need, Fuzzy Delphi method

## 1. Introduction

With the appearance of the World Wide Web in the 1990s and the rapid growth of data thereof the interested relied on the internet to explore valuable information. Users still face difficulties in expressing their information needs, which is one of the most important aspects of information-seeking, and information retrieval and motivates such activities, making Belkin (1980) to come up with Anomalous State of Knowledge (ASK) hypothesis (Kelly and Fu, 2007). Taylor (Davarpanah, 2007) addresses the problems related to the expression of information needs and describes the four levels of visceral, conscious, formalized, and compromised disambiguates of query and devise a query from information needs.

Users express their information needs with respect to information retrieval systems in the form of queries in the query formulation phrase (Parikh *et al.*, 2013). The effectiveness of information retrieval from the web largely depends on whether or not users' queries properly describe their information needs (Cao *et al*., 2008). Short user queries are often imprecise and ambiguous (Cao *et al*., 2008; Qumsiyeh and Ng, 2014) in a sense that a number of studies run by Koshman *et al*

(2006) have revealed that the average length of queries provided for search engines have less than three terms. In this situation, due to lack of understanding of the information needs, information retrieval systems do not provide users with appropriate results. In solving these problems and assisting users in their search for online resources, many information retrieval systems like Google, Yahoo!, Bing search engines, Amazon online Bookstore, Facebook social network and so on provide the *query suggestion* feature (Cao *et al*., 2008; Qumsiyeh and Ng, 2014).

*Query suggestion* is one of the fundamental features in information search tools that provides users with alternative methods for exploring topics and assist searchers develop better understandings of their topics and richer vocabulary through in devising manual queries. *Query suggestions* allow searchers to continue to execute the queries even when they are unable to formulate their own queries (Kelly *et al*., 2010; Niu and Kelly, 2014). For example, The Google search engine, with the keyword *cognitive* typed in the search box provides suggestions to the user, showing various aspects of the subject *cognitive*, Fig. 1. The user may choose one of these suggestions or, with being inspired by them, formulate new queries.

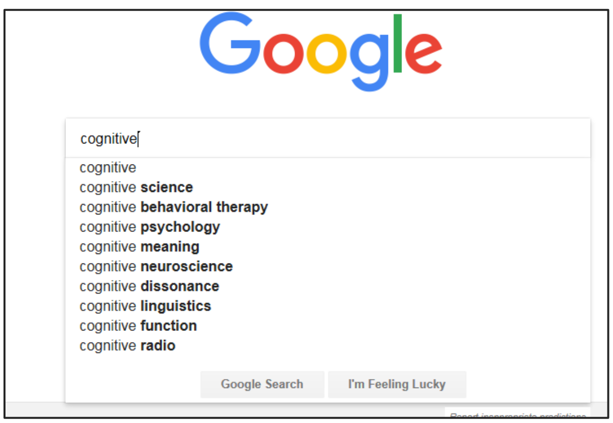


**Figure 1. A sample of query suggestions in Google's search engine for the query *cognitive***

In general, *query Suggestions* is an important assistive feature in all domains that allows users to focus on their intent or discover new content. For focused users, it can assist them reformulating their queries in of appropriate manner in a sense that they will be able to reach relevant results in a shorter time with less effort. *Query suggestions* for exploratory users provide the means of discovery (Parikh *et al*., 2013).

Although the contribution of *query Suggestions* in query formulation is recognized and assist users better describe their information needs in many search tools, how much users use this tool and what factors are effective thereof is questionable. Most studies in the field of *query suggestions* are run on the techniques and algorithms of devising *query suggestions* in a variety of manners like the use and non-use of query logs. In a number of studies that have assessed the factors affecting the use and quality of *query suggestions*, some of the specific features including the method of representation and usage statistics of *query suggestions* by users are examined. Based on knowledge, there exists no study that comprehensively has identified possible factors affecting the quality and extent *query suggestions* use.

The objective of this study is to answer the sole questions: which are factors affecting *query suggestions* use?

## 3. Literature review

Studies related to the research are presented in two sections: 1) Query suggestions' devising techniques and 2) User's behavior and query suggestions.

### *3-1. Query suggestions devising techniques*

These techniques can be classified into three categories: search logs based query suggestions, non-search logs based on query suggestions, and  context based query suggestions

Many of the studies run on query suggestions apply search logs in devising query suggestions. Beeferman and Berger (2000) incorporated the common clicked URLs and through agglomerative clustering algorithm identified related queries and URLs for deriving group of queries. Huang *et al.* (2003) mined co-occurring query pairs from session data together with candidate relevant terms for a user query by drawing on terms that co-occurred in similar search processes and ranked the candidates based on their frequency of co-occurrence with the user input queries. Zhang and Nasraoui (2006) assumed that the degree of similarity of two queries depends on the adjacent degree of the queries, this the more adjacent, the more similar. Boldi *et al.*(2008) proposed a method for drawing a query-flow graph where nodes are queries and an edge from *qi* to *qj* is associated with some weight to indicate how often a user moves from *qi* to *qj* within a session. Ma *et al*. (2008) established a user-query bipartite graph and a query-URL bipartite graph based on click-through. Song and He (2010) applied the clicked URLs and skipped URLs into account and proposed an optimal rare query suggestion framework based on the pseudo-relevance feedback. Sadikov *et al.* (2010) extended the query-flow graph by introducing the clicked documents for each query, where the queries *qj* following a given query *qi* are clustered together sharing many clicked search logs.

