Studying Interaction Patterns for Knowledge Graph Exploration

Loris Grether[a] and Hans Friedrich Witschel[b]

FHNW University of Applied Sciences and Arts Northwestern Switzerland, Riggenbachstrasse 16, Olten, Switzerland

Keywords: Knowledge Graph (KG), Knowledge Graph Exploration, User Guidance, Interaction Patterns, User Study.

Abstract: The flexible data models of knowledge graphs (KGs) are powerful tools for handling large and dynamic data sets and are increasingly used for the tasks of data processing and storage. Although a KG may contain rich data and powerful connections, it is upon the searchers to explore these graphs and make sense out of them. The objective of this research paper is to investigate if and how KG exploration can be improved from a user's point of view, to enhance the discovery of information. A qualitative user study should deliver insights on how different users interact with a KG, at what point they struggle and missed potential discoveries. Recognizing and understanding the intentions of the users is necessary to create solutions that support them best in their particular situation. Based on the findings, new features and improvements are suggested, developed and added to a prototypical KG exploration application, to be finally tested with regard to their impact on user exploration and acceptance. Based on the collected data we could identify the best guidance mechanisms that improve KG exploration the most.

1 INTRODUCTION

Knowledge graphs are considered to be one of the measures that can help to structure the highly dynamic flood of data that is generated at increasing rates. However, KGs are not easily accessible, especially for users that do not know any particular query language or the structure and relations of the stored data (Jayaram et al., 2014; Kuric et al., 2019; Yahya, 2016). In order to enable non-experienced and lay persons to query KGs, user-friendly approaches have been proposed, comprising among others keyword search, natural language questions, querying by example (either textual or visual), several filtering options or various forms of visual cues.

Many search scenarios involve more complex tasks that can only hardly be solved or answered within one query (Hassan Awadallah et al., 2014; Bates, 1989). Additionally, users often do not have a clear conception of their goal and thus start their exploration with a vague information need. Using this rather fuzzy initial question or query as a starting point, the user would then iteratively seek and trawl through the KG for further information until the request is satisfied (Lissandrini et al., 2020; Pirolli, 2009; Witschel et al., 2021). To support the users throughout such an exploration process, the system or tool should not only improve the access to the graph but also give further guidance such as orientation help and navigation advice. Currently, there is a relatively large deficit of user-based studies of the different approaches to searching and exploring a KG (Elbedweihy et al., 2014). Instead, existing approaches estimate their maturity level based on questions answering datasets comprising a ground truth (e.g. (Liang et al., 2021)) or simply provide demonstrations of their functionalities, but none of them is a user-based evaluation (Witschel et al., 2021). It is thus unclear to what extent the given approaches are useful from an end-user point of view, a gap that we intend to close by conducting a qualitative user study.

2 RELATED WORK

To get a better overview and understanding of the wide variety of different KG exploration options, we cluster the different approaches into the following three dimensions.

(1) The first dimension is the **query language** respectively the query structure. A query can be fully structured (typically using a query language (e.g. SPARQL, SQL, Cypher, etc.)), semi structured (e.g. keyword-based) (Wu et al., 2013; Namaki et al.,

[a] https://orcid.org/0000-0002-3024-7130
[b] https://orcid.org/0000-0002-8608-9039

Grether, L. and Witschel, H.
Studying Interaction Patterns for Knowledge Graph Exploration.
DOI: 10.5220/0011548600003335
In *Proceedings of the 14th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2022) - Volume 1: KDIR*, pages 257-264
ISBN: 978-989-758-614-9; ISSN: 2184-3228

2018) or unstructured such as free-text respectively natural language questions (Zafar et al., 2020; Hu et al., 2021). It is also possible to perform a query based on an example by providing a subgraph in either textual (Lissandrini et al., 2020) or visual form (Cuenca et al., 2021; Yi et al., 2017).

(2) The second dimension is the **form and level of interaction**. In this respect, the methods differ regarding (i) the degree of interaction or guidance, (ii) the point in time of interaction or guidance and (iii) the form or type of interaction or guidance.

The basic principle of guidance is a mixed-initiative process where a system assists (guides) the user and in turn receives feedback from the user (Ceneda et al., 2019): This usually happens in an interactive and iterative manner until the knowledge gap is resolved or the goal achieved.

