Understanding the Usability of a Literature-Based Discovery System Among Clinical Researchers in Sarawak, Malaysia

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ABSTRACT

The rapid increase in scientific publications makes it difficult for researchers to keep up with the latest literature and to explore new research directions. The literature-based discovery (LBD) systems aim to resolve this issue by bridging literatures from disparate fields to assist researchers in knowledge discovery and the formulation and testing of research hypotheses. Previous studies have focused mainly on evaluating the efficacy of LBD systems by replicating historical LBD events. The usability of LBD systems has been under-researched, which partly explains the low adoption of the systems. This paper presents a survey study that evaluates the usability of a LBD system for knowledge discovery and hypothesis refinement, and also investigates factors affecting its adoption among biomedical researchers in Sarawak, Malaysia. The findings suggest that the adoption of the LBD system is related to their perceived usefulness and perceived difficulty in interacting with the user interface features of the system.

KEYWORDS

Hypothesis Refinement, Hypothesis Testing, Interaction Studies, Knowledge Discovery, Literature-Based Discovery, Perceived Difficulty, Perceived Usefulness, Usability, User Interface

INTRODUCTION

With the rapid growth of scientific publications, it is hard for researchers to keep track of the latest developments in their field of interest and to perform literature-based knowledge discovery for exploration of new research directions (Simpson and Demner-Fushman, 2012; Pyysalo et al., 2019, p. 1553). This consequently restricts the ability of researchers to generate effective and high priority research hypotheses from literature review. As reported earlier, up to 85% of biomedical research funding is wasted (Chalmers and Glasziou, 2009, p. 1344; Crowe et al., 2015; Moher et al., 2016, p. 1577) on addressing low priority or existing issues. This scenario reflects the uncertainties that arose from the process of research hypothesis formulation. A key step to generate a worthwhile research hypothesis is to support researchers in refining their initial research ideas by enabling them...
to discover new knowledge from large collections of literature (Moher et al., 2016, p. 1587). As a result, numerous Literature-Based Discovery (LBD) systems such as Arrowsmith, Bitola, Spark and LION LBD (Gopalakrishnan et al., 2019) have been developed to assist medical researchers in discovering new knowledge from bibliographic databases for hypothesis generation and testing (Sebastian et al., 2017). LBD is a systematic computational approach that seeks to reveal latent connections by bridging fragments of information from disjoint literatures using innovative technologies such as natural language processing, artificial intelligence, and information retrieval (Swanson, 1986, p. 7; Swanson and Smalheiser, 1997, p. 184; Swanson, 2008, p. 5; Smalheiser, 2011, p. 218; Sebastian et al., 2017; Gopalakrishnan et al., 2019; Pyysalo et al., 2019, p. 1554). The idea of LBD was first employed in medical fields to discover a drug as a treatment for a disease or a gene as the cause of a disease by linking two seemingly unrelated concepts together with a third concept from bibliographic databases (Swanson, 1986). The emergence of LBD systems enables researchers to discover new knowledge automatically from vast collection of literatures. The systems allow researchers to understand the relations between medical concepts and discover implicit links between literatures even though they are seemingly unrelated towards one another (Smalheiser, 2017, p. 51). This in turn enables them to discover useful information from existing literatures and direct them to generate empirically testable research hypotheses.

Several approaches have been taken to evaluate the performance of LBD systems by replicating past LBD discoveries (Yetisgen-Yildiz and Pratt, 2009, p. 634), incorporating experts’ knowledge and reviews (Yetisgen-Yildiz and Pratt, 2009, p. 634; Gopalakrishnan et al., 2019), introducing gap-filling articles (Peng et al., 2017) and conducting user interaction studies (Henry and McInnes, 2017, p. 21; Thilakaratne et al., 2019, p. 28). Most of these approaches are problem oriented and aimed at evaluating the effectiveness of LBD systems in bringing about the desired outcomes. There is little research into the adoption of LBD systems. One relevant study is by Henry and McInnes (2017), who revealed that the absence of interactions between developers and users (p. 28) led to the low adoption of LBD systems. As such, the objective of this study is to investigate the extent to which LBD methods and system designs truly support researchers in research hypotheses formulation and testing. To our knowledge, no study has been conducted to investigate the adoption of LBD systems among researchers in Malaysia. Therefore, to achieve the objective of this study, a user experience study was conducted among 40 researchers from Clinical Research Centre, Sarawak, Malaysia to measure the usability of the LION LBD system in supporting researchers to refine their research hypotheses and discover interesting knowledge. The usability of the LION LBD system was evaluated by measuring the perceived usefulness and perceived difficulty of interacting with six user interface features of the system for knowledge discovery and hypothesis refinement. It has been speculated that the adoption of the system can be improved by refining the usability of LBD systems.

This study is limited to the refinement of research hypothesis and the discovery of knowledge by clinical researchers in Sarawak, Malaysia using the LION LBD system. LION LBD system is built with the state-of-the-art machine learning, natural language processing and graph visualization techniques to facilitate and accelerate the process of revealing plausible novel connections between concepts from various study fields. It is chosen for this study according to its recency, accessibility, and usability. An initial comparison of LION LBD with Arrowsmith and Bitola prior to the present study showed that Arrowsmith has very slow response time; Bitola displays the connections between concepts in traditional tabular form whereas LION LBD displays the connections in graph format; and LION LBD provides a simpler interface for users to filter search results and interact with the system, compared to Arrowsmith and Bitola (Phang et al., 2020). It is also noteworthy that the responses collected in this study is limited to researchers working in general hospital and universities in Sarawak, Malaysia, and with clinical or biomedical science background. The use of two-node search or closed discovery for the evaluation of LBD system is another limitation of this study in order to narrow down the scope of this research.