There exist studies based on Non-search logs where sources provided like document collections, Wikipedia, wordNet, ontology, and so on are applied in devising query suggestions.Shaikh *et al.* (2013) developed their probabilistic query suggestion module (PQS) that generated candidate query suggestions by solely relying on Wikipedia documents. Bhatia *et al.* (2011) proposed a probabilistic mechanism for devising query suggestions from the corpus without applying query logs. They resorted to the document corpus to extract a set of candidate query suggestions. Priya and Rajalaxmi (2013) proposed an approach where alternate queries related to the user query are extracted from the ontology by appling various correlation types.

Since in popularity based methods query popularity might be change by factors likes time, location, search session, and user characteristics, some researches apply this factors devising query suggestions. Shokouhi and Radinsky (2012) proposed a time-sensitive approach for query auto completion, where instead of ranking query completions by their past popularity, they apply time-series analysis and rank candidates according to the forecasted frequencies by modeling the temporal trends of queries. Miyanishi and Sakai (2013) proposed Time-aware Structured Query Suggestion (TaSQS) where query suggestions are clustered along a timeline in a sense that the user can narrow down his search from a temporal point of view. When a suggested query is clicked, TaSQS presents web pages from query-URL bipartite graphs after ranking them according to the click counts within a particular time period.

Hu *et al*. (2018) proposed a new solution to location-aware query autocompletion. They devised a trie-based index structure and integrated spatial information into the trie nodes. Their method is able to answer both range and top-*k* queries. Qi *et al.* (2016) designed a location-aware keyword query suggestion framework and proposed a weighted keyword-document graph, which captures both the semantic significance between keyword queries and the spatial distance between the resulting documents and the user location.

Shokouhi (2013) proposed a supervised framework for personalizing autocompletion ranking where the effectiveness of several user-specific and demographic-based features are compared. The findings there reveal that among them, the user's long-term search history and location are the most effective in personalizing autocompletion rankers. Cai *et al.* (2014) proposed a method where both section the time-sensitivity and personalization aspects are often to concern. In time-sensitivity predicting query popularity is based on their recent trend and cyclic behavior. They applied auto-correlation to detect query periodicity by long-term time-series analysis and anticipate the query popularity trend based on observations within an optimal time window returned by a regression model. They reranked the returned top N candidates by integrating their similarities with a user's preceding queries on a character level to produce a final query autocompletion list.

*3-2. User's behavior and query suggestions*

The behavior of users in using query suggestions is assessed in many studies, and in some are examined the effect of using the query suggestions on the relevance of the search results. Hayati and Taherian (2010), in an empirical study, compared user's satisfaction level of document relevance in terms of unassisted keyword search pattern and assisted keyword search pattern in Google search engine. Their findings indicate that about 70% of Google's suggestions as an assisted keyword search pattern are of moderate to high relevance. Appling of assisted keyword search pattern increases the relevance of resources and the user's satisfaction together with the ease of use and overall performance of the system in reach the desired resources. Khosravi *et al.* (2013) assessed the effectiveness of suggested keywords and phrases offered by Google search engine in search expansion and relevancy enhancement in graduate students' perspective. Their findings reveal that there exists a significant difference between the volume of recall results obtained from the first search query and the results of the search expansion based on the suggested keywords or phrases. Fattahi *et al.* (2016), by appling a mixed method, assessed the Google's suggested keywords impact on the relevance judgment of users to determine how such would the keywords generate to more relevant results as to context. Findings indicate that the suggested keywords by Google improve the retrieval relevance.

How and when users use query suggestions is assessed in some studies in the field. Ward *et al.* (2012) assessed the student's use of an auto-completion implementation on the initial search entry box for a library's primary federated searching feature. Through usability studies, the authors analyzed how and when students use auto-completion as part of typical library research, and assess the value and role of auto-completion in the research process, and they noted any drawbacks of implementing the feature. Findings reveal that participants use autocompletion to correct spelling, known-item searches (specific titles, authors, and so on), to build students' confidence with an unfamiliar topic, to speed up the search process, to focus of broader search, and to augment search-term vocabulary. Kato *et al.* (2013) assessed when and how the user uses query suggestion. They analyzed three kinds of data sets obtained from a major commercial web search engine, Their analysis indicate that query suggestions are often used: 1) when the original query is a rare query, 2) when the original query is a single-term query, 3) when query suggestions are unambiguous, 4) when query suggestions are generalizations or error corrections of the original query and 5) after the user has clicked on several URLs on the first search result page. Niu and Kelly (2014) run a study to answer the three questions of: 1) when do users integrate query suggestions into their searches? 2) How do the query suggestions differ according to search experience, temporal segment of search and topic difficulty? and 3) Does the use of query suggestions assist users find more relevant documents? They revealed that participants integrate the suggestions into their searching fairly quickly and that participants with less search expertise used more suggestions and save more documents. Participants use more suggestions towards the end of their search and when searching for more difficult topics.

Liu *et al.* (2012) in assessing the query suggestion impact on queries of different degrees of difficulty found that query suggestion is much more useful for difficult queries than easy queries.

