Tallinn University
School of Digital Technologies

Confirmatory Web Search and Polarisation: A Correlational Study of a Collaborative Search Task

Master thesis

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Tallinn - Autumn 2017

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Acknowledgement

I would like to express my deep sense of gratitude for my supervisors, Paul Seitlinger, and Tobias Ley, for their constant support and guidance.

For my colleagues at work, friends and family, who were a great emotional and moral support for me.

Table of contents:

List of Tables:

List of Figures:

Chapter 1

Introduction:

Recent years have recorded an increase in using Social Networking Sites (SNSs) (SNSs; Boyd & Ellison, 2007) and other online forums as a space for online discussion, opinion formation and interaction with others. Irrespective to our geographic location, we can gather online to view, share and discuss information in a virtual exchange of opinions and participate in deliberative democracy (Semaan, Bryan, Robertson, Douglas & Maruyama, 2014).

During online discussions, people interact with content shared by others, get influenced by this content, and then, through their own interactions influence others (Danescu-Niculescu-Mizil, West, Jurafsky, Leskovec & Potts, 2013). 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, a notion coined by Peter Dahlgren. Following Habermas' (1962/1989) work, Dahlgren (2005) defines the public sphere as "a constellation of communicative spaces in society that permit the circulation of information, ideas, debates, ideally in an unfettered manner, and also the formation of political will" (Dahlgren, 2005, p. 148).

Though SNSs were not meant in the first place to support processes of a public sphere, they are assumed to cause inadvertent exposure to political difference (Brundidge, 2010) and thereby, to support more deliberate decision-making that draws on alternative information sources (De Liddo & Buckingham Shum, 2013).

In contrast to this positive view of SNSs as a public sphere, other authors contest this scenario of deliberation (e.g., Nikolov, Oliveira, Flammini & Menczer, 2015). Specifically, they argue that participants in online discussions show selective attention toward prior viewpoints, mainly engage with like-minded people and exhibit closed-mindedness about alternatives (MacKuen, Wolak, Keele & Marcus, 2010). This brings about a process, which is denoted polarisation, moving people towards extreme positions or attitudes. One major reason for polarisation is confirmatory search, i.e., the selective exposure to partisan information (e.g., Huckfeldt, Mendez & Osborn, 2002; Stroud, 2010). While the tendency to selectively expose ourselves to the opinion of like-minded people was present in the pre-digital world (Hart et al., 2009; Kastenmüller et al., 2010), the ease with which we can find, follow, and focus on such people and exclude others in the online world may enhance this tendency, through filtering algorithms that can amplify our biases.

Through such selective exposure to consonant views, initial doubts continuously give way to a growing confidence into one's own opinion, leading a person to strengthen her / his original position and attitude (Stroud, 2010). A prominent cognitive explanation of such confirmatory information search bias is the psychological phenomenon of cognitive dissonance (Festinger ,1954; Xiao et al., 2012), according to which people feel stressed when faced with divergent opinions.

Political scientists who take this pessimistic perspective on SNSs assume that the functionalities of social media, such as personalized information filter (Mutz & Martin, 2001), resonate with the human motive of reducing cognitive dissonance and thus, reinforce people in performing confirmatory search. As a consequence, users of an SNS run the risk of getting locked into a perpetual echo chamber (Huckfeldt et al., 2004), a metaphor for an interpersonal phenomenon where other people's opinions become echoes of one's own and start reinforcing instead of challenging prior beliefs (e.g., Nicolov et al., 2015). In many cases, such self-reinforcement fuels the phenomenon of group polarisation and political extremism (Sunstein, 2007).

1.1 Problem statement and research questions

Considering these two opposing positions, we can conclude that SNSs have the potential to foster both the public sphere and the echo chamber scenario (e.g., Kwak, Lee, Park & Moon, 2010). Therefore, particular socio-cognitive dynamics might be in play that unfold among the people and their expressed opinions and give rise to either a deliberate, open-minded or a biased, polarised information behavior (Wang et al., 2016). To derive design implications for depolarising discourse services, the goal of this work is to improve our understanding of such dynamics.

