



A Real-Life School Study of Confirmation Bias and Polarisation in Information Behaviour

Simone Kopeinik¹(✉), Elisabeth Lex^{1,2}, Dominik Kowald¹, Dietrich Albert^{2,3},
and Paul Seitlinger^{3,4}

¹ Know-Center GmbH, Graz, Austria
{skopeinik,dkowald}@know-center.at

² ISDS, Graz University of Technology, Graz, Austria
{elisabeth.lex,dietrich.albert,}@tugraz.at

³ Institute of Psychology, University of Graz, Graz, Austria

⁴ School of Educational Sciences, Tallinn University, Tallinn, Estonia
pseiti@tlu.ee

Abstract. When people engage in Social Networking Sites, they influence one another through their contributions. Prior research suggests that the interplay between individual differences and environmental variables, such as a person's openness to conflicting information, can give rise to either public spheres or echo chambers. In this work, we aim to unravel critical processes of this interplay in the context of learning. In particular, we observe high school students' information behavior (search and evaluation of Web resources) to better understand a potential coupling between confirmatory search and polarization and, in further consequence, improve learning analytics and information services for individual and collective search in learning scenarios. In an empirical study, we had 91 high school students performing an information search in a social bookmarking environment. Gathered log data was used to compute indices of confirmatory search and polarisation as well as to analyze the impact of social stimulation. We find confirmatory search and polarization to correlate positively and social stimulation to mitigate, i.e., reduce the two variables' relationship. From these findings, we derive practical implications for future work that aims to refine our formalism to compute confirmatory search and polarisation indices and to apply it for depolarizing information services.

Keywords: Learning analytics · Real-life school study · Information behaviour · Polarisation · Confirmatory search

1 Introduction

When people engage in online discussions in Social Networking Sites (SNSs) or different online forums, they interact with content shared by others, get

influenced by this content, and then, influence others through their interactions [6]. Particular dynamics between user dispositions (e.g., open- vs. closed-mindedness) and content of interaction (e.g., controversial vs. consensual topics) can create a *public sphere* [14], i.e., a place where people gather, share information and participate in critical debates about public affairs [5]. In principle, SNSs can support processes of a public sphere as they connect people and expose users to political differences online [4]. This confrontation with different viewpoints can encourage decision-making that draws on alternative information sources [7]. However, as discussed in related work (e.g., [1,26]), users of SNSs show a propensity to engage with like-minded others and tend to be closed-minded about alternative information [23]. One reason for the reinforcement of such processes is personalized filtering [27], which helps us find information related to what we prefer or already know. This caters to people's tendency to seeking information that corresponds to their existing beliefs (i.e., confirmatory search). As a consequence, people move towards extreme positions and attitudes [16,33] (i.e., polarization). Messages in the daily press about hateful Facebook postings make us aware that such dynamics quite often result in emotionalized and derogative stances to alternative viewpoints. Thus, it becomes of public interest to strengthen peoples' education in digital literacy. The motivation of this work is two-fold. On the one hand, our long-term goal is to help increase students' awareness and competences to consume information online critically, a skill many students lack to this date [25]. On the other hand, we aim to contribute to the development of learning analytics services for teaching and improving teaching strategies of digital competences in schools. We believe the progress towards these goals should be built upon a thorough understanding of underlying mental processes.

In this work, we propose means to study confirmatory search (search for consensual resources) and polarisation (drifting towards extreme positions) dynamics in an educational context. Our main aim is to better understand socio-cognitive dynamics leading to either deliberate, open-minded or biased, polarised information behavior [35]. To this end, we present a study that observes and interprets students' information behavior in a semi-controlled online environment. In particular, we investigate the impact of shared artifacts (i.e., social tags and bookmarks) on a collective search process and expect two artifact-mediated benefits: (i) the introduction of potentially new ideas (i.e., concepts labeled by freely chosen tags) will help a student activate new associations to a given topic and thereby, mitigate a tendency towards monotonous thoughts regarding a given problem [32], and (ii) the revealing of tags other students have previously chosen to index underlying concepts (e.g., by recommending social tags) will support the collective of students to mitigate the vocabulary problem, i.e., to agree on a common terminology of concepts more quickly [34].