The structure of the paper is as follows. First, an introduction of the Swanson’s ABC model, challenges hindering the adoption of LBD systems, the existing approaches for evaluating the performance of LBD systems and definitions of terms used in this paper are provided. This is followed by a section
that describes the user interface features of the LION LBD system. After that, the methodology used in this study is explained, followed by the presentation and discussion of key findings that determine the adoption of the system among clinical and biomedical researchers in Sarawak, Malaysia.

BACKGROUND

The Swanson’s ABC Model

LBD has been applied predominantly in medicine to discover worthwhile associations and potential solutions for various diseases. The most significant LBD paradigm, Swanson’s ABC model, suggests that where A is related to B and B is related to C in the literature, then it may be syllogistically inferred that A is associated with C (Swanson and Smalheiser, 1997, p. 184; Smalheiser, 2011, p. 219; Smalheiser, 2017; Henry & McInnes 2017, p. 26; Thilakaratne et al., 2019, p. 28). For instance, A represents a disease (Raynaud’s Phenomenon), B for symptoms (blood viscosity, platelet aggregation, vasoconstriction) and C is the possible treatment for A (eicosapentaenoic acid / dietary fish oil). We can thus infer that eicosapentaenoic acid has therapeutic effects on Raynaud’s Phenomenon, a peripheral vascular disease. It is significant to note that this hypothesis was validated clinically (DiGiacomo et al., 1989, p. 158), thus further strengthened the concept of his own model.

Among the existing LBD systems, most of the techniques integrated were built upon Swanson’s ABC model (Swanson, 1987, p. 228; Weeber et al., 2005, p. 282; Bekhuis, 2006, p. 4; Smalheiser, 2011, p. 219; Sebastian et al., 2017; Henry & McInnes, 2017, p. 26; Gopalakrishnan et al. 2019; Thilakaratne et al., 2019, p. 29), which act as a fundamental building block of the systems. Swanson’s ABC model was commonly divided into two variants which are open discovery and closed discovery. Open discovery allows further exploration of information across various domains of science by specifying only the initial concept of interest. This allows researchers to have broader scope of exploration to formulate more interesting and novel hypotheses. In contrast, closed discovery assumes the existence of both initial and ending concepts to search for potential discoveries in connecting both concepts (Pyysalo et al., 2019, p. 1553).

By utilizing an LBD system in clinical research setting, researchers that are expert within their own field could specify their topic of interests in the form of biomedical concepts. The system will automatically search for the possible solutions from the publications among various domains even if they are seemingly unrelated towards each other and present them to the researchers (Smalheiser, 2017). As a matter of fact, LBD systems had brought along many promising benefits to the researchers. One of them is the rapid formulation and validation of nominee research hypotheses without costly and time-consuming experimentation (Smalheiser, 2011, p. 219). LBD systems are also likely to prevent researchers from conceiving research projects based on trivial hypotheses which may in turn lead to unnecessary resources-consuming experiments. The capability of the LBD systems in performing information searching, information retrieval and returning output accurately to the researchers had greatly accelerated the process in answering the research questions raised. Ultimately, more novel, worthwhile, and meaningful fortuitous outcomes that may save human lives and the environments could be constructed by leveraging LBD systems (Henry & McInnes 2017, p. 26).

Challenges Hindering the Adoption of LBD Systems

Rapid growth of massive publications from various domains had resulted in researchers unable to keep track of all publications (Sebastian et al., 2017). As a result, many potential solutions to a problem remain unrecognized, limiting the possibility of researchers in generating more meaningful ideas and hypotheses to address the existing problems. Despite the emergence of LBD systems, their adoption remained limited (Korhonen et al., 2015, p. 90; Henry & McInnes 2017, p. 26) and the public has yet to realize the existence of LBD systems (Smalheiser, 2017). According to Henry & McInnes (2017, p. 28), LBD had not been widely used by researchers in producing medical hypotheses. Two main
reasons may had contributed to the low uptake of LBD systems: (a) the lack of comprehensive and systematic evaluation of LBD software, and (b) the lack of interactions between developers and users. Besides that, prior evaluation studies are solely based on replicating past discoveries to determine the efficacy of the LBD systems which may affect the performance of LBD systems while performing future discoveries in real world environment. On the other hand, user interaction plays a pivotal role in evaluating the effectiveness of a system. It is only possible for users to leverage the system if it is useful and user-friendly. Thus, it is crucial for a system to be evaluated in various aspects.

It has been previously suggested that user acceptance of the systems is one of the grand challenges faced by current LBD systems (Sebastian et al., 2017). The success of LBD systems should be evaluated by the extent to which it supports real life scientific investigations. LBD methods that fail to get acknowledgement by researchers and scientists are expected to have low adoptions in daily research activities. Moreover, the contemporary LBD systems are domain dependent as they were mostly built by researchers from specific domain especially biomedical domain. LBD systems that are domain independent may increase the adoption and user acceptance in real-life environment.

**Existing LBD Evaluation Methods**

The most common evaluation approach used to evaluate the performance of LBD systems is to replicate prior discoveries, particularly Swanson’s initial discoveries (Yetisgen-Yildiz and Pratt, 2009, p. 634; Henry and McInnes, 2017, p. 26). The LBD system is a success if the LBD systems manage to generate the same correlation as Swanson’s. However, it remains unknown whether the overfitting system could perform as expected with other research problems and are able to produce new knowledge discoveries (Henry and McInnes, 2017, p. 26) as the evaluation method is problem oriented. A system that is being assessed with ad-hoc problems may bring uncertainties whether it can perform well when used with other concepts.