As already mentioned, political science studies (e.g., Huckfeldt et al., 2002; Stroud,

2010) have revealed a strong positive relationship between confirmatory search and polarisation: the more people are inclined to expose themselves to partisan information, the more likely they are to take on an extreme pro- or contra-stance. However, the empirical evidence of this relationship is solely based on data coming from survey studies (Wang et al., 2016), where samples of participants are asked for their stance towards a political topic on the one hand and for their information behavior (e.g., media consumption) on the other. And though such surveys take into account participants' online behaviour – e.g., how often they participate in online discussion fora or which online newspaper they frequently read –, it remains unclear whether results based on self-report actually generalise to dynamics of an online discourse.

Following the methodological approach of MacKuen, Wolak, Keele and Marcus (2010), this thesis applies a more direct and behavioral observation technique to provide more clarity on that issue and in further consequence, on questions around the design of depolarising discourse services. Specifically, the first research question of this thesis is *whether the positive relationship between confirmatory search and polarisation holds, if people's online behavior is directly derived from log file recordings of their search and opinion expression activities within a Web-based environment (**RQ 1**)**.***

To observe online search activities around a socio-political topic, 13 people have been involved in a particular collaborative search task: in the course of two weeks, they have had to discover, annotate and post bookmarks of Web resources (e.g., essays, videos, blog posts) on different aspects of a current and controversial topic, namely transhumanism, within a social bookmarking system (for details see Section 2.2.2 **Search Task and Bookmarking system**). To track processes of opinion formation over time, they have had to assign every collected resource to one of several (predefined) aspects (e.g., "cyborgization" or "intervene in evolution") and first, to indicate their current personal stance towards this aspect on a bipolar rating scale ranging from -3 (strong contra-stance) to +3 (strong pro-stance). To determine whether the act of collecting this resource has corresponded to a congenial media exposure (i.e., a confirmatory search), in another step, they also have had to indicate the stance of the resource's author on the same bipolar rating scale.

Recording these activities in a log file has allowed for computing and correlating indices of confirmatory search (e.g., average distance between personal and author stance) and polarisation (e.g., drift towards +/-3 along consecutive bookmarks) and thus, for investigating RQ 1. The methodological byproduct of this approach, namely the definition and test of behavioral indicators for quantifying discourse-related constructs, is a further important contribution of this thesis: If these indicators turned out to be reliable and valid, they would lay the ground for a depolarising discourse service that is able to interpret user behavior automatically and trigger (search) assistance in an adaptive and dynamic way.

Finally, the thesis also aims to investigate particular variables that affect and are affected by the coupling of confirmatory search and polarisation within a cyclical chain of socio-cognitive processes. Referring to depolarising effects of inadvertent exposure during online search (e.g., Brundidge, 2010), we assume that the extent of this coupling can be anticipated more accurately, if processes related to memory and learning, especially to a person's familiarity with a given topic, are taken into account: Confirmatory search is usually conceptualised as a strategy to reduce cognitive dissonance (Festinger, 1964;), i.e., to avoid negative feelings in response to unfamiliar perspectives on a given topic. Consequently, the familiarity with a given topic as well as processes increasing such familiarity should be associated negatively with the tendency to perform confirmatory search. With respect to the design of a depolarising discourse service, such processes should be helpful to mitigate the coupling between confirmatory search and polarisation, which Stroud (2010) denotes the spiral effect. *The second research question therefore is whether empirical evidence can be found for a model, which embeds the spiral effect (as formulated by RQ 1) into a cyclical chain of socio-cognitive dynamics, in which learning processes related to familiarity (with a topic) and the spiral effect mutually affect each other (**RQ 2**)?*

The subsequent section presents this non-linear model in more detail in order to derive the hypotheses of the thesis, whose empirical test will be described and discussed in sections methods and results, respectively.

