CollabGraph: A Graph-Based Collaborative Search Summary Visualization

Eleni Ilkou, Tetiana Tolmachova, Marco Fisichella, and Davide Taibi

Abstract—**Currently, the search history in search engines is presented in a list view of some combination of enumerated results by title, URL, or search query. However, this classical list view is not ideal in collaborative search environments as it does not always assist users in understanding collaborators' search history results and the project's status. We present CollabGraph, a system for graph-based summary visualization in collaborative search learning environments. Our system differentiates from existing solutions by visualizing the summary of the collaboration results in a graph and having its core personal knowledge graphs (PKGs) for each user. Our research questions concentrate around the CollabGraph's usefulness, preference, and enhancement of participation of student's and teacher's feedback compared to the list view of search history results. We evaluate our approach with an online questionnaire in six different project-based searching as learning (SaL) scenarios (LSs). The evaluation of users' experience indicates that the CollabGraph is useful, highly likeable, and could benefit users' participation and teacher's feedback by providing more precise insights into the project status. Our approach helps users better perceive about everyone's work, and it is a highly preferable feature alongside the list view. In addition, the results demonstrate that graph summary visualizations, such as the CollabGraph, are more suitable for closed-end scenarios and collaborative projects with many participants.**

Index Terms—**Collaborative e-learning platforms, collaborative search, group results, personal knowledge graphs (PKGs), search history visualization, searching as learning (SaL), smart learning environment (SLE).**

I. Introduction

WEB search engines are increasingly used by students when they want to shape their understanding of a new topic. However, the most commonly used search engines are not suitable to facilitate students' searches for learning tasks [1]. In fact, web search engines are optimized for general keyword-based searches; therefore, learning-related tasks that require the analysis of the results of multiple queries and search sessions are not well suitable in common search engines.

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Eleni Ilkou, Tetiana Tolmachova, and Marco Fisichella are with the L3S Research Center, Leibniz University Hannover, 30167 Hannover, Germany (e-mail: ilkou@l3s.de; tolmachova@l3s.de; mfisichella@l3s.de).

Davide Taibi is with the Institute for Educational Technology, National Research Council of Italy, 90146 Palermo, Italy (e-mail: davide.taibi@itd.cnr.it).

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The use of the web as a source for learning and exploratory discovery was highlighted by Marchionini [2], thus paving the way for the development of the search as learning (SaL) research field. This field addresses questions related to the different cognitive processes that occur during the search activity [3]. Learning occurs in multiple stages of the search process, starting from query formulation, selection of search results, and their subsequent analysis [4]. In this perspective, to support human learning, web search engines have to be optimized not only in terms of retrieval algorithms but also in terms of user interface that can facilitate knowledge acquisition by learners. Visualizing learners' search history, including the sequence of search sessions and results, as well as the related concepts and their relationships, can help learners reconstruct the knowledge acquired in the explorative search process [5]. The need for specifically designed user interfaces is even more relevant concerning collaborative learning activities such as the ones implemented through project-based learning (PBL) and team-based learning (TBL) pedagogical approaches, where small groups of students adopt active learning strategies for collaborative knowledge building.

In addition, shared views about the past and current states of search processes in which students are involved are also absent. These views are very important for teachers that want to monitor the SaL activity since, as stated by Rieh et al. [1], they may be related to learning behaviors such as comprehending, critiquing, contrasting, and discovering. In the current search engines, the search activity is conceived as a single-user session, and they generally lack collaborative searching features [6]. The visualization of search results commonly as a list is often confusing and time consuming for the project members to understand the areas of search and each user's contribution to collaborative search projects. Although, recently, Google Search announced its interest in gathering search results by topic offering an alternative representation to the classic list view [7], collaborative-friendly visualizations for the search history results are still missing.

On the smart learning environment (SLE) side, the International Association for Smart Learning Environments highlights that one of the main smart features is considered the support for collaboration. In this line, a review on the learning analytics (LAs) for SLEs [8] demonstrates the need for the documentation of every click in e-learning platforms and feedback mechanisms in SLEs. In addition, it provides a meta-analysis guidance map for designing effective SLEs, including insights into the individual and collective learning process (i.e., collaboration). In a recent review in affordances and core functions of SLEs [9], we find that the collaborative affordance is the least representative

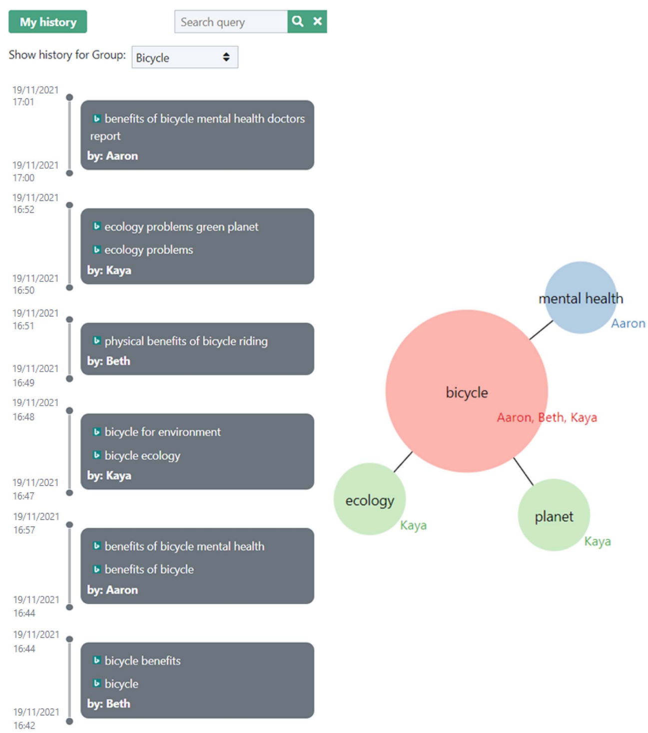


Fig. 1. Left: search results visualization as a list. Right: graph-based collaborative search visualization provided by the CollabGraph.

in associated with SLE with 10.29% of the analyzed papers, while among the most popular technologies used to provide customized cues for action are the desktop computers with 25% and the data visualizations with 17.65%. Another important observation is that one of the most popular pedagogical approaches and learning strategies is PBL with 11.76%.

In this article, we propose CollabGraph, a graph-based collaborative search visualization system to support collaborative web search, which synthesizes web search activities visually and adds color groups based on users who performed the related queries for searching as learning scenarios (LSs). To the best of our knowledge, the CollabGraph is the first suggestion of a graph summary visualization for search history results. The graph visualization leverages the representation of knowledge through knowledge graphs (KGs) and personal or personalized knowledge graphs (PKGs) in particular. SaL needs adequate self-regulated learning strategies [10] to monitor effectively the metacognitive processes underlying the explorative search activity. Our system leverages the studies underlying the Learn-Web platform [11], [12] and, in particular, the need for an abstract summary of each user contribution in PBL and TBL scenarios [12]. An overview of the system is shown in Fig. 1.

In the CollabGraph, data collected during the students' searching sessions are transformed into meaningful graphs to support peers' collaboration and teachers in analyzing the learning activities carried out by students and promptly intervening to guide students toward the achievement of their own learning objectives. Our system is conceived as an SLE aimed at providing learners with semantically enriched data visualization of data collected when searching as learning activities are performed. From the pedagogical perspective, the CollabGraph provides students with a tool to monitor and control their learning progress, thus supporting self-regulated learning. Moreover, the CollabGraph also supports teachers in analyzing the learning processes and mediating the appropriate intervention.

The main research questions (RQs) of the study presented in this article are aimed at investigating whether our proposed graph summary visualization, as seen on the right-hand side of Fig. 1, is perceived as valuable compared to the traditional list view, as seen on the left-hand side of Fig. 1, with the goal to enhance group participation and engagement, as well as teacher's support and feedback.

We can conclude our contributions to the following:

1) a novel SLE that suggests a graph summary visualization for collaborative search that is useful and likeable by the users;
2) the utilization of novel linked data techniques, namely, the PKGs, in the collaborative search;
3) graph summary visualizations in collaborative search are an important feature, and users would prefer having it in a combination of the current list view;
4) graph summary visualizations, like the one CollabGraph is suggesting, could potentially enhance users' participation, involvement, support, and feedback;
5) graph summary visualizations are more valuable as the number of participants is increasing and in closed-end scenarios.

II. Related Work

A. Smart Learning Environments

The analysis of recent trends and barriers in LA adoption in European higher education [13] reveals an imbalance between teachers and students in involvement and leadership. The stakeholders who are often present in involvement and lead are the learning and teaching support unit, information technology services, and head of the institution. Taking into consideration these findings, we aim to promote students' engagement and participation and teachers' feedback in the design of CollabGraph. Feedback is an important feature in SLEs [9], [14] which can improve learners' participation and completion rates in massive open online courses (MOOCs) [15]. Pérez-Sanagustín et al.'s [15] study underlies the importance of clear information about learners' state provided to the teacher to accommodate the teacher's intervention. Analogous to their method, our system focuses on displaying clear information about each user's activity by offering annotation tags with the usernames below each visualized contribution.