(3) The third dimension is about the **presentation of the results**. Here, a basic distinction can be made between a textual and a visual result. The majority of the identified Natural Language Querying (NLQ) and Question Answering (QA) systems generate textual responses. The representation of the visual results can differ from each other. For example, the systems of Mohanty and Ramanath (Mohanty and Ramanath, 2019), Namaki et al. (Namaki et al., 2018) and Witschel et al. (2020) or almost every approach that implements a visual query construction, represents the results as a subgraph. Other studies present multiple subgraphs (Jayaram et al., 2015; Yi et al., 2017) and yet others summarize the result set (Wu et al., 2013; Yang et al., 2014).

3 METHOD

We have conducted two qualitative user studies (see section 4 and 5), to answer our main research question, namely whether guidance mechanisms improve KG exploration and the discovery of hidden information. We have defined 3 (sub-) research questions (RQs) as follows:

- **RQ1:** How does a user interact with a KG and what do they fail to discover?
- **RQ2:** How can one recognize the intents of a user by observing their interactions?
- **RQ3:** What are the best guidance mechanisms?

During the research project of (Witschel et al., 2020), the authors developed a prototypical graph exploration tool as well as a KG containing information from the medical domain (Riesen et al., 2021). Both of these artifacts are used to support the two data collection processes of the present paper.

The purpose of having two phases of data collection was to use the first phase to enable the formation of hypotheses of required guidance and interaction mechanism. For the second phase, a selection of these hypotheses could be tested by implementing the respective guidance functionalities.

The scenario and tasks of both user tests is to perform a basic anamnesis of a patient with the help of the medical KG. Due to the domain of the used KG, the probands are all medical students, who are currently in their final year of studies at the University of Basel in Switzerland. The fact that the medical students are familiar with the content of the graph respectively its entities represented by the node types and their relationships may simplify their initial orientation in the network and should create similar preconditions for all of them. As prospective doctor-to-be, the probands receive a fictitious patient case with only little information about the symptoms and demographics of a patient. They are asked to make an initial diagnosis and gather as much information as possible (assisted by the tool and the medical graph as its basis).

In total, the study counted eight probands that have participated in the user tests and interviews. All sessions were video-recorded and coded using the software tool MAXQDA.

4 FIRST DATA COLLECTION

The first data collection addressed RQ1 and RQ2. Its objective was to gain insights on how different users would interact with a KG by different means and to identify where they might struggle or miss potential discoveries.

Before explaining the task to the individual proband, a short introduction of the tool and its basic functionalities was given. To answer RQ1, the experiment started with all assisting functionalities turned off. In order to not influence the probands during this initial phase in any way, the guidance mechanisms were deliberately not shown in the primary introduction but solely mentioned. Once the exploration had progressed to the point where a certain level of complexity was reached (namely two different relationship types were displayed), the probands were introduced to the two guidance mechanisms of query recommendation and result preview. This was also the start of the second part of the exploration phase where the guidance mechanisms were available to the users. The user tests were terminated when the user had the impression of either having identified enough information (e.g. made the diagnosis) or was stuck. During the whole exploration process, the probands were observed with a special focus on:

- Do they have problems to orientate themselves in the graph?
- Do they know what to do next?
- How easy is it for them to interact with the different functionalities offered by the tool?
- When are they using what functionality?

4.1 Formative Evaluation

(Fox, 2020), p.1 defines the two most important aspects of an exploration system as follows: “The console of the precognitive system will have two special buttons, a silver one labeled ‘Where am I’ and a gold one labeled ‘What should I do next?’”.

At first, we conducted user tests with functionalities as described in (Witschel et al., 2021), comprising the possibility to ask questions in natural language, receive recommendations for further questions when selecting nodes and giving answers in the form of subgraphs.

In all user tests conducted within this first phase of our study, the majority of the detected challenges can be attributed to the area of orientation (i.e. knowing where you are). This could be due to the fact that the probands were all advanced medical students and knew how to proceed to come to a solution. It additionally appeared that the students had enough know-how about the content of the KG to be able to roughly estimate how to deal with the single entities and their relationships. The keyword filter checkbox list was well used by the probands to inspire their actions and to proceed during the graph navigation as it lists all available node types. Further, none of the participants gave the impression of having major difficulties with the handling and use of the various functions of the tool. Especially, after a certain time of interaction, the interplay looked generally intuitive. The general approach of visualizing the answers of the system in the form of nodes and edges was well received by the probands.