Another evaluation approach for LBD systems is expert-oriented evaluation which incorporates experts’ knowledges and reviews for evaluation (Yetisgen-Yildiz and Pratt, 2009, p. 634; Gopalakrishnan et al., 2019). A study by Weeber (2003) discovered a new drug application for thalidomide (p. 252) by manually matching the linking terms generated by a discovery tool with a target set of relevant terms derived from medical researchers. A similar study was conducted by Yetisgen-Yildiz and Pratt (2009, p. 634). In another study conducted by Torvik and Smalheiser (2007, p. 51), the evaluation of the Arrowsmith LBD system was conducted by developing a standard set of closed-discovery searches from medical experts, specifically neuroscientists (Smalheiser, 2017) (p. 51). The experts were responsible to select a number of relevant B-terms and characterized into several features as the gold standard. (Torvik and Smalheiser, 2007, p. 51; Yetisgen-Yildiz and Pratt, 2009, p. 634). This is not practical when there are substantial number of terms to be identified.

On the other hand, Peng et al. (2017) introduced gaps to define the scenario of co-occurrence terms that is expected to co-occur is absence in any of the articles. Several types of gaps had been identified according to their characteristics. The gaps identified are (a) gaps arising as a byproduct of MeSH indexing, (b) gaps that lack biological meaning, (c) gaps that represent “low hanging fruit” and (d) gaps in communication. Peng et al. (2017) had evaluated the LBD system by bridging MeSH terms with study of gap-filling articles for the next 5 years. This helped them to identify whether gaps can be filled with the MeSH pairs. Nevertheless, drawbacks in recognizing the limitations of gaps in biomedical domain has been identified. Firstly, MeSH indexing rules could be one of the reasons that cause the lack of co-occurrence within two MeSH terms. Even if the terms carry similar meaning, they are being categorized differently. Thus, decrease the possibility to co-exist within the same articles. Besides that, some of the MeSH terms pairs appear to have lack of significant meanings which resulted in low co-occurrence. This may cause the lack of research in investigating the relationship between MeSH terms even though they are important. Terms that do not exist in the same category or field is also one of the causes that led to using LBD to seek for meaningful relationships between different domains of knowledge.
Furthermore, there also exists the study of interaction between systems and users (Henry and McInnes, 2017, p. 27; Thilakaratne et al., 2019, p. 28). User experience research is the study of interaction between users and the system (Agosti et al., 2011, p. 663). It is an important source of information to develop systems that can achieve higher user acceptance. Studies on user interaction with systems can lead to refinement of the system which allow users to perform knowledge discovery in a better way. A successful LBD system requires users to interact with to maximize the performance and to achieve the objective. As mentioned by Smallheiser (2011) and Sebastian et al. (2017), the LBD system proved its successfulness if it can support medical researchers in their day-to-day scientific tasks (p. 223). Henry and McInnes (2017) mentioned that evaluating the effectiveness of LBD in assisting users to formulate their research topics and hypotheses could be the key to further enhance the LBD systems (p. 30).

**Perceived Usefulness, Perceived Difficulty, Knowledge Discovery, and Hypothesis Refinement**

The definition of usability is “the ability of being used” (Bevan et al., 2015, p. 143). Bevan et al. (2016, p. 268) extended the definition and described usability as “the extent to which an entity can be used to perform specific tasks by specific users efficiently”. Perceived usefulness describes “the degrees to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989, p. 320). In contrast, according to Trafimow et al. (2002, p. 101), perceived difficulty is the perception of the ease or difficulty of performing a given task or activity. In this paper, perceived usefulness is defined as the degree to which the user interface design of an LBD system is useful for researchers, whereas perceived difficulty refers to the perceived ease of use of the user interface, to perform literature search for knowledge discovery and hypothesis refinement.

A research hypothesis is developed from the research question and the main elements (such as sampling strategy, intervention, and outcome) of a study to establish the basis for statistical testing (Farrugia et al., 2010, p. 280). Accordingly, hypothesis generation is defined as “the pre-decisional process by which it is possible to formulate explanations and beliefs regarding the occurrences observed in a specific environment” (Tiddi et al., 2014, p. 334). On the other hand, knowledge discovery is the process of extracting unprecedented quality knowledge from data (Frawley et al., 1992, p. 58). In this study, knowledge discovery is defined as the process to discover useful information from literature, in order to increase their knowledge base to generate strong research hypotheses; while hypothesis refinement is defined as the process to improve the quality and testability of a research hypothesis through the discovery of new knowledge from literature.

**USER INTERFACE DESIGN**

According to Blair-Early and Zender (2008), a good end-user experience solution is “easy to use” and “intuitive” (p. 86). Thus, it is important to understand the user interface design of LION LBD system and evaluate its usability. The following paragraph introduces three basic categories of user interface elements, followed by a description of the key user interface features of LION LBD system.

User interface elements can be categorized broadly into input controls, navigational components, and information components (Garrett, 2010). Input controls are defined as elements that allow users to enter or give inputs to the system (Galitz, 2007, p. 4) or select the most appropriate options from a suggestion list. Examples of input controls are dropdown, buttons, and toggles. Navigational components include elements that navigate users to different pages or contents with or without offering inputs to the system (Galitz, 2007, p. 350). Examples of navigational components are search fields, icons, sliders, menu, tags, and clickable text links. Elements that present users with information or notifications regarding the system’s output (Galitz, 2007, p. 4) are known as informational components. Examples of informational components are loading spinner, tooltips, and modal window or pop-up (Garrett, 2010).

The user interface features of LION LBD system can be classified broadly into six categories: predetermined suggestion terms, presentation of results, filtering features, co-occurrence terms,
interacting with graph nodes, and co-related mentions. These categories are identified by listing the actions that can be performed on the LION LBD system.