Moreover, differently to commonly used LA dashboards, our graph summary visualization not only provides students with feedback based on quantitative data and learner performance indicators but also includes additional information that increases learners' awareness of learning goals and supports effective regulatory mechanisms by following new concepts in LA dashboard design [16]. The graph visualization of the concepts explored by students during the search task provides, substantially, a knowledge-based visualization that, in turn, has been proven to be effective also in facilitating teachers in the choice of the most appropriate activities at design time [17]. The CollabGraph visualization also supports teachers in monitoring the group-based collaborative activities when students search for information on the web during a learning task. Teachers can analyze the outcomes of the learning activities as well as the contribution of each participant in the different groups. The CollabGraph provides summarized information with a reduced cognitive load needed by teachers for the analysis, thus drawing teachers' attention to the most relevant interactions and increasing their confidence with respect to the analysis of the whole learning process. These characteristics are presented in [18] as relevant characteristics of LA tools to support teachers' regulation in collaborative learning settings. For instance, the learning log data of the search activities can be used to inform the automatic generation of the groups, as presented in [19]. Specifically, in our system, the CollabGraph summaries can be leveraged to implement algorithms that perform different grouping strategies according to the teacher's preferences.

The graph visualization can guide students through the adjustment of their learning behaviors by optimizing the learning strategies they put in place. Several studies connect SaL to self-regulated learning activities [20], [21], [22]. The metacognitive dimension is often related to the knowledge gains and to other factors that intervene in the knowledge acquisition process in SaL environments [23]. The graph visualization proposed in our approach supports students in monitoring and controlling the SaL activities through the PKG that is created from their searches. In an SLE, self-regulated learning activities are more and more often monitored through dashboards that summarize specific indicators [24]. However, in SaL scenarios, those indicators could not be enough since there are other relevant indicators connected to the metacognitive processes, such as the knowledge gain that has to be taken into account [23], [25]. To the best of our knowledge, CollabGraph is the first tool that visualizes and summarizes the key concepts from search activities and supports both teachers and students in monitoring and controlling the behavior of the self-regulated learning process.

B. Collaborative SaL and Self-Regulated Learning

Technologies have influenced learning paradigms supporting the development of personalized learning environments in which learners can have access to personalized learning content and interact with teachers, tutors, and peers. In collaborative learning environments, learning objectives are shared with a group of peers [26]. To this aim, specific tools have been designed to structure the collaborative learning process and support group interactions toward acquiring new knowledge and not merely the exchange of information [27].

The collaborative search takes place when more than one people work together on an online search task. The search activity is performed synchronously and asynchronously. It happens in different domains and occasions [28]. There are several collaborative search systems introduced in the literature and enterprise. Most of them focus on providing collaborative features for communication among the users, such as group chat and document sharing [29], and comments [12]. In addition, the search process is enhanced by visual snippets [30] and annotation snippets from the visited web pages [12]. Despite the increasing popularity of collaborative search as an information-seeking task, there are not many solutions developed, especially for collaborative setting [28].

Until today, no collaborative search interface has become widely used. As suggested by Hearst [31], that could be because there are some design features still left to be investigated and implemented. We are optimistic that the collaborative summary graph presented by the CollabGraph could be one of these features.

In fact, the collaborative summary graph provides the visualization of the students' search by highlighting the most relevant concepts. Similarly to [32], this can be used by teachers to visualize and identify specific collaboration patterns in students' activities. Moreover, the collaborative summary graph helps students in self-regulated learning activities.

In fact, the use of graphs provides a visualization that supports students in reflecting on how they regulate, control, and monitor their learning process. Through the graph, students can monitor their learning progress and identify how to adapt their strategies to achieve their objectives. Students, after each search session, visualize their achievements and progress. Our system supports the analysis of self-regulated learning in a collaborative environment by summarizing the activities of the whole group of students, thus helping teachers in analyzing the learning process and promptly intervening when students are struggling with undertaking the planned activities.

C. Visualizations for Search History Results

Following earlier studies [33], [34], [35], Tran et al. [36] develop an exploratory system capable of visualizing search history results based on a user-friendly entity-centric interface. The system helps the user to search, navigate, and discover entities and new facts and relationships. The evolution of entities over time is recorded and displayed in a timeline that shows the essential versions of the entities. As an additional feature, connections between entities are visualized as text boxes in the timeline, each representing a fact connecting the entities involved. Even though the system provides an easy-to-use interface for entity and event-centric queries and visualizes the timeline of events and entity versions, this system does not create a representation of the search history of single users or group of users or the summary of their results. This limit makes it not really suitable for supporting collaborative search activities.

We are inspired by the work of LogCanvas [6], which suggests a graph visualization for the collaborative search history. They aimed at overcoming the limitations of the current search engines designed to support single-user searches and do not support collaboration. LogCanvas suggests a graph visualization that shows all search history results in a graph and group results by Wikipedia topics. Their findings show that the graph-based visualization is one of the key features of a search history interface. In particular, the graph as a feature is ranked high, with

85% of the users liking it. However, the graph usefulness did not score well, with 3.09 and an average of 3.00 on a five-point Likert scale. We believe the problem lies in the complicated and complex representation design. For this reason, in our approach, we propose a new visualization interface that displays the summary of the users' actions during their collaboration. Consequently, instead of visualizing individual students' searches, we summarize collaborators' search results and insights.

D. Knowledge Graph Visualization

KGs constitute a fundamental basis of artificial intelligence technology, and in the past few years, they have also been suggested to foster the development of innovative SLEs [37]. Recently, a KG of the resources provided by the most popular MOOCs has been proposed with the aim of facilitating concept retrieving and improving learners' experience by supporting them in identifying the most relevant concepts in MOOC resources [38]. Similarly to our approach, KGs are used to extract the most relevant concepts in users' search histories and provide a meaningful visualization of students' search results. The visualization of KGs requires specific strategies and techniques. Elements of a KG are usually explored via graph-based, text-based, or mixed interfaces. Antoniazzi and Viola [39] present a survey of tools designed to visualize the content of KGs. These tools leverage the intrinsic characteristics of the resource description framework (RDF) model; therefore, they are explicitly designed to explore a whole KG and its structure. Differently, in our approach, we aimed at providing users with an effective visualization that only shows the portion of the KG that is relevant to their personal and collaborative search experience. The visualization of a large semantic graph as the ones of the linked data domain has also been investigated in the survey [40]. In this survey, a complete list of visualization tools for linked data has been analyzed. Linked data visualization aims to provide graphical representations of datasets for the information selected by a user to facilitate their analysis. However, this survey highlights the relevance of having graphical features when traversing big data sources and the need for a history that traces how users reached a specific result. In this direction, our system offers both graphical visualizations of the KG entities and support features to organize users' search history efficiently.

A recent study by Cashman et al. [41] shows how additional attributes can be constructed on KGs by allowing users to visually explore the amount of data available. Their system CAVA also provides visualizations of the KG itself to help users understand complex linkages such as multihop aggregations. Our system follows a similar approach but with more emphasis on a PKG.

E. Personal Information Management

Personal information management (PIM) talks about how users retrieve and organize personal information collections [42]. PIMs emphasize on control and centralization of the users. In this line, we find the well-known system "Stuff I've Seen" (SIS) [43]. SIS is a unified search system that utilizes information a person has viewed online. SIS was found to help users refind information online. As a natural complementary effort to address these challenges, we find the PKGs [44] that have been adopted in our proposal.

PKGs concern a new area of research. The underlying idea is that user data and profiles are represented as subgraphs related to one or more KGs. For a visual example of how PKGs can be connected to a larger KG, see Fig. 4. The goal is to personalize recommendations, provide local access to information about the user's previous interests [45], and protect privacy. For example, in the medical domain, a PKG can be used to represent a patient via a domain-specific KG that contains diseases and symptoms. Also, PKGs have been suggested recently in the educational domain for e-learning platforms as an intelligent alternative to users' profiles with the aim of achieving higher personalization, collaboration and semantic recommendations [46]. In addition to this work, our CollabGraph builds on top of PKGs to offer a practical solution in a collaborative e-learning platform.

Recent works increased interest in PKGs [45], [47]. Safavi et al. [47] propose a graph-based activity-centric approach for representing personal data on the web. Their objective is to merge personal information objects, such as emails and messages, to improve relatedness in representing users' activities. Differently from our solution, their scope is broad and far from a collaborative setting, and their PKGs are not weighted. However, we find similarities in our approaches, and we adopt an analogous graph update approach in our model. GLIMPSE [45] is based on PKG summarization. They process query logs from past queries, and they create a personal summary on a user's device or application. They attempt to capture users' preferred areas and infer user preferences. Their constructed summary is inspiring to our work; however, their application, on-device personal summary, is far from ours.

Closer to our approach is the work of He and Bron [48], which uses search logs and knowledge bases (KBs) to create a type of PKG which they call demonstrated potential domain knowledge by computing the unique entities per month. We adopt the initial steps of their work for our system, namely, query understanding and entity recognition, which allows us to link the identified entities with KGs. However, He and Bron [48] do not focus on the visualization of the concepts extracted from the search results, as well as do not consider the summarization of the results for collaborative search activities; while their work is more focused on the use of search logs and KBs to extract the knowledge of a generic users on a specific domain, our system is specifically oriented to support collaborative SaL activities.

III. CollabGraph

We present the LearnWeb platform in which CollabGraph is developed, followed by the system architecture and back-end of CollabGraph. Later, we explain the characteristics of the user interface. We conclude this section with a demonstration of the CollabGraph usage by teachers and students.