We, therefore, raise the following two research questions:

RQ1: What is the impact of shared artifacts (social tags and bookmarks) on confirmatory search and polarisation in collective search processes?

RQ2: Can shared artifacts (social tags and bookmarks) be applied to reduce the vocabulary problem in collective search processes?

To examine these questions under natural conditions, we have conducted a study with 91 high-school students performing an information search task in an adapted version of the open-source social bookmarking system *SemanticScuttle*. This system can be used as a platform to collect and share information online and, from a research perspective, allows for recording user data related to information selection and opinion formation processes. Furthermore, to examine the impact of shared artifacts on these processes, three different conditions have been varied experimentally: As a baseline for comparisons, we had one group of students receiving no recommendations at all. In the following, this baseline is denoted ‘None’. By contrast, the other two groups have been supported by tag recommendations, which we derived either inclusively from the entire group’s tagging activities (‘social’ condition) or exclusively only from the student’s personal tagging history (‘individual’ condition).

The present work contributes to current research on technology-enhanced learning by demonstrating how students’ search and sharing behavior on the Web can be observed under natural conditions and how this behavior can be analyzed automatically in cognitive terms. Beyond that, it highlights a depolarizing impact of shared artifacts and can thus guide future design processes aiming towards more effective recommender systems in computer-supported learning scenarios. We, therefore, believe that the study helps to further learning analytics services for the teaching and training of critical and nuanced search behavior.

2 Related Work

The productive use of online information tools demands teaching strategies that address relevant competences [22]. To date, students’ competencies and awareness to critically consume information are still widely lacking [25]. There is no evidence of digital skills that exceed the level of using technologies frequently [13]. Quite to the contrary, existing research reports on students’ superficial understanding of new technologies and their lack of information seeking and analytical skills necessary to assess and learn from online resources (e.g., [3]).

2.1 Supporting Collective Search

A central motive to engage in SNSs is to acquire information, in private, societal-political, or vocational contexts. Therefore, this engagement can be framed as participation in a collective search, where the term collective means that different individuals act in a common environment and influence each other through shared artifacts, such as links to external news sites. Prior work has shown that even simple features, such as shared keywords (i.e., social tags) can become sources of mutual influences and can alter mental states (e.g., information goals) through the process of semantic priming (e.g., [11, 31]). The term priming refers

to an increased availability of traces in long-term memory evoked by an environmental stimulus (e.g., the tag “polarisation”), which is mentally connected to these traces (e.g., the associations of “echo_chamber” or “confirmatory_search”) as well as to the subsequent behavioral consequences that follow from such priming, like performing a keyword-based search or accepting/declining recommended pieces of information.

When it comes to designing effective learning analytics services, which observe and support students’ search behavior, the question should be raised, in which manner shared artifacts need to be (re)presented to facilitate a collective and open information search. In the context of the present study, we ask for the extent to which the prominence of other members’ ideas and contributions should be increased or decreased to reduce the coupling between confirmatory search and polarisation eventually. Technology-enhanced group creativity provides some answers to these questions (e.g., [28]), which, e.g., explores the effects of shared artifacts on individuals’ divergent thinking abilities during a collective information search (e.g., [32]). Among others, this research demonstrates that the recommendation of social tags (i.e., tags that are semantically related to a user’s search but are generated by someone else) are on average more conducive to each group member’s ideational fluency (i.e., the rate at which new ideas come to one’s mind) than the recommendation of individual tags (i.e., semantically related tags drawn from a user’s own tag vocabulary).

From a cognitive-psychological perspective, neurophysiological processes are stimulated by environmental influences and help trains of thoughts diverge. These processes should function antagonistically to mental processes that would otherwise actuate the convergence of contents of consciousness [15], such as the convergence of a current belief or opinion and an ongoing information goal. Put differently, cognitive processes during a search that support divergent thinking should simultaneously counteract confirmatory tendencies (e.g., the conversion of beliefs into search goals) and in further consequence, mitigate forces driving polarisation. Therefore, we assume and predict that providing social recommendations in the form of shared artifacts (e.g., social tags and social bookmarks) will result in a relatively weaker coupling between confirmatory search and polarisation than providing individual or even no recommendations.