Some other researches have only assessed the impact of a particular factor on the use of query suggestions. Joho *et al.* (2002) compared the effectiveness and efficiency of presentation methods of list and menu hierarchy. Findings indicate that recall and precision measurements are better in the menu hierarchy method than in the list method. Kelly *et al.* (2010) assessed do the manner of how are the presentation usage statistics of query suggestions impact the use of them. In this study 23 subjects used an experimental search system to findq documents on four topics. Eight query suggestions of four high and four low queries are provided for each topic. Findings indicate that the subjects could distinguish between high and low quality queries and were not influenced by the usage information.

Kato *et al.* (2012) proposed a method by which query suggestions are presented to the user with two popular query reformulation actions, namely the specialization and parallel movement (SparQS). They conducted a task-based user study to compare SparQS with a traditional *flat list* query suggestion. Findings reveal that the subjects search more successfully in SparQS method than the *flat list* case, even though query suggestions presented were exactly the same in both the methods.

## 4. Methodology

Here, the two documentary and Fuzzy Delphi methods are adopted.

### *4-1. Documentary method*

To identify the factors affecting the use of the query suggestions, a comprehensive literature review is run using the documentary method, where most of the factors are identified. The documentary method is an analysis of the documents which contain information on the subject under study. In this method, the researcher seeks to use documentary data to discover, extract, classify, and evaluate the content related to his/her research topic in a simultaneous manner (Sadeghi *et al.*, 2016).

Adopting documentary method in extracting the factors influencing query suggestions use is recognized as an appropriate method, because the purpose of the research is to identify the factors influencing this use without considering specific search tools. In this research three types of literature are selected to identify the factors: 1) The studies that propose an algorithm and approach to devise query suggestions, 2) The studies that assesse the behavior of users the query suggestion use and 3) The studies run on user information search behavior that do not directly address the issue of suggestion and it is assumed that a number of factors in them affect the query suggestions use. In general, 135 articles are reviewed in the field of query suggestions and user search behavior in order to extract factors affecting. In the selection of articles it is the algorithms and behaviors related to specific search tools are not of concern while the algorithms related to user behavior is assessed in all tools including public search engines, social networks such as Twitter and and so on.

After the extracted factors from the documentary phase are applied in Fuzzy Delphi method, the extent of their importance is determined.

*4-2. Fuzzy Delphi method*

The traditional Delphi Method is widely applied in obtaining a consistent flow of answers through the results of questionnaires (Hsu *et al.*, 2010). In this method, verbal expressions are used to measure views. Verbal expressions have limitations to reflect fully responded mental latencies. For example, the phrase *high* for A who is a stringent person is different with phrase *high* for B. If both the individuals use a definite number to quantify the view, the results will be oblique and far from reality. The decisions made by the experts rely on their individual competence and are subjective. Therefore, it is more appropriate to present the data by fuzzy numbers instead of crisp numbers until decisions correspond to the real world situation (Habibi *et al*, 2015).

Fuzzy Delphi method is presented by Kaufmann and Gupta in 1988 (Habibi *et al.*, 2015), in order to select fuzzy membership functions, triangular fuzzy number, trapezoidal fuzzy number, and Gaussian fuzzy number, the mostly used.

The present study applied the triangular membership numbers (Hsu *et al.*, 2010). In this method, each expert's opinion is represented as a triangular fuzzy number (TFN), which is displayed with three real numbers (M= (l, *m*, *u*)). The upper bound, symbolized by *u*, is the maximum value of fuzzy number *M*., the lower bound, symbolized by l, is the minimum value of fuzzy number M, and *m* is the most probable value of a fuzzy number (Akyuz and Celik, 2015).

In the implementation of Fuzzy Delphi method an appropriate fuzzy spectrum should be developed for the fuzzification of respondents' linguistic expressions. For this purpose, the fuzzy spectrum development methods or the common spectra. For example, table I indicate the triangular fuzzy spectrum has present for a five-degree Likert scale in expressing the importance of the scales, which is used in this study in fuzzification of linguistic expressions (Habibi *et al.*, 2015).

**Table I. Triangular fuzzy numbers for five-degree Likert scale**

| Very low | Low | Mediocre | High | Very high |
|---|---|---|---|---|
| (0, 0, 0.25) | (0, 0.25, 0.5) | (0.25, 0.5, 0.75) | (0.5, 0.75, 1) | (0.75, 1, 1) |

*4-2-1.The expertise of participants*

In selecting panel members from the field of computer, information technology, and information science two criteria are of concern: first, expertise in the field of knowledge retrieval, then being familiar with query suggestion system. Researchers are aware of the domination of the panel members on the topic. Because the main factors are selected from the available published articles, the field of expertise and the number of panel members provide the appropriate information.

*4-2-2.The number of participants*

There are no explicit rules about the number of panel experts, and their number depends on factors such as homogeneity or heterogeneity of the sample, Delphi objective, the nature of the problem, the quality of the decision, the ability of the research team in the study management, the internal and external credibility, the time of data collection and resources in access, domain scope, and acceptance of the response (Ahmadi *et al.*, 2008). Results obtained from available studies indicate that the panel member's count in studies run through this method is between 10 and 1685. However, when there is a homogeneity among members are recommended about 10 to 20 members (Aliodosti, 2006). In this research were selected 12 experts as panel members to express opinionns on the importance of the factors extracted from the literature and to find whether other factors affect use the query suggestion usage.