A. LearnWeb Platform

The collaborative e-learning platform "LearnWeb" supports collaborative web search [11], [49] and TBL and PBL scenarios, and it has been used in the past for SaL scenarios [12]. Users

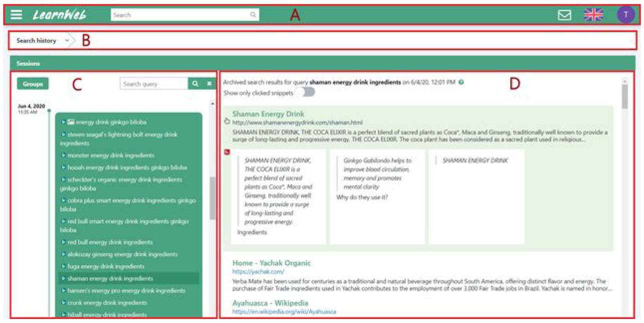


Fig. 2. LearnWeb platform presented by Tolmachova et al. [12].

can register with an email and a username (necessary fields); in addition, the user profile contains full name, gender, student id, affiliation, address, profession, interests, profile picture, and time zone (optional fields).

LearnWeb supports collaboration with various means. Users can view other users' profiles and create groups, and group members can comment on the group's resources, add descriptions, and rate them. Users can utilize the integrated Bing search engine to search for websites, videos, and images and add new resources in the group in private or public mode. The integrated search engine supports the collaborative search as the users can view their individual search history of their results and the group results they are part of. Also, users can open a topic on the group forum and leave a message with a question, e.g., regarding the current task on which he is working.

Part of the LearnWeb interface in individual search history results is shown in Fig. 2, consisting of a search bar (A), a breadcrumbs row (B), the list view of user's search history (C), and the search results on a given query with highlighted the clicked web pages (D). In addition, LearnWeb offers a similar visualization with a list view for the group results, which the CollabGraph is enhancing with the graph summaries, as shown in Fig. 1.

B. System Architecture

The back-end consists of three main parts: the user's input, the intelligence part, and the PKG, as displayed in Fig. 3. The back-end processes are hidden from users, and only the application's output of the CollabGraph is presented in the visualization of search history results as explained in user interface.

1) User's Input: The input of the PKG is the user profile, the search queries and search results, and the clicked, also called visited, web pages. The user profile consists of a username, full name, email address, gender, student id, organization, address, profession, and interests. Also, we can retrieve a list of the groups in which the current user is registered. The search queries are the keywords used to perform the searches. In the search results, we analyze the title and snippets. We gather our user input from log data, and we initiate the intelligence calculation once a user has created a searched query and has visited a web page. We aim to assure that the user is actively participating and has begun finding relevant information to her project goal. This condition

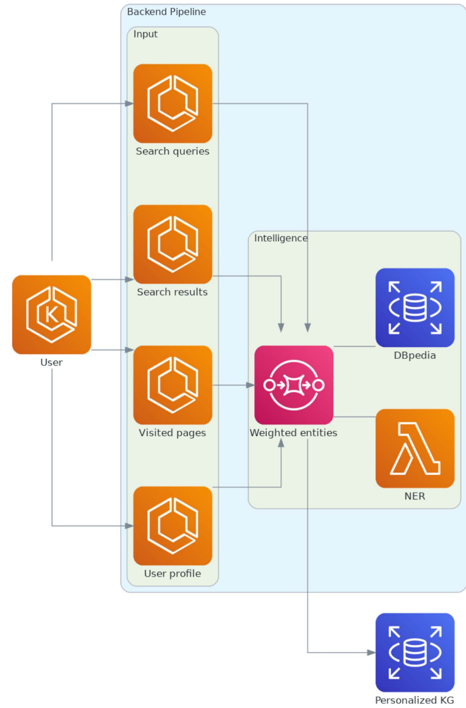


Fig. 3. Back-end pipeline to create each user's PKG.

is set to avoid calculating the PKG too early, meaning when the user has not found interesting information yet, as PKGs and KGs are dependent on time [44].

2) Intelligence Part: We weigh the input data based on their importance before proceeding to the algorithmic identification of the main entities and keywords the user is interested in. We give a higher score to the user profile, which might describe already the goal of the group project, to the search queries and the visited web pages. In this way, we provide a nonstatic graph that updates the weights and importance of each entity based on the user's and group's behavior, search queries, and search results.

In our case, we use the DBpedia spotlight [50] as a named entity recognition (NER) software to extract entities from our input and link them with the DBpedia KG [51], a large-scale multilingual KG in which data are extracted from Wikipedia. An NER software identifies occurrences of named entities in a text associating them with a KB or KG identifier. NER tasks target entities according to the Message Understanding Conference 6 [52] classification, where each entity corresponds to types such as a person, organization, location, and other numeric/temporal expressions. In general, any entity that can be referred to by a proper name is a named entity, but general entities such as concepts (e.g., animals or museums) are also included [53].

3) Personal Knowledge Graph: The back-end is based on a PKG for each user. In Fig. 4, there is a representation of the linking of PKGs for each user with the DBpedia KG and the creation of the graph summary visualization. Each PKG consists of user information and entities, which are identified to their persistent URIs. The PKG is a weighted and directed graph that

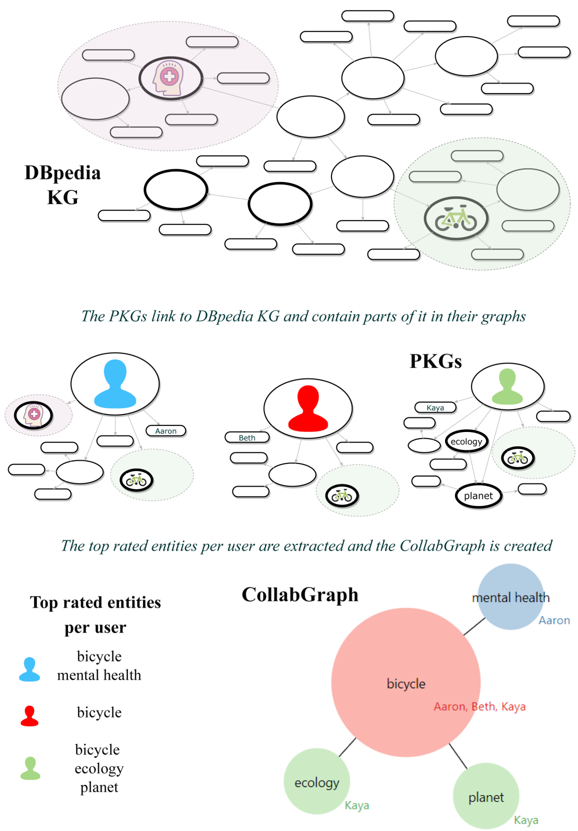


Fig. 4. Link between PKGs, the DBpedia KG, and the creation of CollabGraph.

updates its content every time a user performs an action, such as searching a new query, starting its initiation from the first web page visit. Therefore, the PKG content is highly dependent on the time in which the results it contains were generated and, hence, on which entities it passes to the CollabGraph for the visualization.

Furthermore, privacy is a big concern in PKGs [44]. In our design, we adopt a local online solution for storing users' PKGs. We store the user's data locally on the platform. We maintain privacy by only sharing the top entities per user with the rest of the group. The users' information is not visible or accessible to any other users on the platform or elsewhere. The group's information is shared among team members. The group can also be public, which means that its information and content are publicly accessible by anyone on the platform, but this is indicated in the group's creation before each user joins it. This allows us to perceive users' privacy and hide the processes of the PKG from other users in the system as well as from the chosen search engine and the linked DBpedia KG. In Fig. 4, we see an illustrated example of the interconnection of PKGs with the DBpedia KG created by the authors. Fig. 4 shows a top-down approach of how the general knowledge existing in KGs is then extracted to the PKGs, and after the intelligence part of CollabGraph, the most important entities are extracted and visualized in the CollabGraph. The importance of PKGs is highlighted here, as they additionally provide the input for the graph summary visualization of the CollabGraph.

C. CollabGraph Interface

The CollabGraph is adopted in the LearnWeb platform search history visualization page instead of the list view. The functionality and user interface of LearnWeb are explained in [12] and in Section III-A. The CollabGraph visualizes the summary of the search results and interests of the collaboration. This graph-based collaborative search visualization consists of edges and nodes of a different colors. The nodes represent the main keywords or key phrases or topics the collaborators are interested in, and edges connect them. Next to each node, there is an indication about the user or users who were interested in this topic.

We extract the top high-weighted entities from each PKG to construct our collaborative summary graph, the CollabGraph. We choose our current model to represent the maximum top four entities per user. After extracting the top entities for each user, we identify the duplicates, which are entities with a higher frequency of appearance. We represent those duplicates in bigger radios nodes, as can be seen in Figs. 1 and 4. The edges connect nodes when at least one user is interested in both nodes, based on their PKG, such as in our example, Aaron was interested in "bicycle" and "mental health." We represent each user with a single color and have the common group results represented in a different color. In our case, in Fig. 1, we describe the search results of Kaya in green, Aaron in blue, and the shared group results of Aaron, Beth, and Kaya in red.

By analyzing the pitfalls of previous graph visualizations similar to ours, such as [6], we aimed to avoid creating a complex and complicated interface and focused on a simple design with few elements. We designed our user interface having a user friendly interface as a priority to achieve a maximum understanding of the project status and team members' contributions in minimum time. Our design focuses on better user understanding via simplicity as it visualizes only the most important elements for the user and ignores other nonsignificant data. Based on findings in adaptive learning systems, interactivity could be achieved by providing modules to students to compare their level of results with their peers [54]. We adopt this approach by having the peers' search results visualized together with each username. Our user interface is also highly motivated by findings in special education and color used in learning settings [55]. Zentall and Dwyer [56] have shown that the use of color improves attention. Monotone environments in classrooms have shown to be restless and irritated for the students, while color has a positive impact on productivity as it improves academic performance [57]. Colored information has also been shown that can improve chances of staying in short-term and long-term memory [58]. Also, based on a recent survey on the impact of colors in learning [59], color helps learners retrieve information, and compared to monochromatic information, the color-coded visualizations support better knowledge acquisition.