**Predetermined Suggestion Terms**

The system returns a dropdown list with suggested terms when users enter their search terms into the search field (Figure 1). Users are required to select the exact terms or the most relevant terms from the dropdown list. The biological entity types of the suggested terms are displayed in different colors in the dropdown list. The suggested terms are limited to those associated with six biological entity types, including chemical, disease, mutation, gene, cancer hallmark and species. The search process could not proceed if the input is not selected from the dropdown list. By clicking on the “+” button at the side of the search field, the system returns two search fields for users to enter a start term and a destination term to perform closed discovery. Thus, users must have some knowledge of the field of medicine to select suggested terms that best match their search intents and an understanding of the difference between open discovery and closed discovery to use the system effectively for hypothesis generation and testing.

**Search Results in Graph and Text Modes**

Search results are returned by the system in two presentation modes: graph mode as the initial mode and text mode (Figure 2). Graph mode visualizes search results as a network, where each node represents a concept and each edge represent a relation. The network graph portrays how each concept is related to one another. The node color represents the biological entity type while the thickness of the edge represents the strength of connection between two concepts. Upon clicking or hovering a node, a small panel will pop out, displaying synonyms related to the concept represented by a node, number of mentions and documents relevant to a node, number of edges shown by the network graph, an option to switch to text mode, different actions including expanding, collapsing, and deleting a node from the network graph, and a dropdown list of co-occurrence terms. Text mode presents similar
information to graph mode. In text mode, the key differences are the most frequent co-occurrence terms relevant to a concept are displayed in tags and the number of co-occurrences instead of concepts graph, and a Jaccard Index is used to indicate the strength of connection between the selected node and other relevant concepts. The system allows an interchange of presentation mode based on users’ preference to discover new knowledge and connection between new and previous knowledge for hypothesis generation and testing.

**Filtering Mechanisms**

The system allows users to filter search results dynamically by biological entity type of nodes, publication year of literature and weight of edge between nodes (Figure 3). Users can narrow down their search by dropping the tags represented different biological entity types and by adjusting the sliders to limit the search to specific publication year and edge weight located at the top and the bottom of the search result window, respectively. The filtering features allows users to include biological entity type that match their search intent, refine their search by publication year, and adjust their search by edge weight for a more focused view of network graph and lists of co-occurrence terms.

**Figure 2. Switching between graph and text mode to identify relationship between different concepts**

**Figure 3. Filtering search results by (a) biological entity type, (b) publication year or (c) weight of edges**
Co-Occurrence Terms

Co-occurrence terms are terms that exist simultaneously in an article of a selected node. Upon clicking or hovering a node, a small panel will pop out to display a dropdown list of co-occurrence terms in graph mode. Users can navigate and click on a co-occurrence term to retrieve articles that mentions the two terms. As shown in Figure 4(a), if a user clicks on a node on the graph, the co-occurrence frequency of the node’s term with other relevant terms are displayed in the dropdown list. The list of co-occurrence terms is presented in tags in text mode, as shown in Figure 4(b). By clicking on the co-occurrence frequency in the tags, the page is refreshed to show a new list of co-occurrence terms relate to the selected tag. Regardless of the presentation modes, the list of co-occurrence terms allows user to understand how two terms are linked to each other in the relevant articles, how strong a term is linked to another term in terms of co-occurrence frequency, and how the connection between relevant terms (such as between “Term A” and “Term B” and between “Term B” and “Term C”) can be used to identify potential research hypotheses.

Figure 4. Identifying co-occurrence terms in (a) graph mode and (b) text mode

Figure 5. Expanding, collapsing, or deleting nodes on network graph
Interactive Network Graph

The search results in graph mode visualizes the connections between pairs of terms in a network. Four icons are designed to enable users to perform actions based on their understanding of the connections between pairs of terms (Figure 5). By clicking on the “expand node” icon, the network graph is updated to return more relevant nodes, while by clicking on the “expand by type” icon, the graph is expanded to include nodes with the specified biological entity type only. The actions enable users to expand a particular node of interest to gain a better understand of the connections between pairs of terms. By clicking on the “collapse node” icon, the graph is collapsed to create a new network without the selected node and its connected nodes and edges, while by clicking on the “delete node” icon, the selected node is deleted from the new network. The ability to collapse or delete uninterested nodes allows users to produce a more focused and cleaner graph and focus better on their search when overwhelming number of nodes are returned by the system.

Co-Related Mentions

Co-related mentions are mentions of two terms with a specified span of text, which represents the information contained within a literature. A side panel displaying co-related mentions appears when an edge is selected by the users from the network graph. A show or hide icon is designed to display or hide the list of co-related mentions in text mode. As shown in Figure 6, the co-related mentions are highlighted in red, and users can click on the article title to retrieve the article from PubMed. Other information returned together with the co-related mentions include co-occurrence terms, number of co-occurrences, number of documents containing the co-related mentions, year of first publication and Jaccard index. The co-related mentions enable users to understand how two terms are co-related with each other, which can in turn facilitate the process of hypothesis formulation and validation.