The following subitems describe the observations made during the user tests in terms of orientation issues, establishes corresponding hypotheses and suggests possible solutions.

- **Filter Questions.** The scenario of the user test required to first enter several keywords and then asking a suitable question in natural language. At the latest, after all symptoms were added to the canvas via keyword search, all probands searched for the diseases associated with these symptoms. While one proband directly started with a specific question, looking only for the diseases exhibiting all of the symptoms (i.e. ”Which diseases combine all these symptoms?”), the other two probands both first asked a rather general question that should return all the diseases associated with at least one of the symptoms shown (e.g. ”What diseases cause these symptoms?”) and narrowed the result down to diseases connected to all the available symptoms in a second step. The grammar that translates the natural language questions into cypher queries does support filter questions, e.g. ones starting with “Which of these…” to restrict the result set to certain nodes. However, the grammar did not feature filter questions such as “What diseases cause all of these symptoms?”.
- **Other Filtering Options.** We also observed that, when approximately 60 nodes (from at least two different node types) and 75 edges were shown, the probands had some trouble to make sense of the displayed subgraph. They tried to rearrange the nodes on the canvas to recreate an overview. Overall, they spent a lot of time arranging and rearranging the numerous nodes and yet, due to the many edges, it was still not easy to see if all nodes of interest could be identified.

  The list below describes different functionalities that might be helpful to retain the overview in such situations.

  – *Clustering*: Rástočný et al. (Rástočný et al., 2011) state that result clustering is an established approach to decrease information overload in KG exploration. One of the probands stated during the user test that with a manual arrangement and selection of individual nodes, there is always a threat that one might not be able to detect all nodes that may belong to a specific group. If the probands could use a function to cluster the displayed nodes (e.g. a cluster button in the taskbar), they might be able to orient themselves more easily in confusing subgraphs.
  – *Reduce Result Set Slider*: According to Tominski et al. (Tominski et al., 2009), range sliders are an effective instrument to filter objects by their numerical attributes and values calculated by the system itself could be a suitable measure. A slider filter could be used to reduce the nodes one after another according to a degree that is calculated just in time over the currently displayed subgraph or once upfront through the whole graph.
  – *Node Weight*: Instead of reducing the number of nodes displayed, node weighting is intended

to highlight the degree of relevance through visual means. For instance, Bastian et al. (Bastian et al., 2009) could assist their users by making sense of the network structure and content by indicating the relative importance of nodes by different colors and sizes.

All described functionalities have been implemented and added to the prototypical graph exploration system developed by Witschel et al. (Witschel et al., 2020).

5 SECOND DATA COLLECTION

The objective of the second data collection is to determine to what degree the new functionalities are able to improve graph exploration and thus answer RQ3.

With regard to the first user tests, all probands appreciated the availability of multiple functionalities and the associated freedom to use them depending on the current scenario. It could be observed that the interplay between the different functionalities can improve the exploration process. While choosing from multiple options may be perceived as useful, Donald Norman states: "Complexity probably increases as the square of the features: double the number of features, quadruple the complexity." (Norman, 2002). Therefore, using the evaluation procedure described below, functionalities are examined with regard to their impact on user exploration and acceptance. In general, one can distinguish between the two application areas orientation and navigation. Figure 1 shows the allocation of the individual functionalities with respect to their area of application.

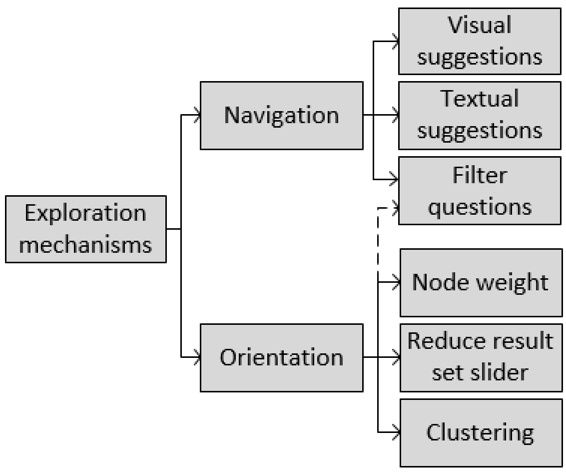

Figure 1: Exploration functionalities of the graph exploration system.