D. Usage for Teachers and Students

Anyone can access the LearnWeb platform, in which our CollabGraph is created. After registering for free and logging in, a user can optionally join a group or create a new group and perform search queries in the search bar. After performing searches, the user can view her search history. The search history interface is divided into three parts: the header, the list of search sessions, and the CollabGraph visualization.

In Fig. 1, on the top, we find the header. The green button "My history" is loading the users' personal search history. Right beneath it, it can choose to "Show history for Group" by clicking on the mentioned button "Group history." Then, the user can choose a group that is registered, in our case is "Bicycle," and view the search history results from all the users of the group. In the input field "Search query," the user can search for a specific search query among all the displayed queries. The feature is very useful, especially when there are a large number of search queries in the personal or group search history. On the left-hand side of Fig. 1 is the list of the search history results. The list is a slightly modified version of any browser's classic search history result visualization with the addition of the search sessions. The search results are grouped by search sessions (grey boxes) and are divided by the start and end time of the first and latest search query in the search session accordingly. In LearnWeb, different types of queries exist, such as text queries (from an integrated Bing search in the LearnWeb system), images, videos, etc. Each type has its own icon.

Finally, on the right-hand side of Fig. 1 is our proposed system. The CollabGraph visualizes the summary of the search results and interests of the collaboration. This graph-based collaborative search visualization offers a quick overview of the group's search results and associates the interests of one user with the others. The nodes are connected with edges if at least one user is interested in both topics. The bigger the side of the nodes, the more critical role this topic plays in the collaborative search. The different colors represent different users or groups of users.

IV. Searching as Learning

In order to evaluate our system, we simulated six different searching as LSs. Each scenario is assigned to a team of four people. We created many different scenarios to demonstrate the suitability of CollabGraph in different settings, such as different educational domains, types of scenarios, and number of participants. The scenarios we present are appropriate for PBL and TBL. There are three open-end and three closed-end scenarios. We adopted three scenarios from the literature [12], [60], [61] and created the rest based on similar homework projects and inspiration we found online for PBL.[1] The scenarios are suited for high-school education and undergraduate courses.

We aimed additionally to evaluate more complex parameters of our system; therefore, we decided to have some of our projects unfinished, meaning that some students did not participate in the project. This is visible as some students do not perform any search queries; this is translated to not actively participating in the project; they just join the search group and perform no further action. The LSs had either two, three, or four active participants. There were two LSs for each different number of participants, as described in Table I.

[1]Scenario B is inspired by the trip to the zoo, and scenarios C and D come from the PBL scenarios.

TABLE I
Different Categories of the LSs

No.	Learning Scenario	Scope	Participants
1	World Wars	Open-end	2
2	Animals	Capybara	4
3	Climate Change	Open-end	2
4	Technology	TikTok	3
5	Bicycle	Open-end	3
6	Energy Drinks	Gingko Biloba	4

A. *Learning Scenario 1: World Wars*

Inspired by Maxwell [61], we adopted their PBL scenario to the comparison of the World Wars. This scenario can be developed in the settings of a history and sociology course. In addition, owing to its open end character, this learning setting could fit in an interdisciplinary project between the history teacher and the economics, sociology, for example. The students are expected to explore the differences between the two world wars and develop a better understanding of global history and the impact of war on different cultural and socioeconomic parameters.

Type: Open-end. Active participants: 2/4. Description: *"Find differences between the WWI and the WWII and present their results in a presentation."*

B. *Learning Scenario 2: Animals*

This is a hybrid LS, the parts of which can be performed in a visit in a zoo and inside the classroom. The goal is to enhance the sensitivity of students in the natural environment and animals and improve their knowledge in zoology. The users are asked to search about the general living conditions of animals and, in the second part of the activity, are requested to investigate further about the selected animal, which was the Capybara.

Type: Closed-end. Special case: Capybara. Active participants: 4/4. Description: *"After visiting a zoo, you are asked to learn about animal habitats and form opinions on which habitats best suit a selected animal."*

C. *Learning Scenario 3: Climate Change*

The climate change is one of the biggest challenges of the 21st century. In an ecology class, the students are asked to investigate closely matters related to climate change and how future cities could become more sustainable. This scenario is also related to the development of critical thinking of students and the fight against fake news related to this topic.

Type: Open-end. Active participants: 2/4. Description: *"With current trends in climate change in mind, design a modern city for the year 2100, or reimagine existing cities and how they might cope with climate change."*

D. *Learning Scenario 4: Technology*

In a digital literature class or an IT course, the students are asked to research the emerging artificial technology (AI) technologies and connect them with popular social media platforms. The goal is for students to develop a deeper understanding of the technologies linked to apps they are using every day.

Type: Closed-end. Special case: TikTok. Active participants: 3/4. Description: *"Which are the emerging AI technologies and imagine how they could be applied in social media platforms."*

E. Learning Scenario 5: Bicycle

We adopt the bicycle LS [62], as presented in platform Aisopos [60]. It is an evaluated scenario, characterized as "optimal," after the evaluation from two reviewers based on the criteria established by the Institute of Educational Policy, Greece. The current project examines the multidimensional role of the bicycle in the lives of young people and the citizens of a modern city. The purpose is for students to investigate the many benefits of the bicycle by focusing on conscious usage of the bicycle in their everyday lives.

Type: Open-end. Active participants: 3/4. Description: *"This project aims to help students know the benefits of using bicycle for physical and mental health, to understand the value of ecological conditions (like using a bicycle), to suggest actions to increase the usage of bicycle."*

F. Learning Scenario 6: Energy Drinks

We adopt the energy drink scenario, as presented in [12]. The learning outcomes of this project are for students to know about chemical components in energy drinks and their effects on health, to find popular brands containing unhealthy components in big doses and become more responsible consumers.

Type: Closed-end. Special case: Gingko Biloba. Active participants: 4/4. Description: *"Identify the most common unhealthy ingredients in the energy drinks, and search about the energy drinks which include these ingredients."*

V. Methodology

A. Context of Research

The research was conducted with interest in evaluating whether the CollabGraph is useful and helpful to users. In addition, we aimed to discover if the collaborative graph search visualization could enhance users' participation and feedback. The preliminary evaluation was developed around two pillars: the visualizations generated by the system, meaning the CollabGraph visualizations, and the system's comparison with the classical linear list for search results.

We identify some RQs we address with the questionnaire, and those are the following.

1) RQ1: Is the graph summary visualization useful?
2) RQ2: Do the users like the graph summary visualization?
3) RQ3: Do the users prefer the graph summary visualization over the classical linear list for group search results display?
4) RQ4: Is the graph summary visualization enhancing the group's participation and involvement?
5) RQ5: Is the graph summary visualization enhancing the teacher's support and feedback?

B. Instrumentation

For the evaluation of our system design, we created a questionnaire. For each RQ, there was a set of questions defined. Our questions for evaluating RQ1 came from the well-established user experience questionnaire (UEQ) [63]. The same authors who propose the UEQ also make suggestions for the application of the questionnaire in different evaluation scenarios [64]. In particular, the independence of two scales, namely, *dependability* and *efficiency*, allows us to remove them from the questionnaire without affecting its validity and reliability. The adapted UEQ can be seen in Table V in the Appendix.

Besides the usage of UEQ, we identified the crucial parameters we want to evaluate in the CollabGraph. Before formulating our questionnaire, we spotted the main parameters for the evaluation of the CollabGraph based on the evaluation of the collaborative learning system presented in [65]. Those parameters correspond to the RQs and are the following: 1) usefulness and effectiveness; 2) supporting and feedback; 3) participation and involvement; and 4) easiness of use. We evaluate the usefulness and effectiveness, and easiness of use from the UEQ. For the other two parameters, we developed a set of questions. In each of the LSs, the participants were given the scenario's description and the visualizations generated from the experiment. After each LS, we asked participants to answer five questions (Q1–Q5).

1) Q1: Which visualization helps you to understand which team members have already participated?
2) Q2: Which visualization helps you to understand which parts of the project have been completed already?
3) Q3: Which visualization helps you to understand which topic has not been searched yet?
4) Q4: Which visualization helps you to understand if the students fulfilled all the parts of the project?
5) Q5: Which visualization helps you to understand if all four students participated in the project?

We developed the first three questions (Q1–Q3) to evaluate the participation and involvement (referring to RQ4) and the last two (Q4 and Q5) for the evaluation of supporting and feedback (referring to RQ5). At the end of each set of questions, for each scenario, participants could leave an open-ended comment, which served in our qualitative analysis. From the average scores of all Q1–Q5, the results for RQ3 were provided.

In the latest part of our questionnaire, we asked participants to provide general feedback for the graph visualizations. Our goal was to evaluate the likeness of the proposed visualization (referring to RQ2). Our five evaluation statements were the following.

1) EQ1: I like the group results visualized in a graph.
2) EQ2: I like the summary of the team members' results.
3) EQ3: I like the graph visualizations.
4) EQ4: I want to have a graph visualization next to the list view of the search results.
5) EQ5: I like the combination of the list and graph view.