1.2 A model of nonlinear dynamics of confirmatory search and polarisation: Hypotheses:

The collaborative information search to be observed in this thesis has taken place in a shared Web environment (social bookmarking system) that, over time, has got populated by joint artifacts, such as shared bookmarks or social tags. Referring to social tagging studies, joint artifacts bear the potential to raise individuals' awareness of each other's contributions and trigger reflections upon them (e.g., Fu & Dong, 2012; Seitlinger & Ley, 2016). We therefore assume that they might play a substantial role in mitigating confirmation biases and the emergence of echo chambers.

One important reason for this assumption is that online search can lead to inadvertent exposure to alternative viewpoints (Brundidge, 2010), causing cognitive conflicts (e.g., Schweiger et al., 2014) and inspiring new ideas for rethinking prior beliefs. The latter assumption can be derived from studies that demonstrate interactions with joint artifacts to have significant effects on associative structures in long-term memory (e.g., Seitlinger, Ley & Albert, 2015) and more specifically, to increase the familiarity with diverse aspects of a topic by increasing the strength of previously weak associations around the topic (Seitlinger et al., 2017).

Therefore, my first hypothesis (H1) is: **the more people interact with joint artifacts, the more familiar with different aspects of a search topic they will get, i.e., the more (mental) associations to the topic they will forge. (see** Figure 1.1)

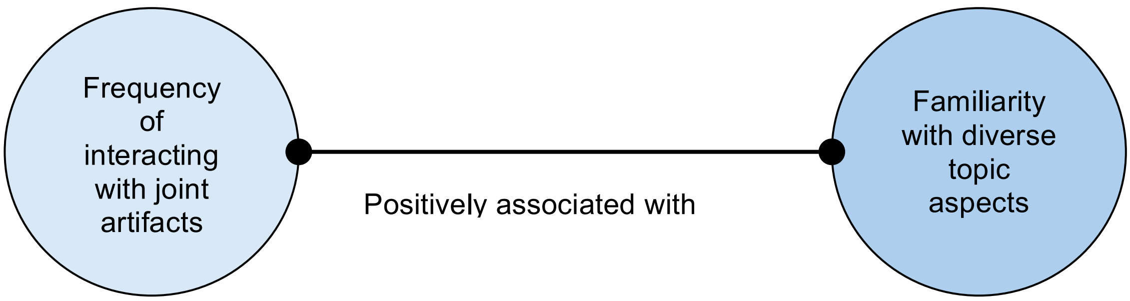

Figure 1.1. First hypothesis (H1) on a positive association between interactions with other people's artifacts and increases in familiarity with diverse aspects of a topic

As stated above, confirmatory search is regarded a cognitive-affective strategy to reduce negative feelings and cognitive dissonance in response to unfamiliar ideas around aspects of a topic. Hence, an increase in one's familiarity with diverse topic aspects should reduce one's need for performing a confirmatory search. A more cognitive argument for the mitigating effect of familiarity (on confirmatory search) can be found in SNIF-ACT (Fu & Pirolli, 2007), a cognitive model of Web-based information search. SNIF-ACT assumes that a person's information goal is constituted by currently available memory units, i.e., associations that can be brought easily into one's current attentional focus. According to this view, confirmatory search would simply be the consequence of a person's failure to retrieve alternative units from memory – a cognitive constraint that could be compensated for by increasing the strength of previously weak associations, i.e., a person's familiarity with alternative topic aspects. Taken together, my second hypothesis (H2) is: **The more familiar a person is with a given topic, the weaker is her/his confirmatory search bias**. (see Figure 1.2)

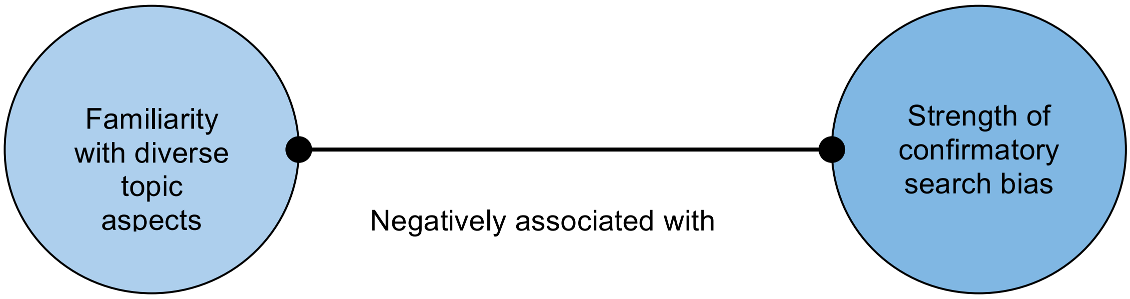

Figure 1.2. Second hypothesis (H2) on a negative associations between increases in familiarity and the strength of a confirmatory search bias