2.2 Tagging and Semantic Stabilisation

Tagging is a mechanism to annotate resources individually or socially [36]. In TEL, it has demonstrated its potential to facilitate search, to foster reflection upon retrieved learning contents [19] and to promote the development of a metacognitive level of knowledge [2]. Throughout the learning process, structures of users in a social tagging environment assimilate [12]. Such implicit agreement on a common vocabulary over time and in meaning is called semantic stability [34]. The term semantic stabilization describes the evolution of convergence in vocabulary choices of different groups [18]. Research has described a mutual influence between learners’ internal knowledge representation and the tagging

vocabulary that emerges in the social information system, in which they interact [10]. Ley and Seitlinger [20] investigate these dynamics and prove a positive influence of semantic stabilization on individual learning. Consequently, it can be argued that a high level of semantic stability provides a structure that supports individual learning activities and therefore, can be conducive to individual learning gains [20]. Because students' typically struggle with the achievement of a semantically stable vocabulary in their usage and amongst their learning peers [20] recommendation mechanisms that introduce shared artifacts (e.g., tags) have been proposed [9]. Thus, expanding prior research in inquiry-based learning [18], we explore the impact of shared artifacts (recommended tags) on semantic stabilization in an information search task.

3 Experimental Setup

For this study, we monitored and explored students' information search behavior in a real-life classroom setting. The study took place at Graz University of Technology, Institute of Interactive Systems and Data Science, as part of a top citizen science funding program, in which citizens are encouraged to participate in research endeavors actively. Three teachers and four high-school classes from two schools were recruited to participate in different project stages during the school terms of 2017 and 2018. In this time, 91 students (60 female and 31 male), aged between 14 and 18, took part in workshops that included completing worksheets, questionnaires, interviews, focus groups, and information search tasks. Here, we report on data insights extracted from the students' information search task.

3.1 Study Procedure and Design

Before the study, each participating student was provided with a brief description of the study setup and its main research goals. They were informed about the tasks they had to complete, the data that was gathered and potential privacy concerns. To ensure data protection and anonymity, students were identified by a pseudonym they created for themselves. After obtaining guardians' informed consent, students attended an introductory workshop to familiarize with the problems of echo chambers, filter bubbles, and fake news. Also, they were informed about the means to evaluate the quality of information. Before the search task, teachers selected a topic and associated topic aspects that fit the curriculum of the age group. This topic was depicted in the environment.

Within the information search task, students were instructed to explore the topic "global nutrition" by collecting information to the four defined aspects "genetic engineering", "conservation", "sustainable consumption" and "development aid". They had to upload their articles as bookmarks to the study environment. Students used the annotation tool shown in Fig. 1 to reflect on their Web resources. They had to select at least one predefined topic aspect, indicate their attitude and an estimation of the author's attitude towards the chosen

aspects. The requested set of information provides insights on different facets of the opinion formation process, such as confirmatory search or polarisation.

To simulate a search environment with social, individual or no stimulation on appearing information dynamics, students were split into three groups. Depending on the group, the environment provided for the social and individual stimulation tag clouds and tag recommendations based on social or individual data. Students of the third group were neither presented with a tag cloud nor tag recommendations. This leads to the independent variable “search condition” with the three levels “Social”, “Individual” and “None”. As dependent variables, we observed semantic stabilization, recommender accuracy, confirmatory search, and polarisation.

Add a Bookmark

1

Address -- Required

Title -- Required

Tags -- Comma-separated

2

How trustworthy do you think is this resource?