Finally, after the evaluation questions (EQs), the users could provide comments related to the graph visualizations in an open-ended comment section. We examine those comments in the qualitative analysis as we do with the ones presented after each LS.

C. Participants

We gathered our answers from a questionnaire we distributed through emails and social platforms. As we mention in the Data Analysis part, we have 105 valid participants. Most of them, 76 users or 72.38%, are between 25 and 34 years old. Sixty-four users have a master degree, and 22 have a bachelor degree, 60.95% and 20.95%, accordingly. Almost a half of the participants, 50 users or 47.62%, are working in the IT sector. For the question "Are you currently a... ?," where the answer options were "Student," "Teacher," "Both," or "None," 60 users or 57.14% are actively a teacher, student, or both, compared to 45 users or 42.86% who are not active members of a learning process. Also, 75 of the participants or 71.43% are working in online group projects. From them, 18 participants or 17.14% works in online projects everyday, 30 participants or 28.57% often, and 27 participants or 25.71% rarely.

D. Data Collection Procedure

Data collection followed the guidelines for handling research data at Leibniz University Hannover [66]. Before completing the questionnaire, the users were informed that participating in the study was voluntary in the process of a research project. The questionnaire was not collecting personal data, and no participant could be identified by the given answers.

E. Data Analysis

We received 177 responses from a time period from November 24 until November 29, 2021. In order to validate that our users were not randomly completing the questionnaire, we established control questions. These questions serve as a checkpoint of whether our users complete the questionnaire responsively. There was one control question in each LS, asking "How many team members participated in this project?" We eliminated the answers of the whole questionnaire from those who did not answer correctly in all control questions, having 109 answers after the cleaning. In addition, we adopted the cleaning of inconsistencies based on the UEQ strategy to detect suspicious data. We identified four critical points with differences ≥ 3 between the best and worst evaluation of an item in a scale. We excluded those four answers ending up in our final number of 105, which is 59.32% of the initially retrieved data.

F. Qualitative Analysis

The participants could provide optional open-ended comments in seven different stages. The comments were collected at the end of each scenario after the questions (Q1–Q5) and after the EQs. The comments were evaluated by applying the content analysis method for qualitative evaluation. In particular, the categories identified as relevant for our study were the ones corresponding to our RQs, with the addition of null and suggestion categories to represent, respectively, general comments and suggestions concerning the use of the tool but not directly connected to the search visualizations. In total, we identify the categories related to graph visualization: usefulness (RQ1), likeness (RQ2), preference compared to list (RQ3), enhancement of participation and involvement (RQ4), enhancement of support and feedback (RQ5), null, and suggestion. Each comment was coded by two experts independently on a binary scale to indicate, respectively, if the comment belonged to a category or not. For the conflicting comments, a final decision was made to identify the category of the comment.

G. Statistical Analysis

For further analysis of our results, we use statistical tests to find significance in our data. In our study design, the same individual tests all conditions (i.e., a choice between the List, Graph, Both, or None approaches) in all six scenarios. The reason for this choice is that repeated-measures studies require fewer participants and minimize random noise, thereby increasing the learning effect. This is a typical case of a repeated-measures study design (within-subjects or repeated-measures). We choose the nonparametric Wilcoxon signed-rank test for our statistical analysis; in the following, we list the assumptions and how they are fulfilled in our study.

1) We have dependent samples that come from two types of scenarios (open-end and closed-end). The same person responds to the same five questions (Q1–Q5) in all scenarios.
2) Paired observations from the two types of scenarios (open-end and closed-end) are drawn randomly and independently of each other.
3) In each type of scenario, we collect the number of times a particular approach (i.e., a choice between the List, Graph, Both, or None approaches) was chosen by each user. This gives us the opportunity to have a continuous and comparable dependent variable. Although the Wilcoxon signed-rank test ranks the differences according to their magnitude and is, thus, a nonparametric test, it assumes that the measurements are theoretically continuous.

By clearly defining and identifying the nature of the scenarios and the dependability of the sample pairs, we can better examine our data. For clarity, the variables in our study design are the type of scenario (open-end and closed-end) and the number of active participants in the group (2/3/4). The type of approach (List, Graph, Both, or None) is the choice of answer to the five RQs included in each scenario. According to these assumptions, it was sufficient to perform nonparametric Wilcoxon signed-rank tests. We use the scipy Python library of Wilcoxon signed-rank test. The data for the Wilcoxon tests are presented at violin plots [67]. The statistical significance is observed if the probability value (p-value) is $p < 0.05$ or less than 5%.

VI. Evaluation

A. Qualitative Results

After the elimination of invalid responses, as discussed in Data Analysis, we received a total of 32 comments per each participant, 20 from the comment session after each scenario and 12 after the EQs related to the graph visualization. The experts further categorize the comments as positive, neutral, and negative with respect to the use of graph visualization. The comments

TABLE II
PRAGMATIC AND HEDONIC QUALITY

Attractiveness	Pragmatic Quality	Hedonic Quality
1.47	1.50	0.95

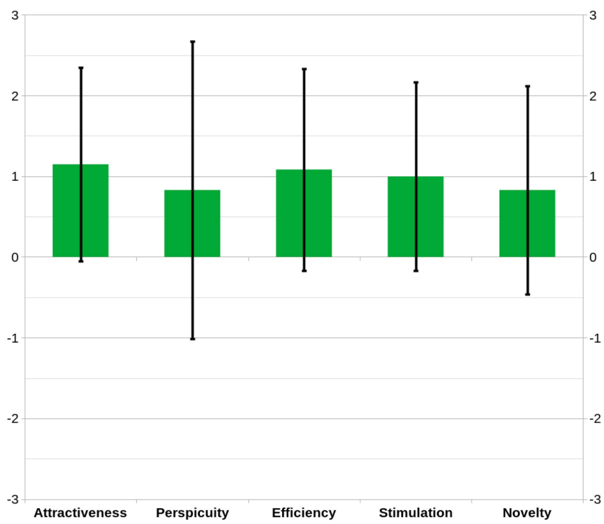


Fig. 5. UEQ scales mean and variances.

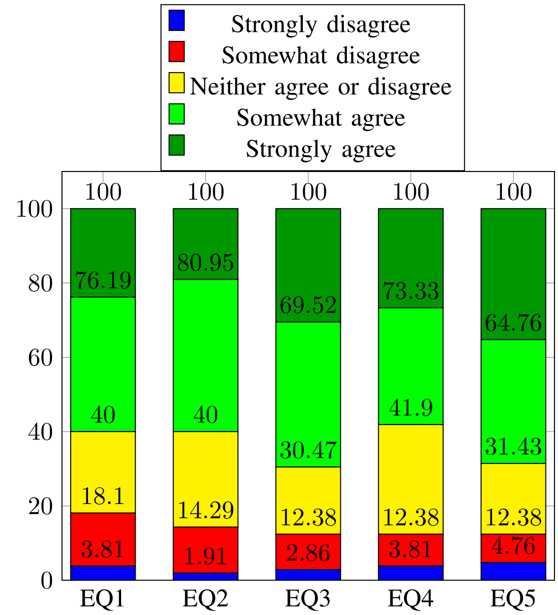


Fig. 6. User general feedback for the CollabGraph. EQ1: I like the group results visualized in a graph. EQ2: I like the summary of the team members' results. EQ3: I like the graph visualizations. EQ4: I want to have a graph visualization next to the list view of the search results. EQ5: I like the combination of the list and graph view.

of the null and suggestion categories were deliberately assigned to neutral. According to [68], the negative and neutral comments are the majority, with half of the comments being neutral. After the analysis, we find 12 negative comments, 12 neutral, and 8 positives. In contrast to [68], we find a significant amount of positive comments corresponding to 25%, over the 2% in positive comments in the analysis in [68]. We provide a further presentation of the qualitative analysis comments in each RQ result.

B. Overall Quality and Likeness

RQ1: Is the graph summary visualization useful? Yes.

The range UEQ scales is between -3 (horribly bad) and +3 (extremely good). The values between -0.8 and 0.8 represent a more or less neutral evaluation, values ≥ 0.8 represent a positive evaluation, and values ≤ -0.8 represent a negative evaluation. Therefore, the results reported in Table II, with the 1.47 score of attractiveness and 1.50 of pragmatic quality, are objectively good evaluation results, while the hedonic quality with 0.95 is decently good. In agreement with our results, we find a comment underlining that "The graph is useful to get an overview...." The scales of the UEQ can be grouped into pragmatic quality and hedonic quality. Pragmatic quality describes task-related quality aspects, and hedonic quality describes the nontask-related quality aspects.

Also, in Fig. 5, we find the UEQ scales with mean and variance. The perspicuity and novelty are scored the lowest with 0.829 and variance of 1.84 and 1.29, respectively. We find the big variance an indication of different opinions among the users regarding the CollabGraph. The stimulation is scored positively with a mean of 0.998 and a variance of 1.17. The efficiency is 1.08 positively evaluated with a variance of 1.25. The highest scores in specific questions are found in "good vs bad" with a mean score of 1.4 and in "annoying vs enjoyable," "valuable vs inferior," and "friendly vs unfriendly" with a mean score of 1.2. It is interesting to mention that "not understandable vs understandable" gives the biggest variance with a mean of 0.7 and a variance of 2.7. We discuss this further in Section VII-C.

RQ2: Do the users like the graph summary visualization? Yes.