Given the interaction with joint artifacts increases familiarity with a topic (H1) and in further consequence, decreases the confirmatory search bias (H2), users should also be less prone to exhibit a polarised viewpoint. This assumption seems to be plausible, especially if the construct of polarisation is regarded as an overestimation of the probability that attitudinally congruent arguments are true (e.g., Stroud, 2010). Referring to contemporary and human memory-based accounts of probability judgments and decision making (e.g., Thomas, Dougherty & Buttaccio, 2014), such overestimation can be attributed to a retrieval failure of attitudinal incongruent arguments (so-called contenders): Failing to populate one's attentional focus with such contenders yields a very constrained set of attended arguments and thus, a biased (mental) reference that lets congruent arguments appear unproportionately likely to be true. As a consequence, this "narrow" and biased attentional state should make the person take on an even more polarized stance towards the topic. In other words, and to frame it more positively, as a person's confirmatory search bias gets weaker and she or he increasingly starts exposing her- or himself to counter-arguments, it should become easier for the person to populate the attentional focus with a more balanced ratio of attitudinally congruent and incongruent arguments. The consequence should be behavioral signs of depolarisation in opinion expression.

Therefore, my third hypothesis (H3) is: **the weaker a person's confirmatory search bias is, the more balanced (i.e., the less polarized) her or his view on the topic is.** (see Figure 1.3)

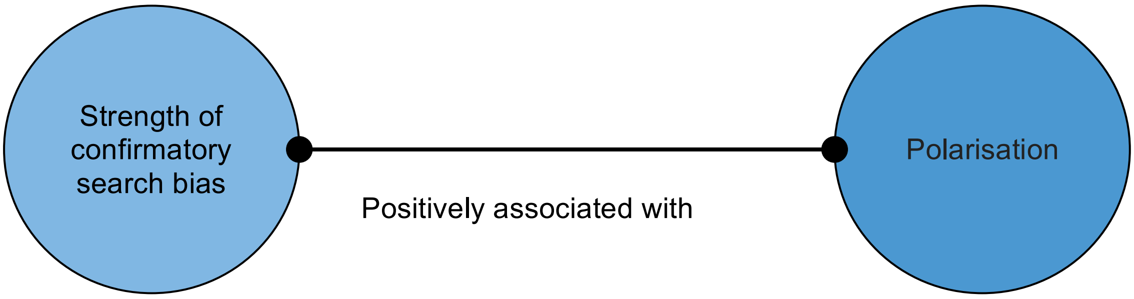

Figure 1.3. Third hypothesis (H3) on the positive relationship between the strength of a confirmatory search bias and polarization

Finally, and to close our cyclical chain of hypotheses, we assume this anticipated coupling of confirmatory search and polarisation (H3) to have in turn an effect on people's tendency to interact with joint artefacts and, in particular, expect depolarisation to increase the frequency of interactions with joint artefacts. The cognitive reason behind this expectation is that depolarisation is accompanied by a somewhat higher subjectively experienced level of uncertainty (e.g., Stroud, 2010) with respect to both the attitudinal congruent and incongruent arguments. Referring to Markant and Gureckis (2014), an increased level of uncertainty increases people's motivation to explore, i.e., continue information search (e.g., to close their knowledge gaps). In the current setting, this increased motivation to explore should manifest in a higher frequency of interactions with joint artefacts. Hence, my fourth hypothesis is: **“the more balanced a person’s view of a given topic is, the more likely she/he is to interact with joint artifacts.”** (figure 1.4)