Table 1: Frequency of usage for the different orientation and navigation aids by probands U1-U5.

Functionality	U1	U2	U3	U4	U5	Sum
Orientation	**4**	**9**	**11**	**7**	**5**	**36**
Cluster	0	3	4	4	0	11
Node weight	1	2	3	2	1	9
Reduce slider	0	1	4	1	1	7
Navigation	**6**	**12**	**9**	**6**	**7**	**40**
Textual	0	1	7	5	3	16
Visual	2	6	0	0	0	8
Filter Question	0	0	0	0	1	1

The scenario and task of the user tests remains the same as in the first data collection. However, five new medical students were recruited i.e. none of them had participated in the previous data collection or had already seen the KG exploration system. All students had to solve the same task and thus received the same introduction to the tool as the first group.

At the first data collection, the navigation mechanisms were only switched on when a certain exploration stage was reached to identify and investigate possible changes in user exploration behavior triggered by these functionalities. For the new user tests, all functionalities were available from the beginning.

Considering the group size of the participants and the likelihood that not every proband would use all the functionalities on their own, it was important that they commented and justified their decisions and actions. Further, they were occasionally asked to go back to certain scenarios and to use one to many alternative functionalities in order to be able to make a better assessment. The individual user tests were concluded by a follow-up interview addressing user preferences regarding interaction functionalities.

6 EVALUATION

We first show a quick overview of how often our probands used the available orientation and navigation aids, see Table 1.

In the following, we will occasionally refer to these numbers. However, because of the small number of participants, we will be very careful to draw any conclusions from them. Rather, the focus of the following discussion will be on our qualitative findings.

6.0.1 Orientation Functionalities

Among the three orientation mechanisms clustering, node weight and reduce result set slider, the cluster functionality was identified as the best approach to improve the orientation of the searcher. According to the users, the main reason for this are its ease of use, its efficient way to simplify the result set and its advantages over the other approaches, especially with large result sets. It turned out that the most effective approach to graph exploration is to keep the subgraph as small as possible. This proved more powerful than solely emphasizing individual nodes based on importance measures. One example that illustrates the advantage of the cluster functionality when it comes to large results is displayed in Figure 2, 3 and 4. Figure 2 shows a subgraph consisting of approximately 49 nodes and 65 edges. The user had to identify all the diseases (blue nodes) that are connected to all three symptoms (red nodes).

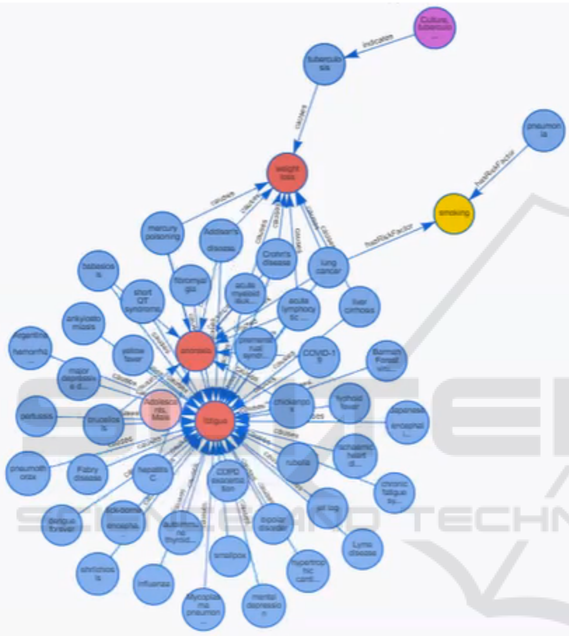

Figure 2: Sample Subgraph.

To simplify the subgraph the user switched on the node weight functionality (see Figure 3). Although, the node weight highlighted the nodes with multiple relationships, manual arrangement of the nodes might be necessary to be sure which nodes are connected to all symptoms. Application of a slider to reduce the result set by removing nodes based on centrality exhibited similar problems. The cluster functionality on the other hand allowed the user a fast and easy detection of the six nodes that are connected to all three symptoms (see Figure 4).