0: not at all trustworthy 2 3 4 5 6 7 8 9 10: very trustworthy

3

Please provide your answer to every aspect that is addressed by the resource:

	What is the author's stance towards the aspect?			What is your stance towards the aspect?		
<input checked="" type="checkbox"/> Self-Optimization	very negative	neutral	very positive	very negative	neutral	very positive
<input checked="" type="checkbox"/> Cyborgization	very negative	neutral	very positive	very negative	neutral	very positive
<input type="checkbox"/> Intervene in Evolution	very negative	neutral	very positive	very negative	neutral	very positive
<input type="checkbox"/> Faith in Progress	very negative	neutral	very positive	very negative	neutral	very positive

Cancel Add Bookmark

About - Powered by SemanticScout

Fig. 1. Study environment: annotation interface.

3.2 Evaluation Measures

Semantic Stabilisation. While there is a multitude of metrics to evaluate semantic stability [34], few methods can deal with narrow folksonomies, where items are tagged only by the uploading user (as it is in our case). Lin et al. [21] present the Macro Tag Growth Method (MaTGM) that measures social vocabulary growth at a systemic level, looking at the social tagging system as a whole. In this study, experimental groups (i.e., “Social”, “Individual” and “None”) are observed as separate environments. The MaTGM is applied to compare the tag growth within these systems. For each group, the collected bookmarks (tag assignments) are sorted according to their timestamps. The tag growth after each bookmark, is calculated as a value pair $(tg_i, f(tg_i))$, where tg_i is the cumulative number of tags, and $f(tg_i)$ is the cumulative number of unique tags occurring in i bookmarks.

Recommender Accuracy. To evaluate the efficacy of the tag recommendation algorithms that operate either on social or individual tagging data, the performance metrics recall and precision [24] were applied. To calculate recall and precision, we determined for each bookmark the relation of tags recommended to a user for a Web resource to the tags that the user assigned to a resource.

Recall (R) indicates how well the recommendation supported the user, giving the relation between correctly recommended tags (i.e., the subset of recommended tags that the user assigned to the Web resource) and the set of tags the user needed to describe the Web resource.

$$R(T_{u,r}, \hat{T}_{u,r}) = \frac{|T_{u,r} \cap \hat{T}_{u,r}|}{|\hat{T}_{u,r}|} \quad (1)$$

Precision (P) is the number of tags that have been recommended correctly divided by the number of recommended tags.

$$P(T_{u,r}, \hat{T}_{u,r}) = \frac{|T_{u,r} \cap \hat{T}_{u,r}|}{|T_{u,r}|} \quad (2)$$

3.3 Behavioral Indicators

Confirmatory Search. Confirmatory search is described as the process of seeking information that is biased towards existing beliefs [29]. Prior research deduces confirmatory search in laboratory studies, by numerical comparisons of experimental and control groups' document selections, which confirm current beliefs or not [30]. With the environments' Annotation Interface (see Fig. 1) such data is tracked with every resource upload. In Eq. 3, we present one option to calculate confirmatory search (CS) with such data:

$$CS_{i,t} = \left(1 - \frac{|AS_{i,t} - US_{i,t}|}{diff_{max}}\right) * (1 - e^{-|AS_{i,t}|}) \quad (3)$$

Here, CS with respect to a Web resource i and a topic t is defined as the difference of a user's stance $US_{i,t}$ towards t and the author's stance $AS_{i,t}$ towards t with respect to i . The second term includes an exponential function to increase the impact of strongly polarised Web resources on the one hand, and to subtract out resources with a balanced author stance (i.e., $AS_{i,t} = 0$) on the other hand. CS of a user u is calculated as the mean value over all observed topic events of u , as formalized in Eq. 4:

$$CS_{u,t} = \sum_{i=0}^n \frac{CS_{i,t}}{n} \quad (4)$$

Polarisation. Equation 5 gives a value for a user's polarisation. In line with [8], we understand polarisation as a twofold construct that is characterized by a state and a process. Polarisation as a state is defined by the distance of an

attitude position to a theoretical maximum of that attitude. The polarisation process $\Delta Pol_{u,t}$ describes the development of the attitude position in relation to this theoretical maximum over time. This is represented by the normalized difference of the user’s stance towards t captured at the first topic event to the n^{th} one.

$$\Delta Pol_{u,t} = \frac{|USt_{n,t} - USt_{0,t}|}{diff_{max}} \quad (5)$$

Equation 6 calculates a users’ polarisation as a combination of polarisation change and the extremes of the final user stance USt_n .

$$Pol_u = \frac{w_1 * \Delta Pol_u + w_2 * \frac{|USt_n|}{o_n}}{2} \quad (6)$$

where o_n is the number of possible absolute values (except zero) the user or author stance can capture.