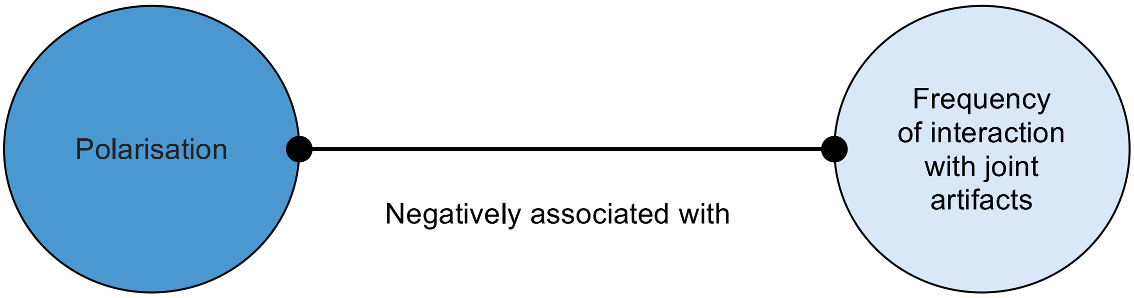

Figure 1.4. Fourth hypothesis (H4) on a negative relationship between polarization and a person’s tendency to interact with joint artifacts

This chain of socio-cognitive processes forms our cyclical model (figure 1.5), where the interaction with joint artifacts is hypothesised to increase a person's familiarity with a given search topic (i.e., the strength of previously weak associations; H1), to weaken a confirmatory search tendency (H2), to depolarise the person's stance towards the topic (H3), and finally, to close the circle, makes her or him interact more frequently with joint artifacts (H4).