Findings suggest that the users liked the CollabGraph *"graphs are important for a quick overview of the data or doing comparisons...."* RQ2 is related to the general likability of the graph summary visualization and not related to usability over the list in a particular scenario. For this purpose, we deployed five EQs, the EQs in which we asked the users whether they liked the graph summary visualization. The EQs build up upon the different elements of the CollabGraph; the group results in a graph, the summary, the graph visualization, and the combination with the list.

By looking on the general feedback we received for the graph visualization from all the participants in Fig. 6, we can notice that the majority like the visualization of group results in a graph. We classify the responses "Somewhat agree" and "Strongly agree" as positive answers. More specifically, 60% of the users liked the group results visualized in a graph and the summary of the team members' results. 69.53% of the users like the graph visualizations.

C. Results From Graph Versus List Display

In general, 52.25% of all users voted in favor of the graph visualization among all scenarios and questions, with 19.65% voting for only the graph and 32.60% the combination of the

TABLE III
AVERAGE PERCENTAGE NUMBER OF USERS PER QUESTION (Q) FROM ALL SCENARIOS

	Q1	Q2	Q3	Q4	Q5	Avg
The list	17.46	**29.52**	24.29	22.06	10.79	20.83
The graph	16.67	25.56	20.79	15.71	19.52	19.65
Both	**63.33**	22.06	8.73	18.73	**50.16**	**32.60**
None	2.54	22.86	**46.19**	**43.49**	19.52	26.92

TABLE IV
AVERAGE PERCENTAGE NUMBER OF USERS OF WHICH PLATFORM THEY WOULD PREFER PER EACH LS

	LS1	LS2	LS3	LS4	LS5	LS6	Avg
The list	22.86	18.67	18.67	20.19	21.52	23.05	20.83
The graph	18.86	22.29	16.57	18.29	21.14	20.76	19.65
Both	**27.43**	**34.29**	**34.10**	**32.95**	**31.24**	**35.62**	**32.60**

The highest score is identified with bold.

list and the graph. At the same time, the list view scored only 1.18% higher than the stand-alone graph score with 20.83% of the participants liking the list view only. We further analyze the results of Table III per question in the next paragraphs.

RQ3: Do the users prefer the graph summary visualization over the classical linear list for group search results display? No, but they preferred the combination of both.

In Table IV, there is an overview of which visualization would the users prefer to utilize if they needed to choose between the classical list view, the graph presented by the CollabGraph, or the combination of the two. We observe that the combination of the list and graph view is, on average, the most dominant among the other choices for understanding some characteristics about the project status and everyone's contribution. The average scores are extracted from the users' preference in answering the set of questions Q1–Q5, as presented in Section V-B. It is worth mentioning that there was a significant amount of users who were confused in answering some of the questions Q1–Q5, as also visible in Table III.

As seen in Fig. 6, 58.10% of the users want to have the CollabGraph next to the list view of search results, with only 12.38% of all users responding negative. Also, 68.57% of all prefer the combination of the list and the graph view. Some comments in this line underline that *"Graph visualization are somehow helping to better understand some part of information, notably interconnected areas on a topic. But the list view is from far the best to summarize all tasks, which are done/undone...," "The combination of list and graph view appears to be more helpful...*, *"In general, the list provides more detailed descriptions, but the graph shows the big picture of the team actions, i.e., how they are related...*, and *"As a stand-alone, the graph does not depict the search results and the exact topics that were searched for clear enough for me. I personally like detail and think that the graph cannot give the depth of the searches that have been done. However, if both list and graph are paired, the graph gives a quick, rough overview of what has happened so far and the list provides the necessary details to maybe conduct a search that nobody has done before. But for me, I would still always need the list for detail."*.

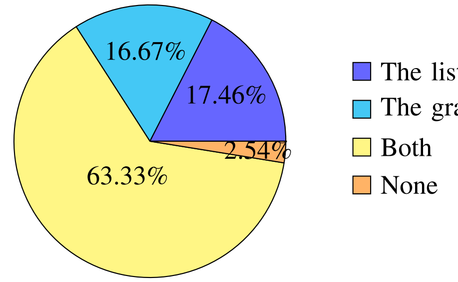


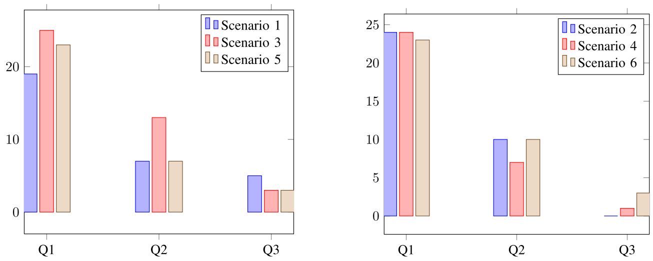
Fig. 7. Answers on the question Q1: "Which visualization helps you to better understand which team members have already participated?"

RQ4: Is the graph summary visualization enhancing the group's participation and involvement? Yes, the graph is enhancing participation and involvement especially in closed-end scenarios with many active users.

For the evaluation of RQ4, we developed Q1–Q3 after each LS. Fig. 7 presents the result from Q1: "which visualization helps you to better understand which team members have already participated?" We see that 80% of the users preferred graph visualization as stand-alone (16.67%) or as the combination with the list view (63.33%). Some further clarification might be important at this point. As the list view is the classical element offered by any search history, our evaluation and analysis focuses on the usability and likeness of the graph visualization. As we conclude in Section VII-B1, "RQ3: Do the users prefer the graph summary visualization over the classical linear list for group search results display?: No, but they preferred the combination of both." Therefore, it is not a matter of preference of the one (list) over the other (graph), as we plan to enhance rather than replace the list view with the graph summary visualization. That is why, we report the preference the graph visualization has gained in total (as stand-alone and in combination with the list) in order to demonstrate the high preference on this additional feature.

In Q2 "which parts of the project have been completed already?" we notice that there were some users who were undecided on which visualization they preferred. 47.62% of participants preferred the CollabGraph as stand-alone (25.56%) or in combination with the list (22.06%), compared to 29.52% who strictly preferred the list view. Particularly, in the open-end scenarios, it was challenging for most to identify which visualization helps them better to understand which parts have been completed and which topics have not been searched yet (Q3). Especially, in Q3, we noticed an important indecisiveness by almost half of the participants, as 46.19% of them on average chose that "None" of the visualizations can help them understand which topics have been searched yet. Fig. 8 presents the combination of the list and graph view preference in absolute values per each question (Q) in open- versus closed-end scenarios in RQ4.

Based on the Wilcoxon signed-rank test, we found a statistical significance on the preference of the CollabGraph graph summary visualizations in comparison of open-end two-active-participant scenarios versus the closed-end four-active-participant scenarios in RQ4. In Fig. 9, we report our data which show that there is statistical confidence in violin



(a) Open end scenarios (b) Closed end scenarios

Fig. 8. Combination of the list and graph view preference in absolute values per each question (Q) in open- versus closed-end scenarios in RQ4.

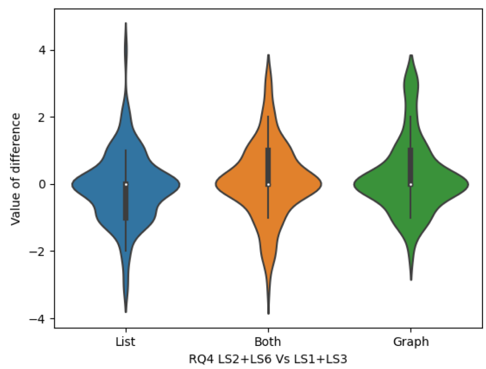


Fig. 9. Violin plot of the comparison for RQ4 between open-end two-participant versus closed-end four-participant scenarios.

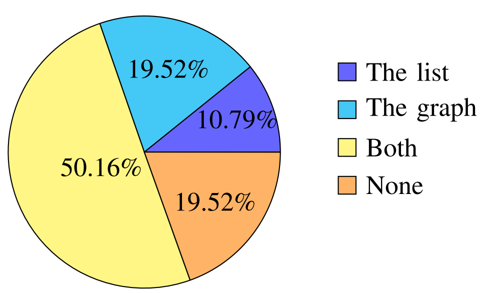
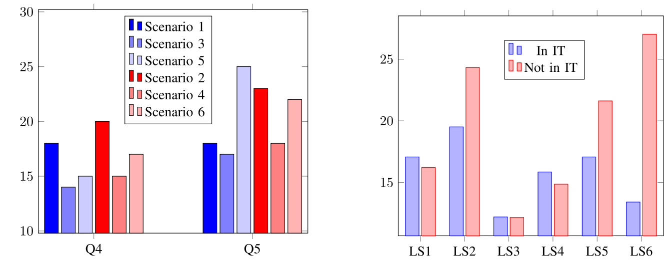


Fig. 10. Answers on the question Q5: "Which visualization helps you to better understand if all four students participated in the project?"



(a) Scenarios comparison. Blue: open-end, red: closed-end (b) Average scenarios performance for subgroup of Msc and PhD holders.

Fig. 11. Related to RQ5, on the left: the graph view preference in absolute values per question (Q) in open versus closed end scenarios; on the right: the average graph preference per LS for M.Sc. and Ph.D. holders compared to those in IT and not in IT sector.