3.4 Study Environment

The study environment is based on the open-source social bookmarking system *SemanticScuttle*¹, which is a collaborative platform to collect and share information online. To fit the requirements of the experimental setting, it was adapted in its annotation and browsing interfaces and expanded by matching log data services. This has been realized with adaptations in the platform’s range of functionality, in its database, user interfaces and the deployment of data logging services. To support users’ reflection on their collected Web resources, the Annotation Interface was adapted as illustrated in Fig. 1. It is designed to enable the observation of students’ ability in assessing the credibility of information, their tendency of polarisation during information search and information consumption as well as their ability to embed new concepts into their knowledge representation. Figure 1 illustrates the interface that takes basic information about the resource in input fields labeled with “one”. It consists of the URL, a name and freely chosen keywords (i.e., tags). Tags assigned by a user can be used to observe particular semantics of the opinion formation process. Marked with “two” is a slider that asks for the user’s perception of trustworthiness towards the selected resource. The slider ranges from 0 (“not at all trustworthy”) to 10 (“very trustworthy”). In combination with the resource’s URL, this information can be used to better understand users’ ability to evaluate the quality of information and information sources. In the last block marked with “three”, a set of topic aspects is presented to the user. These aspects vary with the search topic and therefore, can be configured by the site administrator. A bipolar rating scale is given by two sliders, ranging from -3 (“very negative”), over 0 (“neutral”) to 3 (“very positive”). The sliders ask for the author and user stance towards single aspects and allow for inferring confirmatory search behavior and polarisation. Further details on the study environment and its technical adaptations are given in Kopeinik et al. [17].

¹ <http://semanticscuttle.sourceforge.net/>.

3.5 Data Characteristics

Table 1 shows the data characteristics separated according to the three experimental conditions: “Social”, “Individual” and “None”.

Table 1. Illustration of the data characteristics, given by the number of users ($\#users$), bookmarks ($\#bmks$) and tags ($\#tags$), the average number of topics covered by a user ($\overline{T_{user}}$) and the captured events of topic attitudes ($\#E_{TA}$).

	$\#users$	$\#bmks$	$\#tags$	$\overline{T_{user}}$	$\#E_{TA}$
Social	35	407	1078	3.86	603
Individual	35	362	753	3.83	527
None	21	276	895	3.76	297

The final dataset combines collected data from students of four participating school classes. Students of each class were randomly assigned to one experimental condition.

4 Results and Discussion

This section presents the result of our study that examines the impact of shared artifacts on aspects of information selection and opinion formation processes.

4.1 RQ1: What Is the Impact of Shared Artifacts (Social Tags and Bookmarks) on a Coupling Between Confirmatory Search and Polarisation in a Collective Search?

Based on prior empirical work, we expected a coupling, i.e., systematic relationship between participants’ tendency towards confirmatory search (CS) (Eqs. 3 and 4) and polarisation (Eqs. 5 and 6). According to our theoretical assumptions (see Sect. 2.1), we predicted this coupling to be smaller under the “Social” condition, when users are supported by social tag recommendations and shared bookmarks, than under the “Individual” and “None” search condition. To test both of these predictions, we performed a linear regression of CS (criterion) on the continuous predictor “polarisation” and the categorical predictor “search condition”, and included an interaction term to quantify potential differences in the slope (as an index of the CS-polarisation coupling) across the three search conditions. 91 data points have entered the regression ($N_{None} = 20$, $N_{Individual} = 35$, $N_{Social} = 36$ participants) explaining about 50% of variance in polarisation (adjusted $R^2 = .467$, $p < .001$). This effect is represented well by the scatter plot of Fig. 2, which draws polarisation against CS and whose best fitting regression lines indicate a positive and moderate slope for each of the three conditions. The outcome for the “None” condition is represented by the steep red line, for which