*4-2-3.Experts recruitment process*

After specifying the number and expertise of the participants, a letter containing information on the introduction of researchers and the purpose of Delphi is sent to each expert to get information about their collaboration or non-cooperation. After the collaboration is announced by 12 experts, the first round questionnaire is sent to them and the phases of Delphi began.

*4-2-4.Questionnaire of Delphi*

The questionnaire of Fuzzy Delphi which consists of 48 multi-option questions together with an open question is sent for experts. After collecting the filled questionnaires of first round, statistical analysis is run and some questions are removed. In the second round of Delphi the questionnaires, together with statistical analysis are sent to experts to express their views. The questionnaires are analyzed at this round and the results of the two round are compared and Delphi process stops according to the difference between the two rounds.

### *4-2-5. Fuzzy aggregation of opinions*

After collecting data, the experts' opinions should be aggregated. There exist many proposed methods for fuzzy aggregation, one of which is the calculation of the fuzzy average. If any expert's opinion is displayed as a triangular fuzzy number (*l*, *m*, *u*), the simplest method is to calculate the fuzzy average of the experts' opinions (Habibi *et al*., 2015):

$$F_{AVE} = \frac{\sum l}{n}, \frac{\sum m}{n}, \frac{\sum u}{n} \qquad Equation 1$$

In this study, the fuzzy average method is applied in fuzzy aggregation.

### *4-2-6. Defuzzification*

After fuzzy aggregation of the experts' opinions, the values should be defuzzified. In the different methods adopted in fuzzy approach, researchers ultimately convert the final fuzzy values into a crisp and understandable number. Typically, the aggregation of triangular and trapezoidal fuzzy numbers can be summarized by a crisp value, the best average. This process is known as defuzzification (Habibi *et al*.; 2015). There exist several complex methods for defuzzification, referred to as Center of gravity ( COG), Center of area (COA), Mean of maxima, total center, and Weighted average of centers (Radfar *et al*., 2011). In this study, the Center of Area Method (COA), modified by Tzeng and Teng (1993), is adopted and calculated through equation 2 (Liu, 2013):

$$DF_{ij} = \frac{[(u_{ij}-l_{ij})+(m_{ij}-l_{ij})]}{3} + l_{ij} \qquad Equation\ 2$$

### 4-2-7. *Calculation of the difference between any expert's opinion in the rounds*

In step is calculated the difference between the defuzzy numbers in both the round. If the difference between the defuzzy numbers is less than 0.2, Delphi process is stoped (Mirzaei *et al*., 2017).

## 5. Findings

Through an assessment run in this field, there exist 48 factors affecting query suggestions use, categorized in 13, Table II.

**Table II. Factors affecting query suggestions use**

| Category | Factors | Questions | Components of Factors |
|---|---|---|---|
| 1 | Demographic Characteristics | F1 | User's age |
| | | F2 | User's gender |
| | | F3 | User's discipline |
| | | F4 | User's level of education |
| 2 | Search Experience | F5 | The skill level of the user in searching and using the Internet |
| | | F6 | The level of Internet usage |
| 3 | Domain Knowledge and Expertise | F7 | The level of user's expertise in the field of search |
| | | F8 | The level of lexical knowledge in the field of user's expertise |
| 4 | Linguistic features | F9 | The level of linguistic knowledge of the user |
| | | F10 | General level of the user's vocabulary knowledge |
| | | F11 | The difference between the user's original language and the search information |
| 5 | User's Query | F12 | Complexity / simplicity of the user's query |
| | | F13 | Specificity/ generality of the user's query |
| | | F14 | The level of general and partial of the user's original query |
| | | F15 | Single-term being of the user's original query |
| | | F16 | Scarcity of the user's query |
| 6 | Creativity | F17 | Developing creative thinking through breaking the existing mental patterns |
| | | F18 | Presenting ideas for completely new queries |
| | | F19 | Assessing users express what they have in mind, but cannot deliver with proper vocabulary |
| 7 | Psychological and Cognitional aspects | F20 | Reducing the user's uncertainty and confusion |
| | | F21 | Building confidence in user about their knowledge and validate their research idea |
| | | F22 | Satisfying users curiosity |
| | | F23 | Increasing search domain learning |
| | | F24 | Increasing the user's perception on the topic by introducing different aspects of the search topic |
| | | F25 | Assessing users in focusing on topics by specifying the search domain |
| | | F26 | Providing information on usage frequency of query suggestions usage |

| | | | |
|---|---|---|---|
| 8 | Source of Creation of Query Suggestions | F27 | The applied source of (query logs, document collections, thesauruses, ontology, Wikipedia, vocabulary) in developing query suggestions |
| 9 | Contextual Factors | F28 | Appling location information (spatial information in the documents and user's location) in developing query suggestions |
| | | F29 | Appling time information (the time the questions are provided and the time provided for search query) to develop query suggestions |
| | | F30 | Appling information related to personalized features (user's topic priorities previous search history, and current search history) to develop query suggestions |
| | | F31 | Appling task-aware information (queries with same information need) to develop query suggestions |
| 10 | Semantic Features of Query Suggestions | F32 | Providing semantic correlation between user's queries and the query suggestions including broad, specific, related, and synonyms |
| | | F33 | Providing the list of query suggestions in the order of relevance to the user's query |
| | | F34 | Maintaining semantic for relation between the user's query and the query suggestion for the same vocabulary with the plurality of meanings and words associated with the different form in writing |
| | | F35 | Maintaining semantic correlation between the user's query and the query suggestions for abbreviated queries |
| 11 | Structural Features of Query Suggestions | F36 | The method of organization of query suggestions (categorized and clustered against flattened) |
| | | F37 | Location placement of query suggestions (high or below) |
| | | F38 | The count of location placement of query suggestions (in one place or in several places) |
| | | F39 | Highlighting user's query from query suggestions |
| | | F40 | Other features including the menu height and the width of the query suggestions box |
| 12 | Increased User's Performance | F41 | Savings in the user's time and efforts for query formulation |
| | | F42 | Keystrokes count reduction by user |
| | | F43 | Reformulation count by user |
| | | F44 | Retrieval of more relevant documents |
| 13 | Ease of Use | F45 | The count of prefixes and characters required to present query suggestions in search box |
| | | F46 | Spelling correction of search terms in the search box |
| | | F47 | Assessing term spelling to of search in the search box |
| | | F48 | Simultaneous typing query by user and present query suggestions in search box |