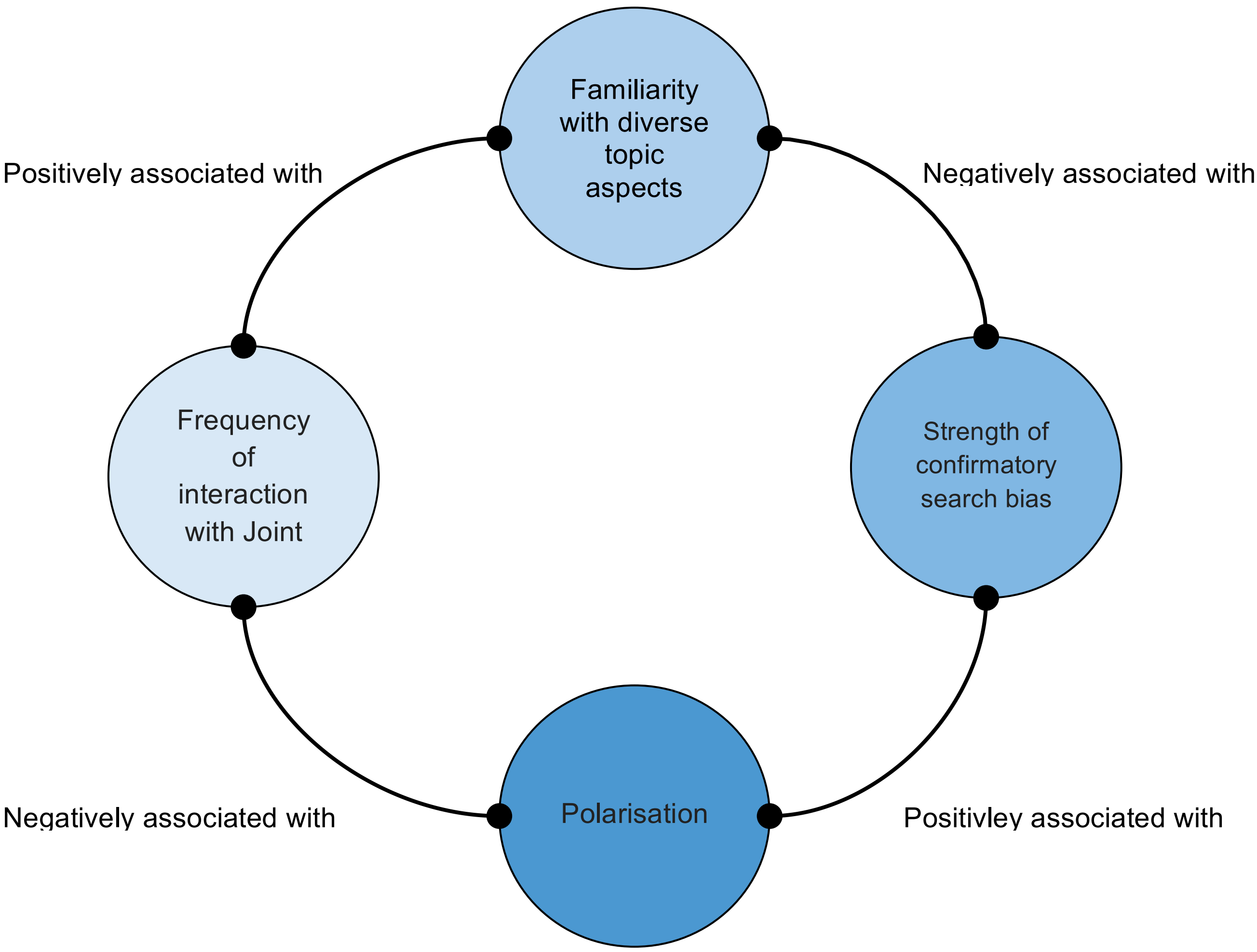

Figure 1.5: Cyclical model of socio-cognitive dynamics around the phenomenon of polarisation

The methods applied to test this model empirically will be described in the next section, followed by the report and discussion of the results in sections 3 and 4, respectively.

Chapter 2:

Methods:

To investigate the hypothesis according to the model that was suggested above (Figure 1.5), it was necessary to conduct a study in which participants continuously search over a long period of time. Using an online bookmarking system, participants had to collect and tag bookmarks of web resources on the topic of "Transhumanism", and then interact with others' tags and bookmarks, i.e., joint artifacts to become aware of their thoughts and contributions. Based on our assumptions, these joint artifacts will increase the likelihood of inadvertent exposure and thus, familiarity with topic aspects, thereby mitigating the spiral effect, i.e., the coupling between confirmatory search and polarisation.

2.1 Participants:

Recruitment took place via Facebook, I shared the call for participants with a detailed information about the study, couple of facebook groups for students were targeted as I expected they have the time to help. The initial number for participants was 20 participants, because I assumed that due to the workload, some would choose to leave the study later on.

Initial sample comprised of 21 participants who contacted us to participate in the study, the communication with the participants happened using email mainly and messaging platform (Facebook messenger), when they had questions to be answered.

Participants had to spend between 15 to 30 minutes on a daily basis to finish their tasks, and for that I considered reimbursing the participants for the time they are going to spend and that would serve as incentive to keep them engaged, the reimbursement took the shape of an amazon gift card worth 30 Euros, the conditions and agreements related to this gift card was mentioned in the informed consent.

Using google forms I sent out a survey to participants where I outlined the description of the study with the various tasks they are going to undertake, the dates for these tasks and the study's research goals. This was then followed by a survey to capture demographic data, where I asked the participants about their contact information, age, gender, place of residence, nationality, education, job, native language, and if they have any unanswered questions about the study. In the last section of the survey I outlined
the study's research goals and data management (according to the Estonian Code of Conduct for Research Integrity), and then asked the participants to sign using their names, to indicate that they have read and gave their informed consent.

After excluding the participants who did not continue the study, the final sample included 13 participants (46.15% females) with an average age of 26.3 years (SD=6.8, ranging between 21 and 48 years).

Participants were from 5 different nationalities (Estonia, Syria, Ukraine, Czech Republic, Columbia) and they resided in 7 different countries (Estonia, Syria, Canada, Czech Republic, Netherlands, Russia, Germany). They came from multidisciplinary academic background, such as Architecture, Mechanical engineering, Literature and Humanities, and chemistry, from whom 5 undergraduate students, 7 graduated, 2 with Master's degree and one doing her PhD.