Thus, our results indicate a strong preference for the clustering approach, as the most efficient and effective way of compressing large and complex subgraphs for fast user orientation.

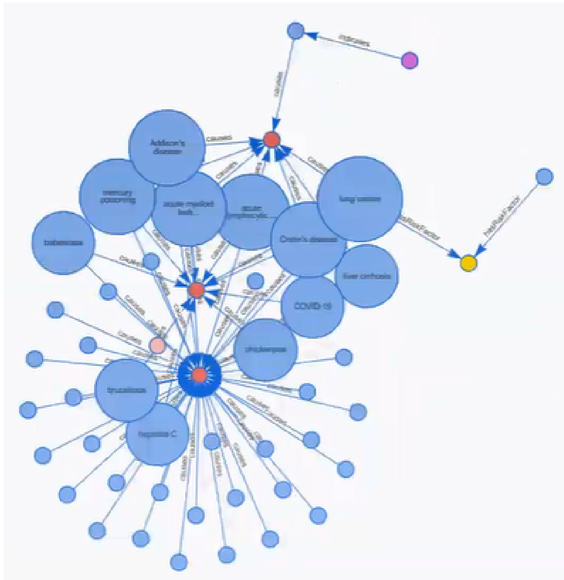

Figure 3: Applied node weight to the subgraph shown in Figure 2.

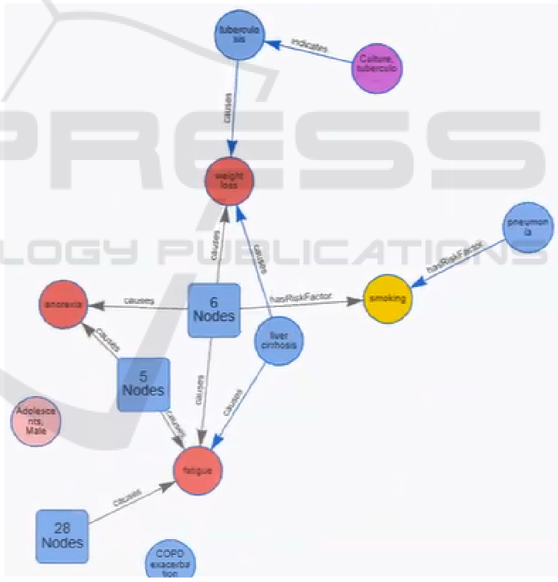

Figure 4: Applied cluster to the subgraph shown in Figure 2.

6.0.2 Navigation Functionalities

Beside the navigation functionalities that were elaborated within the scope of the first data collection procedure, the exploration system also encompasses a keyword search. In our basic exploration approach, a keyword search is always the first step of an exploration session (see (Witschel et al., 2020)). The keyword search is not complemented by any assisting system functionality or any form of guidance. With regard to the navigation functionalities, the following observations could be made.

- If the node i.e. the object or attribute (e.g. symptom, behaviour and patient characteristic) was known to the user, they generally and initially preferred to use the keyword search to look for it. With two exceptions, the probands only switched to another search or exploration functionality, such as visual (see figure 6) or textual (see figure 5) guidance, when the keyword search was unsuccessful.
- If the node i.e. the object or attribute (e.g. disease and diagnostic test) was not known to the user, they generally used either the textual or visual guidance mechanism to look for it.

Only one user really broke the search pattern described above, as he primarily used the keyword search to explore and navigate through the graph – and was even quite successful with his strategy due to his advanced domain knowledge. The circumstance that finally convinced the proband to use the visual guidance was that he wanted to ensure that he finds all diseases that are pointing to all three symptoms named before.

Overall, test persons had different preferences regarding visual vs. textual navigation, see also the usage statistics in Table 1 where Users 1 and 2 show strong preference for visual aids, all other users preferred textual guidance. One could argue that the visual suggestions are more straightforward because one does not have to read through the proposed list of questions in the textual suggestions. On the other hand, some of the users stated that the textual suggestions better inspired their next actions when they were stuck during the exploration. Finally, it could not be determined that one approach could lead to a more successful exploration than the other. Both approaches are regarded as equal and both might be improved and adjusted in the scope of future work.