After identifying the factors affecting the query suggestion use in literature, they are given to experts in the form of a questionnaire to express their opinions on the significance of each factor in the fuzzy Delphi method and to find out whether are aware of other effective factors expressed except factors mentioned in the questionnaire. The results of the first round of the fuzzy Delphi which contains fuzzy mean counts and the crisp count of each question are tabulated in Table III, where *L* is lower bound, *M* is the most probable value and *U* is upper bound.

**Table III: Mean of triangular fuzzy count and crisp count of each query in the first round**

| Factors | L | M | U | Fuzzy Mean | Crisp | Result |
|---|---|---|---|---|---|---|
| F1 | 0.56 | 0.81 | 0.96 | (0.96,0.81,0.56) | 0.78 | Accepted |
| F2 | 0.31 | 0.52 | 0.75 | (0.75,0.52,0.31) | 0.53 | Rejected |
| F3 | 0.65 | 0.90 | 0.98 | (0.98,0.9,0.65) | 0.84 | Accepted |
| F4 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F5 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |
| F6 | 0.65 | 0.90 | 1.00 | (1,0.9,0.65) | 0.85 | Accepted |
| F7 | 0.67 | 0.92 | 1.00 | (1,0.92,0.67) | 0.86 | Accepted |
| F8 | 0.52 | 0.77 | 0.96 | (0.96,0.77,0.52) | 0.75 | Accepted |
| F9 | 0.50 | 0.75 | 0.98 | (0.98,0.75,0.5) | 0.74 | Accepted |
| F10 | 0.65 | 0.90 | 1.00 | (1,0.9,0.65) | 0.85 | Accepted |
| F11 | 0.69 | 0.94 | 1.00 | (1,0.94,0.69) | 0.88 | Accepted |
| F12 | 0.56 | 0.81 | 0.98 | (0.98,0.81,0.56) | 0.78 | Accepted |
| F13 | 0.63 | 0.88 | 1.00 | (1,0.88,0.63) | 0.84 | Accepted |
| F14 | 0.48 | 0.73 | 0.94 | (0.94,0.73,0.48) | 0.72 | Accepted |
| F15 | 0.54 | 0.79 | 0.98 | (0.98,0.79,0.54) | 0.77 | Accepted |
| F16 | 0.31 | 0.54 | 0.79 | (0.79,0.54,0.31) | 0.55 | Rejected |
| F17 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |
| F18 | 0.60 | 0.85 | 0.96 | (0.96,0.85,0.6) | 0.80 | Accepted |
| F19 | 0.58 | 0.83 | 0.96 | (0.96,0.83,0.58) | 0.79 | Accepted |
| F20 | 0.63 | 0.88 | 1.00 | (1,0.88,0.63) | 0.84 | Accepted |
| F21 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |
| F22 | 0.29 | 0.50 | 0.71 | (0.71,0.5,0.29) | 0.50 | Rejected |
| F23 | 0.63 | 0.88 | 1.00 | (1,0.88,0.63) | 0.84 | Accepted |
| F24 | 0.52 | 0.77 | 0.96 | (0.96,0.77,0.52) | 0.75 | Accepted |
| F25 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F26 | 0.38 | 0.60 | 0.83 | (0.83,0.6,0.38) | 0.60 | Rejected |
| F27 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F28 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |

| Factors | L | M | U | Fuzzy Mean | Crisp | Result |
|---|---|---|---|---|---|---|
| F29 | 0.54 | 0.79 | 0.98 | (0.98,0.79,0.54) | 0.77 | Accepted |
| F30 | 0.71 | 0.96 | 1.00 | (1,0.96,0.71) | 0.89 | Accepted |
| F31 | 0.58 | 0.83 | 0.98 | (0.98,0.83,0.58) | 0.80 | Accepted |
| F32 | 0.65 | 0.90 | 1.00 | (1,0.9,0.65) | 0.85 | Accepted |
| F33 | 0.58 | 0.83 | 0.98 | (0.98,0.83,0.58) | 0.80 | Accepted |
| F34 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F35 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |
| F36 | 0.56 | 0.81 | 0.98 | (0.98,0.81,0.56) | 0.78 | Accepted |
| F37 | 0.65 | 0.90 | 1.00 | (1,0.9,0.65) | 0.85 | Accepted |
| F38 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F39 | 0.58 | 0.83 | 0.96 | (0.96,0.83,0.58) | 0.79 | Accepted |
| F40 | 0.29 | 0.48 | 0.73 | (0.73,0.48,0.29) | 0.50 | Rejected |
| F41 | 0.60 | 0.85 | 0.98 | (0.98,0.85,0.6) | 0.81 | Accepted |
| F42 | 0.63 | 0.88 | 0.96 | (0.96,0.88,0.63) | 0.82 | Accepted |
| F43 | 0.69 | 0.94 | 1.00 | (1,0.94,0.69) | 0.88 | Accepted |
| F44 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F45 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |
| F46 | 0.56 | 0.81 | 0.98 | (0.98,0.81,0.56) | 0.78 | Accepted |
| F47 | 0.56 | 0.81 | 0.98 | (0.98,0.81,0.56) | 0.78 | Accepted |
| F48 | 0.54 | 0.79 | 0.96 | (0.96,0.79,0.54) | 0.76 | Accepted |