we have found a standardized beta coefficient of $\beta = 1.07$ ($t = 5.86, p < .001$). The other two lines appear to be flatter ($\beta_{Individual} = 0.65; \beta_{Social} = 0.46$), suggesting an interaction between the two predictors of CS and search condition. In line with our expectation, however, this decrease in the CS-polarisation relationship is significant only under the social condition ($t = -2.59, p < .05$) but not under the individual ($t = -1.98, n.s.$). We can therefore conclude that (i) similar to [33], the present study provides evidence of a CS-polarisation coupling too, which (ii) gets mitigated through the influence of shared artifacts (under the “Social” condition).

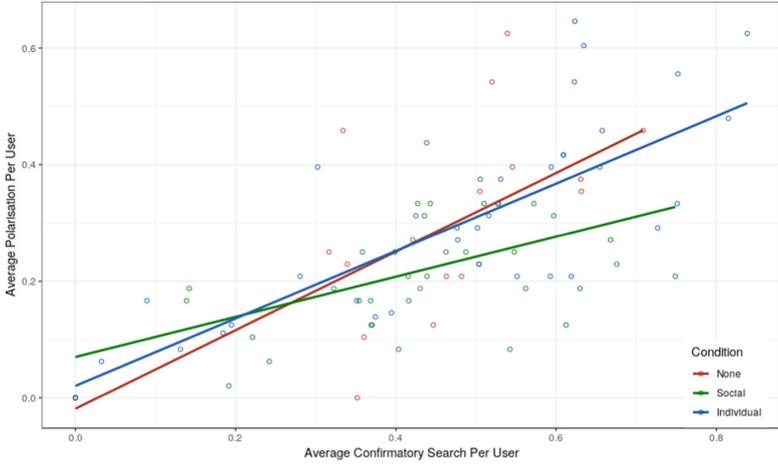


Fig. 2. Correlation between confirmatory search and polarisation illustrated in the three experimental conditions.

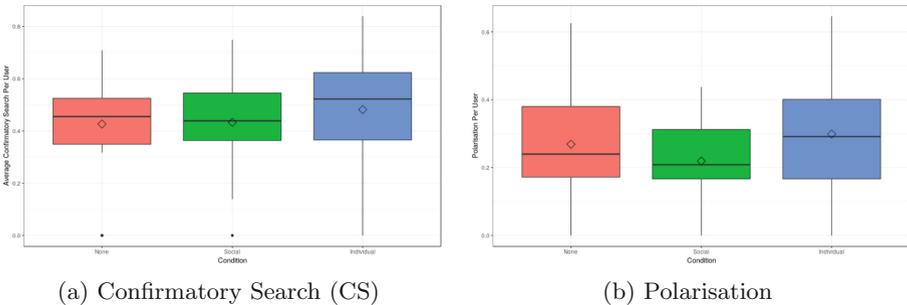


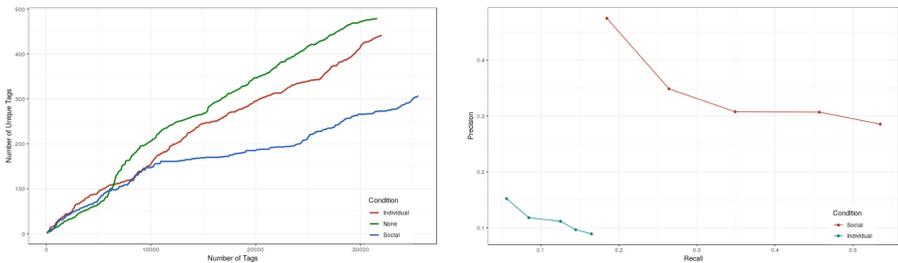
Fig. 3. Box plots depicting medians and quartiles of the CS and polarisation scores separately for the three groups “None”, “Social”, and “Individual”.

As we now gained clear evidence that the CS-polarisation coupling is looser under the “Social” than the other two conditions, we further examined whether these group differences are also reflected by differences in the overall range of

values in the two variables. Given that the two variables fuel each other in this coupling, the main group effect for both polarisation and CS should come about, with relatively smaller levels under the “Social” condition.