In order to gather data in an anonymized way, participants were visible to each other using pseudonyms. Each pseudonym was generated by the participant her- or himself by combining the first letters of the mother's and father's first name as well as the personal birth year. The mapping between a user's pseudonym and her or his email-address, which was necessary for communicative reasons, was deleted after data gathering was completed.

2.2 Search Task and Bookmarking system:

Search Topic

For the purpose of this study we introduced the participants with the topic of Transhumanism as to be the focus of their search. This topic was chosen because it sparks a strong controversy between proponents and opponents of the idea to put science at the service of overcoming limitations of human nature. Additionally, as this controversy involves people from a wide spectrum of disciplines across science and humanities, we expected the topic to be appealing to participants independent of their backgrounds. For two weeks, the participants were instructed to collect Web resources (e.g., articles, blog posts, videos) within SemanticScuttle, i.e., the social bookmarking system, which deal with transhumanism and particularly, address at least one of five pre-defined aspects, namely "Artificial Intelligence", "Self-optimization", "Cyborgization", "Intervene in evolution", and "Faith in progress". These aspects were derived from a content analysis performed before study start on pertinent articles on transhumanism.

Adding and searching bookmarks within SemanticScuttle

To bookmark and annotate a resource, an annotation interface was used which was designed specifically for this study, it first prompted a participant to enter the URL, title and some freely chosen keywords, so-called tags, to annotate the bookmark. Below, the five aspects were listed (see Figure 2.2), from which the resource-related aspects had to be selected, i.e., ticked. Then, after selecting an aspect, the participant had to provide two ratings, one expressing the author's and one expressing the personal stance towards the aspect. As the figure shows, the corresponding rating scales were bipolar ranging from -3 ("very negative"), over 0 ("neutral") to +3 ("very positive").

This form of categorization, i.e., aspect assignment followed by the stance ratings, was used for analyses (i.e., calculating the indices of confirmatory search and polarisation; see next subsection) and exploited by a particular search functionality, namely the aspect-based search. This functionality is shown in Figure 2.1: each aspect was displayed as a clickable keyword within both a "Pro Arguments" and a "Contra Arguments" box, acting as a search aid to filter available resources. E.g., clicking on "Cyborgization" within the "Pro Arguments" box displayed all bookmarks that previous participants had assigned to the

“Cyborgization” aspect and regarded as a resource representing a positive stance towards “Cyborgization” – as indicated by a positive (i.e., > 0) author stance rating. An alternative (but rarely used) functionality that allowed searching bookmarks within SemanticScuttle was a conventional keyword-based search by typing in freely chosen keywords into the search box depicted in Figure 2.2 (circled number 1).

Participants were instructed to add one bookmark per day at least. Furthermore, they were instructed to regard other participants' contributions as inspiration sources during search and to explore them also on a daily basis by making use of either the aspect- or keyword-based search functionalities.

All bookmarks and tags had to be in English to enable interactions among all participants who were not native English speakers coming from different countries . This was made clear to the participants in a detailed introduction. Based on their academic level, I assumed that their level of English was good enough to participate in the study.