Figure 6. Exploring co-related mentions in (a) graph mode and (b) text modes
METHODOLOGY

Survey Instrument

A survey was designed and conducted among researchers with biomedical background to measure the perceived usability of LION LBD system and the perceived difficulty in using the system for hypotheses refinement and knowledge discovery. Power and sample size estimations were used to statistically determine the number of subjects needed to conduct the usability study. There are approximately 100 biomedical researchers working with Clinical Research Centre at Sarawak General Hospital (SGH), Malaysia. A minimum sample of 28 subjects (90% Confidence Level and 10% Margin Error) is sought to enable quantitative analysis, with a maximum target of 50 subjects. In this study, 60 potential survey participants from SGH and universities in Sarawak were contacted via email to complete a 20-item online questionnaire through Google Form. The questionnaire was designed to include tasks that can be performed by a user while discovering literature using the LION LBD system. The items were designed to collect information described in Table 1. Items 1 - 4 asked participants regarding their gender, medical specialty, years of research experience and place of work. Items 5 and 6 asked participants regarding their experience in using LION LBD system and PubMed for hypothesis formulation and testing. Items 7 - 12 asked participants to indicate the perceived usefulness of LION LBD system on a five-point Likert scale. The items were designed using Likert scale to measure the degree to which the participants believe that the system can help them in completing their search tasks. Each of the items contains three sub-items to evaluate the perceived usefulness of the user interface features of LION LBD system. Items 13 to 18 were designed with both multiple choice and fill-in-the-blank options for participants to collect both objective and subjective feedback from the participants regarding the difficulties faced by them while using the LION LBD system to complete the search tasks. Items 19 and 20 asked participants about the usability of LION LBD system for the refinement of initial hypothesis and the discovery of interesting knowledge. The survey was distributed from 9th October 2020 to 5th November 2020.

Table 1. Survey items

| Item     | Descriptions                                                   | Format                                   |
|----------|----------------------------------------------------------------|------------------------------------------|
| 1 - 4    | To collect respondents’ demographic information               | Multiple Choice, Fill in the Blank       |
| 5 - 6    | To investigate respondents’ prior experience with LBD          | Multiple Choice                          |
| 7 - 12   | To explore perceived usefulness of LION LBD system             | Five-point Likert scale                  |
| 13 - 18  | To explore perceived difficulty faced by respondents while using LION LBD system | Multiple Choice, Fill in the Blank       |
| 19 - 20  | To investigate the usability of LION LBD for hypothesis refinement and knowledge discovery | Multiple Choice                          |

Survey Procedure

The questionnaire was divided into three sections. The first section asked participants to answer Items 1-6. The second section required participants to perform a computer-based experiment. The experiment aims to provide guidance to participants in performing searches for hypothesis refinement and knowledge discovery using the LION LBD system. Participants were given five sets of ABC terms (Table 2) to perform the experiment. In the third section, participants were asked to generate a new hypothesis that contains “Term A” and “Term C” to perform closed discovery using LION LBD system and answer Items 7-20. The items aim to gather feedback from participants regarding the perceived usefulness of LION LBD system and the perceived difficulty faced by them while discovering new knowledge and refining their initial hypothesis using the system.
Statistical Analysis

All statistical analyses on the items were performed using SPSS Statistics version 27 (IBM corporation, New York, USA). Descriptive statistics (frequency, percentage and median) were generated for all survey items. Due to small sample size, the five-point Likert scale of Items 7 - 12 were collapsed into three categories: 3 = “very useful” (“extremely useful” and “very useful”), 2 = “somewhat useful” (“moderately useful” and “slightly useful”) and 1 = “not at all useful” to increase the number of responses for each category of the Likert scale. The percentage of each rating and the median rating scores of sub-items of Items 7 - 12 were calculated to investigate respondents’ perceived usefulness of different user interface features. Spearman’s RHO test was performed to estimate the correlations between the perceived usefulness of user interface feature (Items 7 - 12) and the outcomes of LBD (Items 19 - 20), and to investigate the effect of user experience (Item 3 and Item 5) on the outcomes of LBD (Items 19 - 20). The most common difficulties faced by respondents were identified by calculating the percentage of respondents choosing each option of Items 13 - 18. The perceived difficulty in using LION LBD system was evaluated by counting the number of difficulty options selected by respondents for each user interface feature for different levels of difficulty: 3 = “very difficult”, 2 = “difficult”, 1 = “moderately difficult” and 0 = “easy”.

RESULTS

Survey Sample Demographics

After two rounds of survey distribution, a total of 40 surveys were received (a response rate of 67%). Items 1-4 were used to collect demographic information about the respondents. The demographic characteristics of the respondents are summarized in Table 3. As shown in the table, 60% of the respondents were female and 40% were male; 55% were medical professionals and 45% were clinical

Table 2. Five sets of ABC terms for computer-based experiment

| User-Defined Domain 1 (Term A) | → | Output of Closed Discovery (Term B) | ¬ | User-Defined Domain 2 (Term C) |
|-------------------------------|---|----------------------------------|---|-------------------------------|
| NF-κB                         | Bcl-2 | Adenoma                        |
| NOTCH1                        | Senescence | C/EPBβ                    |
| IL-17                         | P38α | MKP-1                           |
| Nrf2                          | ROS | Pancreatic cancer               |
| CXCL12                        | Senescence | Thyroid cancer            |

Source: (Pyysalo et al., 2019, p. 1558)

Table 3. Demographic characteristics of respondents (Items 1-3)

| Characteristics                | No. of Respondents (%) |
|--------------------------------|------------------------|
| Item 1 Gender                  |                         |
| Female                         | 24 (60%)               |
| Male                           | 16 (40%)               |
| Item 2 Medical Specialty      |                         |
| Medical Professionals          | 22 (55%)               |
| Clinical Research Associates   | 18 (45%)               |
| Item 3 Years of Research Experience |                   |
| £ 5 years (‘Less Experience’) | 20 (50%)              |
| > 5 years (‘More Experience’) | 20 (50%)              |
research associates; half of them (50%) with more than five years of clinical research experience. Based on their years of clinical research experience, the respondents were categorized into two groups: ‘more experienced’ and ‘less experienced’. Item 4 revealed that 70% of the respondents were from Clinical Research Centre at Sarawak General Hospital, and another 30% were researchers with medical science background from higher education institutions in Sarawak, Malaysia. An analysis of Items 5-6 shows that most of the respondents had no prior experience with the LION LBD system. 85% of them responded that it was their first-time using the LION LBD system and another 15% of them used the system on need basis. In contrast, all respondents (100%) responded that they used PubMed frequently for literature searches and research hypothesis formulation.