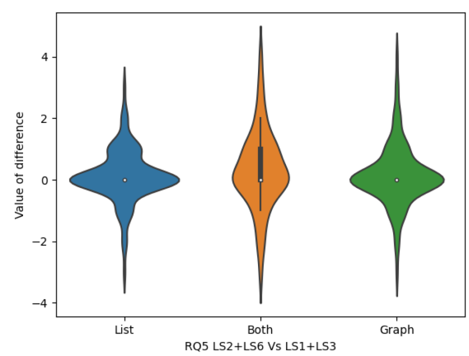


Fig. 12. Violin plot of the comparison for RQ5 between open-end two-participant versus closed-end four-participant scenarios.

plots among the List, Both, and Graph, meaning the CollabGraph distribution of the absolute value of differences. The Graph enhances the participation and involvement in closed-end four-active-participant scenarios with a p-value equal to 3.1%.

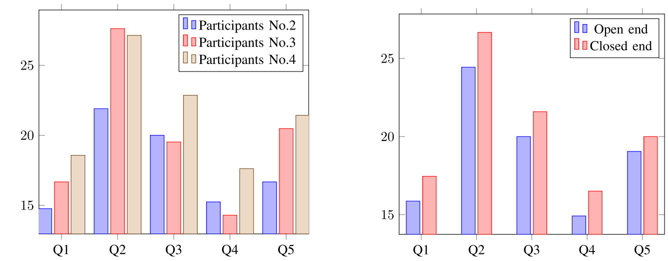
RQ5: Is the graph summary visualization enhancing the teacher's support and feedback? Yes, the graph is enhancing the support and feedback, especially in closed-end scenarios with many active participants.

For the evaluation of RQ5, we developed Q4 and Q5 after each LS. Fig. 10 presents the result from Q5: "which visualization helps you to better understand if all 4 students participated in the project?" We see that 69.68% of the users preferred the graph visualization as stand-alone (19.52%) or in combination with the list view (50.16%). In Q4 "if the students fulfilled all the parts of the project?" we notice again that the users were undecided between the visualizations, with 43.49% of them replying that "None" of the visualizations helps them. 34.44% of the participants preferred the CollabGraph as stand-alone (15.71%) or in combination with the list (18.73%), compared to 22.06% who strictly preferred the list view. Some further results are presented in Fig. 11, which displays the results for RQ5 in open- versus closed-end scenarios. On the list side is the graph view preference in absolute values per each question (Q), and on the right is the average graph preference per scenario for M.Sc. and Ph.D. holders compared to those in IT and not in IT sector.

Based on the Wilcoxon signed-rank test we ran, we find that there is a statistically significantly importance in the preference of the combination of the CollabGraph and list view (the option "Both") in favor of the closed-end scenarios with many participants with the p-value equal to 1.93%. The computation results for RQ5 are reported in Fig. 12, which presents the violin plots of the differences among the open-end scenarios with two active users versus the closed-end scenarios with four active users. Fig. 12 presents the distribution of absolute values among List, Both, and Graph.

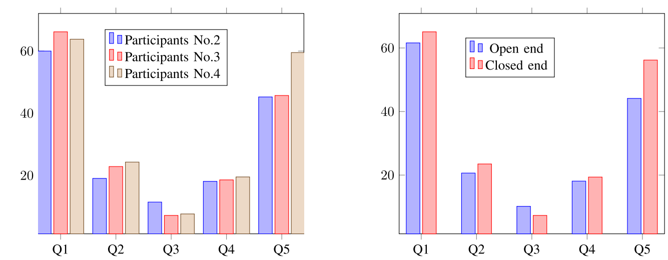
D. Performance of Different Learning Scenarios

Figs. 13 and 14 display some interesting realizations regarding the performance of different LSs. The graph clearly performs better in closed-end scenarios among all asked questions, and



(a) Number of participants (b) Type of scenario

Fig. 13. Graph preference in percentage among all LSs per each question (Q).



(a) Number of participants (b) Type of scenario

Fig. 14. Preference of the combination of list and graph in percentage among all LSs per each question (Q).

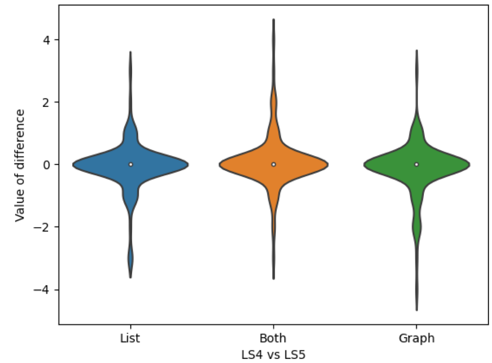


Fig. 15. Violin plot of the comparison between open- versus closed-end scenarios with three active participants.

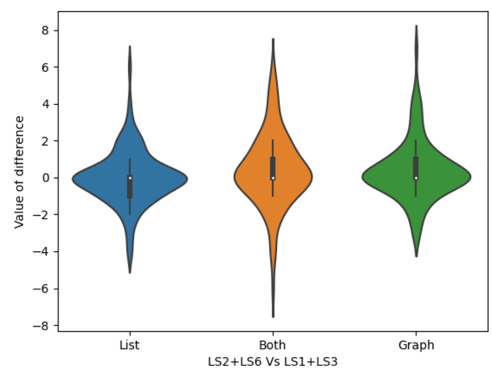


Fig. 16. Violin plot of open-end two-participant versus closed-end four-active-participant scenarios.

there are indications that the bigger the number of participants, the most likable for users to prefer the graph view only. This could be because many participants create a lot of search results and sessions, making it more difficult to track everyone's actions into detail. Therefore, the graph or the combination of the list and the graph could be more useful.

It is important at this point to remember that the combination of the list and graph in Fig. 14 is underperforming in questions Q2–Q4 because almost half of the users were undecided between the visualizations. In those questions, the answers "None" were almost 50% in most cases of the participants in the questions for identifying which visualization helps them understand some characteristics for the project.

We display the results we received from conducting the Wilcoxon signed-rank tests based on the samples demonstrated in Figs. 15 and 16. Results show that there is a statistical significance in the difference between the open-end and closed-end scenarios and in the number of participants in each group search. We find that the graph in the small number of participants (two active participants) and open-end LSs versus the bigger number of participants (four active participants) and closed-end LSs generates statistically significant results in favor of the latter. More specifically, in Fig. 16, we observe the violin plots of List, Both (combination of List and CollabGraph), and Graph (the CollabGraph) distribution of differences among the different scenarios. We find significant results in the combination of CollabGraph and list with $p = 0.0227$ and the Graph with $p = 0.0299$, as shown in Fig. 16. Also, the closed- versus open-end scenarios give an almost significant results ($p = 0.0654$) in the LSs with three active participants within the preference of both visualizations, as shown in Fig. 15.

VII. Discussion

A. Connections With Previous Works

The CollabGraph, as shown in Fig. 1 on the right-hand side next to the list, provides a graph summary visualization of search history results, which establishes the foundation toward the development of an SLE feature [9] in collaborative web search, and in TBL and PBL scenarios, and SaL [12]. It provides visualizations that assist users to better understand the group project's status as well as their group mates' contributions. At the same time, it enhances participation and feedback. Our study is aligned with previous works that highlight the importance of feedback in adaptive learning environments and their benefits [14], [15].

Furthermore, research has shown that motivated and self-regulated learners have higher chances of using e-learning systems like LearnWeb and the CollabGraph feature [69], [70]. However, coming back to Hearst's concern regarding features in collaborative platforms [31], we could assume that if more features like the CollabGraph are explicitly developed for collaboration and are not adapted from individual to group settings, then we might increase the usage of collaborative platforms.

It is apparent that the task of developing usable adaptive learning systems is challenging [71]. However, there is a high demand for personalization and assisting collaboration in SLEs, and this study indicates that features developed with an explicit focus on the collaboration support could be beneficial and preferred by users. On the other hand, the CollabGraph, as well as previously suggested graph models for search history results [5], [6], comes to complement existing standards in e-learning platforms rather than replacing existing features.

B. Contributions

1) CollabGraph Is Useful: The first RQ (RQ1) in this study investigated the usefulness of the CollabGraph. The CollabGraph evaluation demonstrated objectively good results as they are demonstrated in Table II. The CollabGraph scored with 1.47 in attractiveness and 1.50 in pragmatic quality, while the hedonic quality with 0.95 is decently good with positive values defined above 0.8. Qualitative analysis findings also align with these results. Furthermore, UEQ results are presented in Fig. 5, where we find the stimulation score with a mean of 0.998 and a variance of 1.17, and the efficiency is 1.08 positively evaluated with a variance of 1.25. The highest scores in specific questions are found in "good vs bad" with a mean score of 1.4 and in "annoying vs enjoyable," "valuable vs inferior," and "friendly vs unfriendly" with a mean score of 1.2.

2) Users Like the CollabGraph and Prefer Having It in Combination With the List: RQ 2 and RQ3 examine whether users like the CollabGraph (RQ2), and if they prefer the graph summary visualizations, the CollabGraph provides the classical list view of search history results (RQ3). Our findings from the EQs suggest that a graph summary of the collaborative search results, like our system CollabGraph, is highly preferable by users. However, the CollabGraph could not replace the current classical list view; it is indicated that the users prefer having the combination of both the detailed list and the graph summary.

3) CollabGraph Enhances Participation and Feedback: When it comes to user participation and feedback, we can say that students highly preferred the CollabGraph visualizations either as a stand-alone feature or in combination with the list view of the search history results. We formulated RQ4 and RQ5 in order to further explore the participation and involvement (RQ4) and support and feedback (RQ5). From the statistical analysis of our results based on the Wilcoxon signed-rank test, we found that there is significantly better performance of the combination of the CollabGraph and the list view in feedback, when comparing open-end few-active-user LSs versus the closed-end many-active-user LSs. Again, in the comparison of the same type of LSs, the CollabGraph shows statically significant better performance in the closed-end many-active-user LSs in participation.