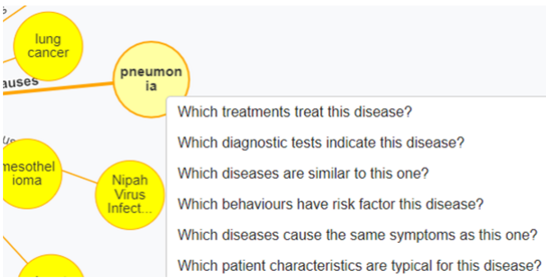

Figure 5: Example of a textual suggestion when the node "Pneumonia" is clicked.

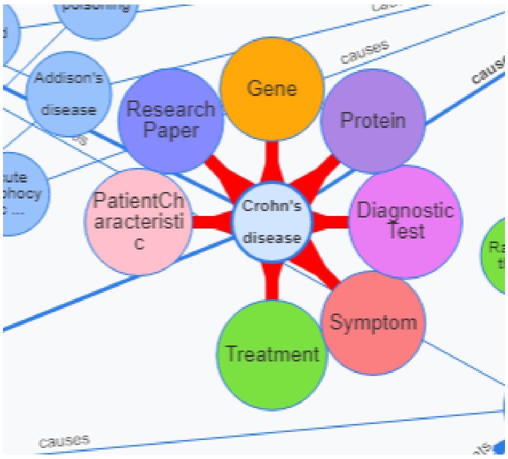

Figure 6: Example of a visual suggestion when the node "Crohn's disease" is clicked.

6.0.3 User Types

During the user tests it could be observed that the user type can have considerable influence on the exploration.

White et al. (White et al., 2009) and Elbedweihy et al. (Elbedweihy et al., 2012) differentiate between domain experts i.e. users that have knowledge in the topic or subject of the information need and casual users or novices that have little or no domain knowledge at all. White et al. (White et al., 2009) thereby divide the search behavior in to the three categories (1) query attributes (wording, syntax and query length), (2) search strategies and tactics (sequence of actions, mix of querying and browsing) and (3) search outcomes (accuracy and time). For both user tests conducted in the scope of this paper, all probands were medical students and thus can be regarded as domain experts. The search strategy of the proband who mainly used the keyword search to navigate through the KG corroborates this distinction of user type. Without an advanced medical knowledge, such a proceeding would not have been possible. Tabatabai & Shore (Tabatabai and Shore, 2005) also distinguish between experts and novices. However, their separation is made between strategies and attributes of the users that may influence the success rate of the search. Their defined strategies are navigation, evaluation, metacognition, cognition, affect and prior knowledge and the attributes include age, sex, information seeking knowledge, years of experience and computer knowledge. The last three attributes are also considered as separators between users in the study of Rogers et al. (Rogers et al., 1999). Two of the probands of this study, user 4 and especially user 3, showed to have only little technological knowledge and experience with search engines. Their selection of search and exploration functionalities seemed to be rather arbitrary which redound to a rather inefficient and ineffective exploration. Considering the information above, we can carefully conclude two things. First, the user type may have influence on the chosen exploration mechanism or functionality of a search system by the individual users. Second, computer knowledge, technical affinity and system knowledge influence the efficiency and effectiveness or even the success of the exploration. According to Lazonder et al. (Lazonder et al., 2000), novice users only need little hands-on experience to significantly improve their browsing skills in the web. Similar behavior could be determined with regard to the exploration process of the probands 3 and 4 as their confidence grew during the user test, which had positive influence on their findings.

Based on the currently available data, it is not possible to make further founded statements. For example, there are multiple strategies and attributes that may explain why some searchers are more successful than others. Further research is needed to more accurately determine the key person-related success factors of a KG exploration.

7 CONCLUSION

The overall objective of this study was to investigate if and how KG exploration can be improved from a user's point of view, to enhance the discovery of information. The literature research carried out in this context provided information on the current state of the art of available approaches and functionalities. A large deficit of user-based studies and user centric tests could be identified.