The crisp counts greater than 0.7 are accepted and less than 0.7 are rejected (Wu and Fang, 2011). As a result, factors 2, 16, 22, 26, and 40 are deleted and the remaining factors are applied in the second round.

The result of the second round of Delphi are tabulated in Table IV.

**Table IV: Mean of triangular fuzzy count and crisp count of each query in the second phase of Fuzzy Delphi**

| Factors | L | M | U | Mean | Crisp | Result |
|---|---|---|---|---|---|---|
| F1 | 0.39 | 0.64 | 0.89 | (0.89,0.64,0.39) | 0.64 | Rejected |
| F3 | 0.64 | 0.89 | 0.97 | (0.97,0.89,0.64) | 0.83 | Accepted |
| F4 | 0.64 | 0.89 | 1.00 | (1,0.89,0.64) | 0.84 | Accepted |

| Factors | L | M | U | Mean | Crisp | Result |
|---|---|---|---|---|---|---|
| F5 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F6 | 0.61 | 0.86 | 1.00 | (1,0.86,0.61) | 0.82 | Accepted |
| F7 | 0.56 | 0.81 | 1.00 | (1,0.81,0.56) | 0.79 | Accepted |
| F8 | 0.56 | 0.81 | 1.00 | (1,0.81,0.56) | 0.79 | Accepted |
| F9 | 0.36 | 0.58 | 0.83 | (0.83,0.58,0.36) | 0.59 | Rejected |
| F10 | 0.53 | 0.78 | 0.94 | (0.94,0.78,0.53) | 0.75 | Accepted |
| F11 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F12 | 0.53 | 0.78 | 1.00 | (1,0.78,0.53) | 0.77 | Accepted |
| F13 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F14 | 0.72 | 0.97 | 1.00 | (1,0.97,0.72) | 0.90 | Accepted |
| F15 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F17 | 0.56 | 0.81 | 0.97 | (0.97,0.81,0.56) | 0.78 | Accepted |
| F18 | 0.50 | 0.75 | 0.97 | (0.97,0.75,0.5) | 0.74 | Accepted |
| F19 | 0.56 | 0.81 | 0.97 | (0.97,0.81,0.56) | 0.78 | Accepted |
| F20 | 0.47 | 0.72 | 0.97 | (0.97,0.72,0.47) | 0.72 | Accepted |
| F21 | 0.58 | 0.83 | 0.97 | (0.97,0.83,0.58) | 0.79 | Accepted |
| F23 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F24 | 0.64 | 0.89 | 0.97 | (0.97,0.89,0.64) | 0.83 | Accepted |
| F25 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F27 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F28 | 0.64 | 0.89 | 0.97 | (0.97,0.89,0.64) | 0.83 | Accepted |
| F29 | 0.50 | 0.75 | 0.94 | (0.94,0.75,0.5) | 0.73 | Accepted |
| F30 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F31 | 0.53 | 0.78 | 0.97 | (0.97,0.78,0.53) | 0.76 | Accepted |
| F32 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F33 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |
| F34 | 0.61 | 0.86 | 1.00 | (1,0.86,0.61) | 0.82 | Accepted |
| F35 | 0.58 | 0.83 | 0.97 | (0.97,0.83,0.58) | 0.79 | Accepted |
| F36 | 0.61 | 0.86 | 0.97 | (0.97,0.86,0.61) | 0.81 | Accepted |
| F37 | 0.56 | 0.81 | 1.00 | (1,0.81,0.56) | 0.79 | Accepted |
| F38 | 0.28 | 0.50 | 0.75 | (0.75,0.5,0.28) | 0.51 | Rejected |
| F39 | 0.67 | 0.92 | 0.97 | (0.97,0.92,0.67) | 0.85 | Accepted |
| F41 | 0.61 | 0.86 | 1.00 | (1,0.86,0.61) | 0.82 | Accepted |
| F42 | 0.58 | 0.83 | 1.00 | (1,0.83,0.58) | 0.80 | Accepted |

| Factors | L | M | U | Mean | Crisp | Result |
|---|---|---|---|---|---|---|
| F43 | 0.58 | 0.83 | 0.97 | (0.97,0.83,0.58) | 0.79 | Accepted |
| F44 | 0.67 | 0.92 | 0.97 | (0.97,0.92,0.67) | 0.85 | Accepted |
| F45 | 0.58 | 0.83 | 0.97 | (0.97,0.83,0.58) | 0.79 | Accepted |
| F46 | 0.61 | 0.86 | 1.00 | (1,0.86,0.61) | 0.82 | Accepted |
| F47 | 0.58 | 0.83 | 0.97 | (0.97,0.83,0.58) | 0.79 | Accepted |
| F48 | 0.67 | 0.92 | 1.00 | (1,0.92,0.67) | 0.86 | Accepted |

In the second round, factors 1, 9, and 38 are deleted, because the crisp count of these factors are less than 0.7.