4) CollabGraph Is More Useful as the Number of Active Participants Increases and the LS Has a Predefined Goal: We find that the graph summary of the collaborative search results becomes more useful when there are plenty of results by the team members and the LS is closed end. As a counterexample, we can think of the cases with only two active participants that performed one or two search sessions, where the list is a better option. However, besides the group members' summary, our CollabGraph provides a novel feature in the collaborative search environments by adding color and a different size on the nodes, depending on which users performed searches and the topics of the searches.

C. Findings

1) Users Need Time to Familiarize With a New Feature: It is noticed in the literature that users became more engaged after a rather slow beginning with a new system or feature [70]. Another interesting finding comes from one of the comments. The CollabGraph is a novel feature in search history visualization, and as a user noticed in learning scenario 3 saying, *"Getting better at reading the graph now and I do prefer it. I notice now that there is color coding, and that helps me identify who worked on the project. Also, the keywords in the graph are more understandable...."* It is often common that people prefer things they are used to, in our case the list visualization, and it might take some time before they get used to a new interface they are introduced to.

2) Negative Comments Mostly Come From Users Who Preferred "none" of the Visualizations: Regarding our qualitative analysis, we see some interesting observations with respect to users who provided negative feedback. Half of them preferred in high-frequency none of the two visualizations in all the scenarios and different questions (Q1–Q5), i.e., neither the classical list view, which is always provided, nor our proposed CollabGraph. This defines a curious direction for future work to further investigate the characteristics of this group of users and what could enhance their experience and preference.

D. Limitations

Nonetheless, there were some limitations we came across in the evaluation of CollabGraph. We used Google Forms for our online questionnaire, which is not a mobile-friendly version. Some comments we received mentioned that it was hard to complete the questionnaire on phone. Also, a comment wondered why there was no positive feedback possible in the general feedback questions of preference because the mobile version did not display the "Somewhat agree" and "Strongly agree" options. Other comments suggested that the visualizations were not clear enough in the questionnaire. The control question "How many team members participated in this project?" also seemed to be confusing for some users who thought that the answer was always "4" since the project was assigned to four students each time, even if not all four participated in some cases. A comment from an invalid response in this line stated that *"The answer could always be 4. If a team member is inactive in the search (he is) technically still a team member ? Potentially yes...."*

Although some users liked having the CollabGraph, they pointed out that there could be additional functionalities in it, such as indicating which tasks are completed and a list of all the tasks to be made. A comment pointed out that *"...I couldn't tell which tasks were not carried out. That is, there is no indication for the complete set of tasks so that we know which ones are* *missing."* Furthermore, the color coding was unclear for some invalid users who commented that *"Unclear what colors mean in the graph visualization."* and *"I think it's helpful to unify the color for the same person's name."*

On the other hand, there are potential directions left to be explored in future work. At first, we are currently limiting the entities represented in the graph only to those with URIs. Also, currently, due to our back-end algorithms, we support online search in English only. In addition, we have made the assumption that each user joins a single group and performs search queries related to their project.

VIII. Future Work

We believe this work opens a new line of research and applications both in visualizations of collaborative results in SLEs and in PKGs. More specifically, we foresee more personalized visualizations in SLEs with emphasis on the collaborative search. Sequentially, we hope to develop a feature to switch ON and OFF between the visualization of the PKG and the current group results. This extra feature can potentially enhance self-regulated online learning and SaL toward more personalized visualizations. In addition, we expect eye-tracking technologies to be implemented to enhance the input stream. Furthermore, we could advance the visualization to host annotations made by teachers. This could improve educators' ability to find answers and support learning in the process. These annotations could provide feedback in the form of highlighted text and comments that emphasize the students' useful search queries. In addition, the teacher could add a topic to search and assist students by giving hints for what to do next. This extension is encouraged by literature findings in feedback's importance in SLEs and is intended to increase the preference of usage of CollabGraph. Supplementary to the current version of the system, we perceive the importance of semantic search systems to our work. We anticipate automatically generating recommendations for relevant search key terms that were not searched yet by the group. These recommendations could be linked to semantically related words, such as "work" and "job," often found in KGs. Intelligent systems could benefit from such an approach to promote adaptive recommendations depending on learner-based filtering [72]. Besides personalization, the analysis in the visualizations could investigate the optimal number of visualized nodes. At the current model, we represent the maximum top four entities in nodes from each user. However, based on our knowledge, no research indicates the optimal number of designated entities per user or the desirable number for nodes represented in a graph from the user experience perspective.

Another development part involves the exploration of PKGs. The latter is a new area in the literature, and we are joining this wave at its early steps [46]. Ontologies in education and user modeling can assist in personalization and is an addition to PKGs [73]. Also, PKGs offer the technological substrate to the open learner modeling aimed at representing students' knowledge acquisition to foster self-reflection and self-organized learning processes. The CollabGraph visualization can support in facing one of the key challenges of open learner model creation, namely, presenting and interacting with students' data through an effective interface [70]. In addition, an always crucial point of personalized applications is privacy. Currently, this issue is addressed by adopting a local development solution; nonetheless, there are concerns raised even in dealing with the display of multiple users' actions. We consider this matter an appeal of a multidisciplinary work with the legal domain. Some interesting points of investigation would be the maintenance and update of these graphs. We believe that some results on temporal KGs could adopt into PKG settings. Also, the construction of PKGs could rise a new line of work as in the future work, we could include the references from more KGs and provide a more sophisticated algorithm for the calculation of the top entities per user. Beyond the PKGs, we realize the potential need for a group graph that could be located in the middle of PKGs and the KGs and search recommendations. This group graph could offer to users better overview of their team members' activities on the fly, improving their search results and involvement in the group project.

IX. Conclusion

In this article, we presented CollabGraph, a novel graph-based visualization for the summary of the collaborative search results. The CollabGraph provides the foundation for developing SLE features in collaborative search history results by providing alternative graph visualizations next to classic list-view search results. It is developed with its basis on linked data by creating a PKG for each user. Our evaluation shows that the CollabGraph is useful and highly likeable by the users. In addition, the results suggest that the users prefer the combination of a list and a graph for the visualization of the search history results. Finally, we observe that graph summary visualizations are preferable for closed-end scenarios and for collaborative projects with many participants.

Appendix A
Adaptive User Experience Questionnaire

TABLE V
Adaptive User Experience Questionnaire

	1	2	3	4	5	6	7	
annoying	○	○	○	○	○	○	○	enjoyable
not understandable	○	○	○	○	○	○	○	understandable
creative	○	○	○	○	○	○	○	dull
easy to learn	○	○	○	○	○	○	○	difficult to learn
valuable	○	○	○	○	○	○	○	inferior
boring	○	○	○	○	○	○	○	exciting
not interesting	○	○	○	○	○	○	○	interesting
fast	○	○	○	○	○	○	○	slow
inventive	○	○	○	○	○	○	○	conventional
good	○	○	○	○	○	○	○	bad
complicated	○	○	○	○	○	○	○	easy
unlikable	○	○	○	○	○	○	○	pleasing
motivating	○	○	○	○	○	○	○	demotivating
inefficient	○	○	○	○	○	○	○	efficient
clear	○	○	○	○	○	○	○	confusing
impractical	○	○	○	○	○	○	○	practical
organized	○	○	○	○	○	○	○	cluttered
attractive	○	○	○	○	○	○	○	unattractive
friendly	○	○	○	○	○	○	○	unfriendly
conservative	○	○	○	○	○	○	○	innovative

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Eleni Ilkou received the B.Sc. degree in mathematics from the University of Ioannina, Ioannina, Greece, in 2016, and the M.Eng. degree in applied computer science from Vrije Universiteit Brussel, Brussel, Belgium, in 2019.

She is currently an early stage researcher with Know-Graphs ITN, L3S Research Center, Leibniz Hannover University, Hanover, Germany. She has a demonstrated experience as a Teacher and Tutor, and she is excited about applications in the educational domain. Her research interests include domain and personal knowledge graphs.

Tetiana Tolmachova received the B.Sc. and M.Sc. degrees in informatics from the Kharkiv National University of Radio Electronics, Kharkiv, Ukraine, in 2016 and 2018, respectively, and the M.Sc. degree in Internet technologies and information systems from Leibniz University Hannover, Hannover, Germany, in 2019.

She is currently a Project Coordinator and Researcher with L3S Research Center, Leibniz University Hannover. She is also working with students, but is also involved in web development and work on LearnWeb project.

Marco Fisichella received the Doctoral degree (Magna cum Laude) in computer science on clustering information entities based on statistical methods from the Leibniz University Hannover, Hannover, Germany, in 2012.

From 2015 to March 2021, he was at Otto Group where he was directing the Department in Charge of implementing algorithms against online fraud for big corporate clients (e.g., Zalando, Vodafone, etc.). Since April 2021, he has been with the research group of L3S Research Center, Leibniz University of Hannover, with a focus on AI and intelligent systems. He has more than 14 years of experience in AI both in the industry and in academia.

Davide Taibi received the degree (full Hons.) in computer engineering from the University of Palermo, Palermo, Italy, in 2001.

He is currently a Senior Researcher with the Institute for Education Technology, National Research Council of Italy. He is also a part-time Lecturer with Computer Science Department, University of Palermo. Since more than 20 years, he has been working in the educational technology research area, and his main research interests concern pedagogical applications to smart environments, learning analytics, and enriched reality in education.