**Perceived Usefulness**

Table 4 summarizes the responses from respondents regarding the perceived usefulness of interacting with six user interface features of the system. As shown in the table, more than half of the respondents indicated that the search suggests drop-down list, search results in graph and text modes and filtering features are “very useful” (each received a median rating score of 3), while the co-occurrence terms, interactive network graph and co-related mentions, are “somewhat useful” (each received a median rating score of 2).

Besides that, up to 65% of respondents reported that the search suggest drop-down list helps them identify the best matching keywords and 55% reported that the drop-down list is useful because they do not need to enter the full terms into the search fields and suggested search terms help them in constructing testable research hypotheses. Similar ratings were obtained from the respondents regarding the presentation of search results in graph and text modes. 55% of them indicated that the ability to present the search results in graph and text modes allow them to discover new relationships and identify the most frequent co-occurrence terms for hypothesis formulation. Moreover, high percentages of them indicated that the filtering features are “very useful” for them to narrow down the search results based on publication year (70%), weight of edge between nodes (60%) and biological entity types (60%).

On the other hand, only about 30-40% of respondents indicated that the list of co-occurrence terms is “very useful” for them to understand how two terms are linked with the relevant articles (40%), how strongly a term is related to another term (35%) and the connection between “Term A” and “Term B” and “Term B” and “Term C”. More than half of them (> 50%) responded that the ability to interact with the graph nodes such as expanding, collapsing, and deleting the nodes were only “somewhat useful” for them to gain a better understanding and focus better on their search intent. None of the respondents rated the interactive network graph and co-related mentions as “not at all useful”. There is a difference in ratings for sub-items of Item 12 regarding co-related mentions. Up to 60% of them responded that the co-related mentions are “very useful” for them to retrieve relevant articles from PubMed; whereas only 45% responded that the co-related mentions enable them to understand how two terms are co-related and estimate the strength of connection between two terms.

Spearman correlation analysis was performed to estimate the correlation between perceived usefulness (Items 7-12) and two outcomes of LBD (Items 19-20). The results, as shown in Table 5, reveal that: (1) search suggest drop-down list is more strongly correlated with the discovery of interesting knowledge ($r = 0.51$, $p < 0.01$) than the refinement of initial hypothesis ($r = 0.37$, $p < 0.05$); (2) co-related mentions are more strongly correlated with hypothesis refinement ($r = 0.55$, $p < 0.01$) than interesting knowledge discovery ($r = 0.49$, $p < 0.01$); (3) filtering features and interactive network graph are significantly correlated with the discovery of interesting knowledge ($r = 0.37$, $p < 0.05$; $r = 0.33$, $p < 0.05$); and (4) the presentation of search result in graph and text modes are significantly correlated with the refinement of initial hypothesis ($r = 0.37$, $p < 0.05$).

**Perceived Difficulty**

Table 6 summarizes the difficulties faced by respondents in using the LION LBD system. The main difficulties include limited biological entity types that do not match the search intent (40%),
overwhelmed number of co-occurrence terms for knowledge discovery (40%), identifying the most relevant co-related mentions (40%), understanding how Term A and Term C are linked via Term B in text view (35%), and using a list of co-occurrence terms to formulate a new hypothesis (30%).
Table 5. Spearman correlation analysis of perceived usefulness

| User Interface Features | Item 19: Allow refinement of initial hypothesis | Item 20: Allow discovery of interesting knowledge |
|------------------------|-----------------------------------------------|--------------------------------------------------|
| Item 7: Search suggest drop-down list | 0.370* | 0.514** |
| Item 8: Search results in graph and text modes | 0.370* | 0.131 |
| Item 9: Filtering features | 0.102 | 0.375* |
| Item 10: Co-occurrence terms | 0.302 | 0.298 |
| Item 11: Interactive network graph | 0.201 | 0.328* |
| Item 12: Co-related mentions | 0.553** | 0.492** |

(‘*’ correlation is significant at the 0.05 level (2-tailed) and ‘**’ correlation is significant at the 0.01 level (2-tailed))