In the next step, in order to determine the consensus of the experts, the differences between the crisp counts of the first round and the second round are tabulated in Table V.

**Table V. The difference between crisp counts of the first and second phases**

| Factors | Crisp number (first round) | Crisp number (second round) | Difference |
|---|---|---|---|
| F3 | 0.84 | 0.83 | 0.01 |
| F4 | 0.76 | 0.84 | 0.08 |
| F5 | 0.81 | 0.80 | 0.01 |
| F6 | 0.85 | 0.82 | 0.03 |
| F7 | 0.86 | 0.79 | 0.07 |
| F8 | 0.75 | 0.79 | 0.04 |
| F10 | 0.85 | 0.75 | 0.1 |
| F11 | 0.88 | 0.80 | 0.07 |
| F12 | 0.78 | 0.77 | 0.01 |
| F13 | 0.84 | 0.81 | 0.02 |
| F14 | 0.72 | 0.90 | 0.18 |
| F15 | 0.77 | 0.81 | 0.04 |
| F17 | 0.81 | 0.78 | 0.03 |
| F18 | 0.80 | 0.74 | 0.06 |
| F19 | 0.79 | 0.78 | 0.01 |
| F20 | 0.84 | 0.72 | 0.12 |
| F21 | 0.81 | 0.79 | 0.02 |
| F23 | 0.84 | 0.80 | 0.03 |
| F24 | 0.75 | 0.83 | 0.08 |

| Factors | Crisp number (first round) | Crisp number (second round) | Difference |
|---|---|---|---|
| F25 | 0.80 | 0.80 | 0.00 |
| F27 | 0.76 | 0.81 | 0.05 |
| F28 | 0.81 | 0.83 | 0.02 |
| F29 | 0.77 | 0.73 | 0.04 |
| F30 | 0.89 | 0.81 | 0.08 |
| F31 | 0.80 | 0.76 | 0.04 |
| F32 | 0.85 | 0.81 | 0.04 |
| F33 | 0.80 | 0.80 | 0.01 |
| F34 | 0.76 | 0.82 | 0.06 |
| F35 | 0.81 | 0.79 | 0.02 |
| F36 | 0.78 | 0.81 | 0.03 |
| F37 | 0.85 | 0.79 | 0.06 |
| F39 | 0.79 | 0.85 | 0.06 |
| F41 | 0.81 | 0.82 | 0.01 |
| 42 | 0.82 | 0.80 | 0.02 |
| 43 | 0.88 | 0.79 | 0.08 |
| 44 | 0.76 | 0.85 | 0.09 |
| 45 | 0.76 | 0.79 | 0.03 |
| 46 | 0.78 | 0.82 | 0.04 |
| 47 | 0.78 | 0.79 | 0.01 |
| 48 | 0.76 | 0.86 | 0.1 |

According to Table V, since the difference between crisp counts in the first round and second round is less than 0.2, it can be claimed that the panel counts have consensus, then the stoppage of fuzzy Delphi.

## 6. Discussion and Conclusion

Here, the possible factors that influence query suggestions use is reviewed in its comprehensive sense, through assessing Delphi fuzzy method. The extracted factors come in 13 categories of: 1) Demographic characteristics, 2) Search experience, 3) Domain knowledge and expertise, 4) Linguistic features, 5) User's query, 6) Creativity creation, 7) Psychological and Cognitional, 8) Source of creation of query suggestions, 9) Contextual factors, 10) Semantic features of query suggestions, 11) Structural characteristics of query suggestions, 12) Increasing the user's performance and 13) Ease of us.

*Demographic Characteristics* including field of study and level of education, recognized affective in query suggestions use. Shokouhi (2013) and Weber and Castillo (2010) assessed the effectiveness of personal characteristics use specifically in query suggestions. The impact of the user's field of study on query suggestions use can be due to the level of difference in familiarity with the methods of searching and the degree of complexity of the vocabulary of some others domains. Designers of query suggestions systems can use demographic features to present algorithms.

Because the user's expertise in the search and Internet use is the begging point for the user's success in interaction with the computer and familiarity with the possibilities of the search tool, it is recognized as effective factor. Niu and Kelly (2014) found that less experienced people used more query suggestions and stored more documents than experienced ones did in designing query suggestions the user levels of the *search experience* must be of concern. For example, in a public search engine of different users with different search experiences, the query suggestion system should consider features like simplicity and ease of use by users with level of low experience.

The impact of the level of *knowledge domain and expertise* of the user is recognized as other effective factor because it is related to their familiarity with different aspects and terminology of the search field. Individuals with a low level of expertise in a domain will be need more query suggestions. Query suggestions assist people with less expertise to become acquainted with different aspects of the subject, vocabulary of the field and their usage in formulating appropriate queries. Researchers like, Monchaux *et al*. (2015) and Wildemuth (2004) have examined the impact of knowledge domain and expertise on the effective user's search behavior. Designers of query suggestions can use the domain expertise factor to provide the algorithm. If the level of expertise of individuals is clear, they can present algorithms where people with a low level of expertise obtain the required information. The level of expertise does not differentiate, and can use the context of the user search session to specify the level of users.