The first phase of our work was intended to further clarify how different users interact with a KG, where they might struggle or miss potential discoveries. Recognizing and understanding the intentions and pain points of the users was necessary to create solutions that support them best in their particular situation. We found that users face above all orientation difficulties when results (in the form of subgraphs) grow large. Based on these findings, new features and improvements were suggested, developed and added to the prototype in order to be again tested with a special focus on the users. On the one hand, these features comprised orientation aids for situations where result graphs grow large, namely: a size-based node weight visualization, a subgraph clustering and a node centrality-based slider for result set reduction. On the other hand, we also included again navigation aids, namely both visual navigation suggestions (result previews) and textual query suggestions (including filter questions).

The second data collection phase evaluated the relative utility of all resulting features from a user perspective. It was an important finding that – while for orientation the node clustering approach was clearly preferred by our study participants – there was no clear preference regarding navigation aids. It seems that different user types have different preferences here and thus both textual and visual cues are needed.

Future work and further research could be motivated by the one-sided selection of the participants or the unchanged scenario of the user tests conducted within the scope of this study. Changing these parameters may lead to different results and could thus help to clarify whether an exploration mechanism or even a KG exploration system can be equally efficient and effective for all user types and use cases. KGs and their exploration are attracting increasing interest from both industry and academia and it is expected that this interest will continue to grow in the future. Some of the opportunities and benefits but also some of the associated challenges of these topics could be illustrated by this study. The gained knowledge may encourage researchers to not only test their solutions on models or statistics but also to increasingly involve potential end users in the evaluation process.

REFERENCES

Bastian, M., Heymann, S., and Jacomy, M. (2009). Gephi : An open source software for exploring and manipulating networks. page 2.

Bates, M. J. (1989). The design of browsing and berrypicking techniques for the online search interface. *Online Review*, 13(5):407–424. publisher: MCB UP Ltd.

Ceneda, D., Gschwandtner, T., and Miksch, S. (2019). A review of guidance approaches in visual data analysis: A multifocal perspective. *Computer Graphics Forum*, 38(3):861–879.

Cuenca, E., Sallaberry, A., Ienco, D., and Poncelet, P. (2021). Vertigo: a visual platform for querying and exploring large multilayer networks. *IEEE Transactions on Visualization and Computer Graphics*, pages 1–1. event: IEEE Transactions on Visualization and Computer Graphics.

Elbedweihy, K., Mazumdar, S., Wrigley, S. N., and Ciravegna, F. (2014). Nl-graphs: A hybrid approach toward interactively querying semantic data. In Presutti, V., d' Amato, C., Gandon, F., d' Aquin, M., Staab, S., and Tordai, A., editors, *The Semantic Web: Trends and Challenges*, volume 8465, pages 565–579. Springer International Publishing, Cham.

Elbedweihy, K., Wrigley, S. N., and Ciravegna, F. (2012). Evaluating semantic search query approaches with expert and casual users. Lecture Notes in Computer Science, pages 274–286, Berlin, Heidelberg. Springer.

Fox, E. A. (2020). How should one explore the digital library of the future? JCDL '20, page 1–2, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-05-16].

Hassan Awadallah, A., White, R. W., Pantel, P., Dumais, S. T., and Wang, Y.-M. (2014). Supporting complex search tasks. In *Proceedings of the 23rd ACM international conference on information and knowledge management*, pages 829–838.

Hu, X., Duan, J., and Dang, D. (2021). Natural language question answering over knowledge graph: the marriage of sparql query and keyword search. *Knowledge and Information Systems*, 63(4):819–844.

Jayaram, N., Khan, A., Li, C., Yan, X., and Elmasri, R. (2014). Towards a query-by-example system for knowledge graphs. GRADES'14, page 1–6, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-04-12].

Jayaram, N., Khan, A., Li, C., Yan, X., and Elmasri, R. (2015). Querying knowledge graphs by example entity tuples. *IEEE Transactions on Knowledge and Data Engineering*, 27(10):2797–2811. event: IEEE Transactions on Knowledge and Data Engineering.

Kuric, E., Fernández, J. D., and Drozd, O. (2019). Knowledge graph exploration: A usability evaluation of query builders for laypeople. Lecture Notes in Computer Science, pages 326–342, Cham. Springer International Publishing.