We find a strong effect in the case of polarisation and a weak effect in the case of CF. First, the descriptive results, as represented by the plots in Figs. 3a and b, point towards a pattern that is in line with both expectations, i.e., the median is relatively lower in the social than in the other two groups. However, the test of significance, for which we have run a non-parametric, i.e., the Kruskal-Wallis test, to take into account the apparent violation of the equal variance assumption (see the box plots’ interquartile ranges), has underlined this pattern only in case of polarisation ($\chi^2(2) = 7.20, p < .05$) but not of CS ($\chi^2(2) = 4.55, n.s.$).

We conclude that a relatively stronger CS-polarisation coupling indeed manifests in a higher CS value range and that prospectively, the same can be anticipated for polarisation as well, given a sufficiently long period of observation and a relatively more extensive sample of participants. Of course, the latter anticipation needs to be validated in future work.



(a) Macro Tag Growth Method shows the semantic stabilization on a system level. The graphs plot the search conditions: “None”, “Social” and “Individual”.

(b) Recall/Precision plots showing the accuracy of recommendation algorithms in the “Social” and the “Individual” experimental condition.

Fig. 4. The impact of shared artifacts on vocabulary development in the individual and collective search task.

4.2 RQ2: Can Shared Artifacts (Social Tags and Bookmarks) Be Applied to Reduce the Vocabulary Problem in Collective Search Processes?

We address this research question considering two angles. First, we look at the semantic stabilization itself. Second, we investigate which recommendation approach can best support the process of semantic stabilization in the context of online information. Figure 4a illustrates the tag growth in the three experimental conditions represented as Macro Tag Growth Function. Comparing the vocabulary development of the groups, we find that while initially, the graphs overlap in all three groups, students in the two groups that receive tag recommendations (i.e., “Social” and “Individual”), start to introduce less new vocabulary in relation to tags than the group with no recommendations. This effect is even

stronger for the group in the “Social” condition. In other words, we can observe two phenomena: (i) students in the “Individual” condition reuse their own words more frequently and thus, apply a more consistent terminology in their personal resource annotation; (ii) students in the “Social” condition start to reuse and pick up the vocabulary of their peers faster. This demonstrates the positive effect of social tag recommendations on semantic stabilization. In summary, results show the benefit of tag recommendations on semantic stabilization, even when applied in the context of individual information scenarios, which implies that previous findings [18] can be generalized to a collective information setting.

Results presented in Fig. 4b pay attention to the efficiency of provided tag recommendations. The recall/precision plot highlights the strong performance of tag recommendations based on the collaborative vocabulary of a group (“Social” condition) in comparison to recommendations based on individual tag traces. To the best of our knowledge, such an effect has not been reported in any other TEL recommender study. We explain the effect with the open and dynamic nature of the information search task itself. Students were asked to research a given topic and related aspects throughout four school lessons. This constitutes an explorative learning endeavor, where information takes place within a specific scope, while also developing over time. Consequently, we observe that social tag recommendations can support the explorative process within the information task, while tag recommendations that are based on the historic word traces of an individual are not suited to depict such continuous development.

5 Conclusion

In this paper, we presented an approach to study opinion dynamics in a collaborative search task. In a two-week real-life classroom study, we collected data on students’ information behavior, their ability to evaluate information, and their tendencies towards confirmatory search and polarization. Based on the data that we gathered in the presented semi-controlled study environment, we proposed a formalism to calculate confirmatory search and polarisation in information behavior and found a strong correlation between the two constructs. This is in line with prior research and constitutes a proof of concept of the platform’s field application. We understand the presented platform with its functionality and the formalism of behavioral indicators as a starting point for further discussion and exploration towards understanding and supporting critical information behavior in formal and informal learning. Gained insights will contribute to the prospective design and development of depolarising discourse services, learning analytics services, and visualizations.

Moreover, we found a positive impact of shared artifacts on polarisation and semantic stabilization. This highlights the benefit of social influence on the early ideation process. In the future, we plan to corroborate our findings in long term studies.

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