Table 6. Difficulties faced by respondents in using LION LBD system

| User Interface Features | Survey Items | % of Respondents |
|------------------------|--------------|------------------|
| Search suggest drop-down list | 13a. The system failed to return terms that match my information needs. | 15% |
| | 13b. When entering misspelled terms into the search fields, the system returns “NO RESULT”. | 20% |
| | 13c. The search terms must be selected from the resulting dropdown list to initiate a search. | 25% |
| Search results in graph and text modes | 14a. The graph view is too complicated to understand the relationships between nodes. I prefer to discover new relationships using text mode. | 20% |
| | 14b. The text view does not illustrate how Term A is linked to Term C via Term B. I prefer to discover new relationships using graph mode. | 35% |
| | 14c. Both the graph mode and text mode failed to help me identify interesting relationships for hypothesis formulation. | 5% |
| Filtering features | 15a. I found it hard to adjust the results by publication year. I do not know to what extent I should adjust the publication year. | 20% |
| | 15b. I found it hard to adjust the results by weight of link. I do not know to what extent I should adjust the link weight. | 25% |
| | 15c. The biological entity types provided are suitable for certain research fields only. Some of the biological types provided DO NOT match with my search intent. | 40% |
| Co-occurrence terms | 16a. The list returns overwhelmed number of co-occurrence terms. It’s very time consuming to go through the articles in which the terms co-occurred. | 40% |
| | 16b. I have no idea how a term (or node) is linked to other terms (or nodes) although the frequency of co-occurrence is provided in the list. | 15% |
| | 16c. I have no idea about how to formulate a new hypothesis by exploring the list of co-occurrence terms. | 30% |
| Interactive network graph | 17a. I found it difficult to understand the graph. The graph returns overwhelmed number of nodes | 20% |
| | 17b. I found it difficult to explore the graph. I get confused after I expand or delete some of the nodes. | 15% |
| | 17c. I found it difficult to formulate a new hypothesis by exploring the relationships between nodes of the graph. | 25% |
| Co-related mentions | 18a. I found it hard to identify the most relevant co-related mention. There are too many co-related mentions to go through | 40% |
| | 18b. There is no way to filter the co-related mentions by study type and publication year. I need to go through them one by one | 20% |
| | 18c. I have no idea how to improve my search by checking the first publication year and the number of co-occurrence. | 25% |
The perceived difficulty or ease of use of LION LBD system was investigated by counting the number of difficulties faced by users while interacting with the user interface features of the system. The results, as shown in Figure 7, indicate that: (1) search suggest drop-down list is the easiest to use among the six user interface features; (2) half of the respondents had difficulty in exploring the search results in graph and text modes; (3) 20% of the respondents found the filtering features and co-related mentions “very difficult” or “difficult” to use; and (4) more than half of the respondents encountered difficulties in exploring the list of co-occurrence terms (65%) and co-related mentions (55%).

**Figure 7. Perceived difficulty of user interface features**

| Feature                          | Percentage of Respondents |
|---------------------------------|---------------------------|
| Search suggest drop-down list   | 5% 10% 35% 45% 50% 65%  |
| Search results in graph and text modes | 5% 10% 45% 50% 60% 70% |
| Filtering features              | 5% 15% 30% 40% 50% 60% |
| Co-occurrence terms             | 5% 10% 45% 50% 60% 70% |
| Interactive network graph       | 5% 10% 45% 50% 60% 70% |
| Co-related mentions             | 5% 10% 45% 50% 60% 70% |

**User Experience**

The goal of LBD is to discover interesting knowledge from large collections of literature for hypothesis generation and testing (Crichton et al., 2020). Item 19 and Item 20 aim to discover two LBD outcomes: refinement of initial hypothesis and discovery of interesting knowledge, using LION LBD system. An analysis of the influence of respondents’ research experience (Item 3) and prior experience in using LION LBD system (Item 4) on the outcomes of LBD, and the perceived usefulness and perceived difficulty of interacting with the user interface features of the system are presented in this section. As shown in Table 7, a higher percentage of more experienced respondents indicated that the LBD process allowed them to refine their initial hypothesis and discover interesting knowledge than those with less research experience (90% vs. 70% and 70% vs. 50%, respectively). There is a marked difference in the number of respondents with and without prior experience in using LION LBD system. Despite this difference, up to 81% of them without prior experience and 71% of them with prior experience responded that the LBD process helped them in refining their initial hypothesis. Only about 58% of respondents without prior knowledge indicated that the LBD process helped them in discovering interesting knowledge, compared to those with prior knowledge. Spearman’s RHO test

| Survey Items                       | No. of Respondents (%) | Allow refinement of initial hypothesis | Allow discovery of interesting knowledge |
|-----------------------------------|------------------------|---------------------------------------|-----------------------------------------|
| < 5 years (‘Less experienced’) (n = 20) | 14 (70%)               | 10 (50%)                              |                                         |
| > 5 years (‘More experienced’) (n = 20) | 18 (90%)               | 14 (70%)                              |                                         |
| Without prior experience (n = 33)  | 27 (81%)               | 19 (58%)                              |                                         |
| With prior experience (n = 7)     | 5 (71%)                | 5 (71%)                               |                                         |
was applied to further evaluate the correlation between Items 3, 5, 19 and 20. As shown in Table 8, the discovery of interesting knowledge (Item 20) was significantly correlated with the refinement of initial hypothesis (Item 19) ($r = 0.612, p < 0.01$).

Figure 8 shows that more experienced respondents rated a higher perceived usefulness for each of the user interface features, compared to less experienced respondents. On the other hand, Figure 9 shows that less experienced respondents encountered higher levels of perceived difficulties than more experienced respondents. Both figures present descriptive analysis of the responses whilst inferential analyses were performed and described in Table 8.

Table 8. Inter-item correlation matrix of Items 3, 5, 19 and 20

| Survey Items               | Spearman’s RHO |
|----------------------------|----------------|
|                            | Item 3 | Item 5 | Item 19 | Item 20 |
| Item 3 Years of research experience | 1.00   |       |         |         |
| Item 5 Prior experience with the system | -0.14  | 1.00   |         |         |
| Item 19 Allow refinement of initial hypothesis | 0.25   | -0.14  | 1.00    |         |
| Item 20 Allow discovery of interesting knowledge | 0.20   | 0.06   | 0.612** | 1.00    |

($**$Correlation is significant at the 0.01 level (2-tailed))

Figure 8. Perceived usefulness by level of user experience (1 = “Not at All Useful”, 2 = “Somewhat Useful”, 3 = “Very Useful”)

Figure 9. Perceived difficulty of user interface features by level of user experience
DISCUSSION

The sample demographics described in the results section revealed that most of the respondents had no prior experience in using the system prior to taking the survey. This suggested that most of the respondents were unfamiliar with the LION LBD system while completing the computer-based experiments for the survey. LION LBD system is designed with graph visualization tools and knowledge discovery features that differ to those in conventional biomedical literature search engines such as PubMed for hypothesis generation and testing (Pyysalo et al., 2019, p. 1557). The evaluation on the usability of LION LBD system may be affected by researchers’ lack of experience in using the system and their willingness to use a new system which behaves unconventionally.