Lazonder, A. W., Biemans, H. J., and Wopereis, I. G. (2000). Differences between novice and experienced users in searching information on the world wide web. *Journal of the American Society for Information Science*, 51(6):576–581.

Liang, S., Stockinger, K., de Farias, T. M., Anisimova, M., and Gil, M. (2021). Querying knowledge graphs in natural language. *Journal of Big Data*, 8(1):3.

Lissandrini, M., Mottin, D., Palpanas, T., and Velegrakis, Y. (2020). Graph-query suggestions for knowledge graph exploration. WWW '20, page 2549–2555, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-04-12].

Mohanty, M. and Ramanath, M. (2019). Insta-search: Towards effective exploration of knowledge graphs. CIKM '19, page 2909–2912, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-04-12].

Namaki, M. H., Wu, Y., and Zhang, X. (2018). Gexp: Cost-aware graph exploration with keywords. SIGMOD '18, page 1729–1732, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-04-12].

Norman, D. A. (2002). *The design of everyday things*. Basic Books, New York, 1st basic paperback edition.

Pirolli, P. (2009). Powers of 10: Modeling complex information-seeking systems at multiple scales. *Computer*, 42(3):33–40. event: Computer.

Riesen, K., Witschel, H.-F., and Grether, L. (2021). A novel data set for information retrieval on the basis of subgraph matching. In Torsello, A., Rossi, L., Pelillo, M., Biggio, B., and Robles-Kelly, A., editors, *Structural, Syntactic, and Statistical Pattern Recognition*, volume 12644, pages 205–215. Springer International Publishing, Cham.

Rogers, Y., Scaife, M., and Navarro-Prieto, R. (1999). Cognitive strategies in web searching. *Proceedings of the 5th ...*. [Online; accessed 2021-11-09].

Rástočný, K., Tvarožek, M., and Bieliková, M. (2011). Supporting search result browsing and exploration via cluster-based views and zoom-based navigation. WI-IAT '11, page 297–300, USA. IEEE Computer Society. [Online; accessed 2021-04-12].

Tabatabai, D. and Shore, B. (2005). How experts and novices search the web. *Library & Information Science Research*, 27:222–248.

Tominski, C., Abello, J., and Schumann, H. (2009). Cgv—an interactive graph visualization system. *Computers & Graphics*, 33(6):660–678.

White, R. W., Dumais, S. T., and Teevan, J. (2009). Characterizing the influence of domain expertise on web search behavior. WSDM '09, page 132–141, New York, NY, USA. Association for Computing Machinery. [Online; accessed 2021-11-02].

Witschel, H. F., Riesen, K., and Grether, L. (2020). Kvgr: A graph-based interface for explorative sequential question answering on heterogeneous information sources. Lecture Notes in Computer Science, pages 760–773, Cham. Springer International Publishing.

Witschel, H. F., Riesen, K., and Grether, L. (2021). Natural language-based user guidance for knowledge graph exploration: A user study. In Cucchiara, R., Fred, A. L. N., and Filipe, J., editors, *Proceedings of the 13th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, IC3K 2021, Volume 1: KDIR, Online Streaming, October 25-27, 2021*, pages 95–102. SCITEPRESS.

Wu, Y., Yang, S., Srivatsa, M., Iyengar, A., and Yan, X. (2013). Summarizing answer graphs induced by keyword queries. *Proceedings of the VLDB Endowment*, 6(14):1774–1785.

Yahya, M. (2016). Question answering and query processing for extended knowledge graphs. page 172.

Yang, S., Xie, Y., Wu, Y., Wu, T., Sun, H., Wu, J., and Yan, X. (2014). Slq: a user-friendly graph querying system. pages 893–896, Snowbird Utah USA. SIGMOD/PODS'14: International Conference on Management of Data, ACM. [Online; accessed 2021-03-09].

Yi, P., Choi, B., Bhowmick, S. S., and Xu, J. (2017). Autog: a visual query autocompletion framework for graph databases. *The VLDB Journal — The International Journal on Very Large Data Bases*, 26(3):347–372.

Zafar, H., Dubey, M., Lehmann, J., and Demidova, E. (2020). Iqa: Interactive query construction in semantic question answering systems. *Journal of Web Semantics*, 64.