Level of *linguistic knowledge* including the level of general vocabulary knowledge, and the difference between the user's original language and the search information can effect user's behavior in formulation query and the query suggestions use. Users with a lower level of general vocabulary knowledge, require more query suggestions. Users, when searching for information in a language other than their own need assistance of lexical tools.

*The user's query* is an effective factor in query suggestions use. Kato *et al*. (2013) revealed that query suggestions are often used when the original query is a rare query and the original query is a single-term query. Liu *et al.* (2012) and Niu and Kelly (2014) revealed that the rate of query suggestions use in queries with high complexity level is high. Researchers can use of the level of complexity of the query factor to devise appropriate algorithms as in a sense that the system would be able to offer different query suggestions for queries of various complexity or provide suggestions only for problem queries. Liu *et al.* (2012) proposed an adaptive suggestion approach that only makes suggestions for difficult queries.

*Psychological and cognitional factors* are effective in query suggestion use and include reducing the user's uncertainty and confusion, creating creative thinking and presenting ideas for completely new queries, building confidence in the user about their knowledge and validating their research idea, Increasing search domain learning, Increasing the user's perception of the topic, assisting the users focus on topics, assisting the users express what they have in mind, with no proper vocabulary.

In devising of query suggestions, a variety of *sources* like query logs (Beeferman and Berger (2000), Boldi (2008), *Huang et al*.(2003), Ma *et al*.( 2008), Song and He (2010), Sadikov *et al*.(2012), Zhang and Nasraoui (2006)), document collection (Bhatia *et al.*, 2011), ontology ( Priya and Rajalaxmi, 2013), wikipedia (Shaikh *et al*.,2013), and so on are applied. Rating the use of meanings and the correlation among words vary in these resources. For example, ontologies and the word network are more contributive in establishing correlation and meanings, and this affects the quality of the suggestions of the queries. Today the focus is more on the meaning of the words, reading to devise more semantic search engines. To identify the user's actual needs, researchers need to focus more on the meaning among words when devising suggestions of query.

In addition to the main source of query suggestions, contextual factors like: location, time, user search session, and user characteristics in many studies is recognized effective on the quality and use of query suggestions, (Cai *et al*. (2014), Myllymaki *et al*. (2012), Qi *et al*. (2016), Shokouhi and Radinsky (2012), Shokouhi (2013)). Researchers can use this contexts to devise query suggestions in appropriate tools. For example, in search engines with a global domain, the use of a user's location to devise query suggestions provides appropriate suggestions as to the needs of the users, because analyzing the query logs it is reveal that.

*The semantic features* which can in creation of query suggestions has attended including providing semantic correlation between the user's queries and the query suggestions including broad, specific, related, and synonyms correlation, provide a list of query suggestions in the order of relevance to the user's query, maintaining semantic relation between the user's query and the query suggestion for the same vocabulary with the plurality of meanings and words associated with the different forms of writing, and maintaining semantic relationship between the user's query and the query suggestions for abbreviated queries. The use of semantic features in devising query suggestions has a significant impact. The method proposed by Kato *et al*. (2012) and Joho *et al.* (2002) was compared presentation methods of query suggestions and found that various presentation methods impact query suggestion use. In this context, researchers must use semantic tools like ontologies and WordNet to obtain the appropriate semantic correlation between the user's query and the query suggestions.

*Structural Features of Query Suggestions* including placement location of query suggestions; query suggestions placement locations count (in one place or in several places), highlighting user's query from query suggestions an effect on use of query suggestions. When the query suggestions are at the top of the results page, the user may resort to them more, while when at the bottom of the results page, the user is able to use the query of suggestions after reviewing the search results. Highlighting query suggestions of user's query prompts the user to quickly review the query suggestions and quickly decide their use or non-use.

Query suggestions through reducing the user's time and effort for query formulation, the keystrokes' count, and reformulation by user, retrieve more relevant documents affected by user's Performance. Kamvar and Baluja (2008) in assessing the query suggestions in mobile devices found that query suggestions use reduces the keystrokes count in mobile. the objective in any human-computer interaction is to achieve relevant documents where the query of suggestions can be contributive. Studies run by Hayati and Taherian (2009) and Khosravi *et al*. (2013) reveal that the use of query of suggestions results obtaining more relevant documents.

*Ease of use* of query suggestions consist of prefixes count and characters required to present query suggestions, correcting spelling of search terms and assisting in spelling search terms, all in the search box. These factors can be attributed to *principle of least effort*. Because misspelling is a common phenomenon among search engine queries, designers of the query suggestion systems should focus it in all search tools. In order to assist users to express their information needs' mechanisms like online spelling correction, automatic correcting misspelled queries are required.

The finding obtained here can assist researchers in the field of query suggestions to have a complete and comprehensive understanding of possible effective factors. Researchers and designers of search tools can apply the knowledge gained from these influential factors in devising algorithms for query suggestions in their search tools.

The identified factors are not assigned to any specific search tool, but they be considered when devising and improving the existing query suggestions of all search tools, including search engines, social networks, scientific databases, and so on The factors extracted in this study are the fundamental and basic ones that researchers can use when assessing the performance and status of the query suggestion of each search tool. All the identified factors in turn are important and should be considered in devising query suggestions.

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