Perceived usefulness and perceived ease of use are significantly correlated to the usability of a system (Davis, 1989, p. 320). In this study, the usability of LION LBD system was evaluated by measuring the perceived usefulness and perceived difficulty of interacting with six user interface features of the system for hypothesis refinement and knowledge discovery. The key findings of the survey are summarised and discussed as follows:

1. A drop-down list of suggested terms with the associated biological entity types is enabled to appear when an input is entered into the search field by the users. The feature was rated by more than half of the respondents as “very useful” for identifying the best matching keywords to construct a testable research hypothesis and is found strongly correlated with the ability to refine research hypothesis and to discover interesting knowledge. The main difficulty faced by respondents is the search terms must be selected from the resulting dropdown list to initiate a search. A drawback of this feature is the suggested terms are limited to those that map to the six predetermined biological entity types. A search input that does not map to the predetermined entity types return irrelevant information. The autocomplete search query feature however allows the generation of a searchable query for knowledge discovery.

2. The system allows users to switch the presentation of search results from graph mode to text mode based on their preferences. This feature was rated as “very useful” by more than half of the respondents to discover interesting relationships and the most frequent co-occurrence terms for hypothesis formulation. Correlation analysis shows a significant correlation between this feature and hypothesis refinement. The respondents find it difficult to understand how a start term (“Term A”) is linked to a destination term (“Term C”) by intermediate terms (“Term B”) for the discovery of interesting knowledge using text view. The results suggested that it could be difficult for users to understand the presentation of the search results without any prior knowledge about closed discovery and prior experience in using the system (Phang et al., 2020).

3. Filtering features were rated as “very useful” to narrow down the search results. Correlation analysis revealed that the filtering features were strongly correlated with the discovery of interesting knowledge. The features enable users to narrow down the search results by adjusting the sliders for different publication periods and different edge weights, and by crossing out irrelevant entity types. This in turn enables users to discover the changes in intermediate nodes (“Term B”) before and after a specific publication year on the network graph and the changes in strength of connection between nodes for the discovery of interesting or hidden knowledge. The usability of the filtering features is limited by the predetermined biological entity types and users’ ability to adjust the publication year and edge weight adequately (Phang et al., 2020).

4. The list of co-occurrence terms was rated as “somewhat useful” for users to understand how strongly two terms are linked with the number of relevant articles. The feature has the potential to lead users to discover previously unknown relationships and thus facilitate users to refine or test their initial hypothesis. However, a high percentage of them had difficulty in exploring relevant articles based on the list of co-occurrence terms for hypothesis formulation and the exploration process can be very time consuming if overwhelmed number of co-occurrence terms are returned by the system.
5. Interactive network graph allows users to expand and collapse a node for more co-occurrence pairs or delete nodes for a cleaner overview of how “Term A” and “Term C” are linked via “Term B”. The feature was rated as “somehow useful” for better understanding of a search intent. There is a significant correlation between interactive network graph and the discovery of interesting knowledge. Half of the respondents had difficulty in interacting with the graph nodes.

6. Co-related mentions allow users to estimate the strength of connection between two terms and understand in depth how the information provided can be utilized to refine initial hypothesis and knowledge discovery by portraying the relevant articles retrieved from PubMed. The system also highlighted the sentences from the articles that comprised of the co-occurrence terms to allow researchers to know instantly how the co-occurrence terms related to each other. In addition, co-related mentions could determine the usefulness and efficacy of the nodes and information provided by the system in refining hypotheses or discovering quality knowledge. Correlation analysis revealed that co-related mentions allow users to better understand the relationships via articles, which are useful both for the discovery of new knowledge and the refinement of hypothesis.

The findings also suggested that years of research experience could also be one of the contributing factors towards the usability of the system. More experienced researchers found the system more useful and easier to use than less experienced researchers. It is significant to note that LION LBD system was built predominantly to assist in cancer-related discoveries (Pyysalo et al., 2019, p. 1553). Due to its limitation in selecting only the terms that the system suggested, respondents are recommended to have a clear search intent in order to identify the information and keywords that best match their needs and requirements. Failure to do so may create confusion and unable to identify the best keywords when the terms that they entered were not part of the listed terms. It is also important for respondents to enter precise search terms into the search field as general keywords may be categorized under an unwanted category. This may be nuisance for some researchers which led to certain difficulties in performing this task.

CONCLUSION

This paper presents the findings on the perceived usefulness and the facets influencing the ease of use of the LION LBD system. The survey results demonstrated that research experience is a significant variable to determine the usability of the system for either initial hypothesis refinement or discovery of interesting knowledge. The results also revealed the importance of co-occurrence terms for knowledge discovery albeit the challenges faced by the participants due to lack of knowledge in utilizing the system. It is noteworthy that LION LBD system is designed predominantly for cancer-related discoveries. Thus, it may not be suitable for researchers from other fields of study. Besides, prior knowledge is required for users to select quality associations from the knowledge graph for hypothesis generation or refinement. To conclude, this study explored the effect of perceived usefulness and perceived difficulty on the use of LBD system among clinical researchers in Sarawak, Malaysia for knowledge discovery and hypothesis refinement.

FUNDING AGENCY

The publisher has waived the Open Access Processing fee for this article.

ACKNOWLEDGMENT

This research was supported by the Malaysian Ministry of Education under the Fundamental Research Grant Scheme (FRGS) [FRGS/1/2018/ICT02/SWIN/03/2].
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