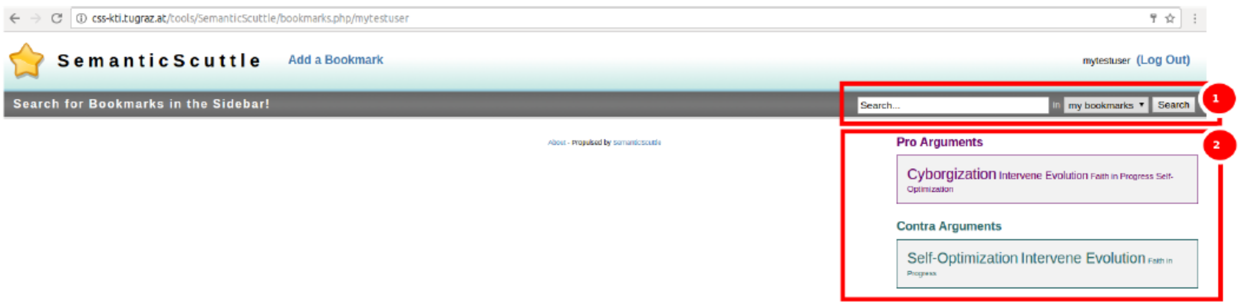

Figure 2.1. SemanticScuttle home page

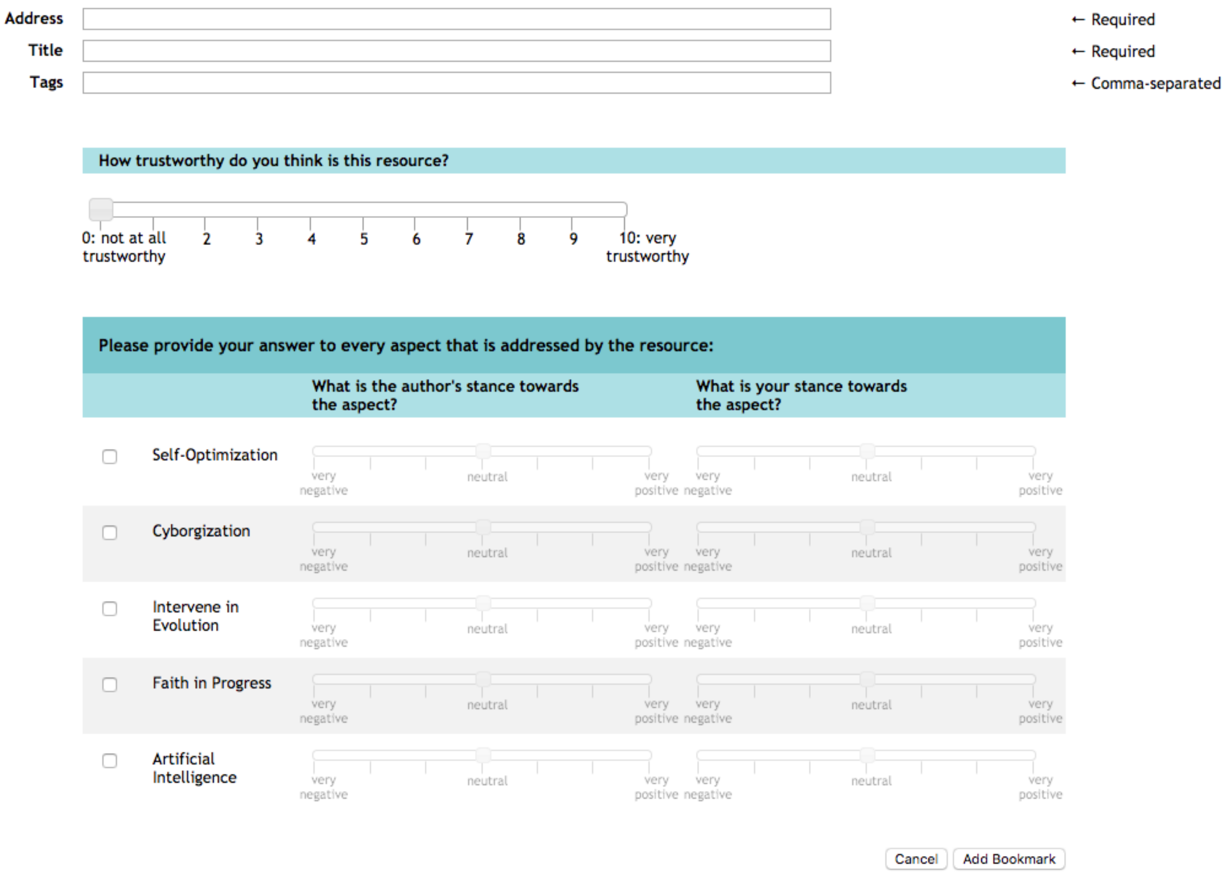

Figure 2.2. SemanticScuttle adding a bookmark

2.3 Behavioural Indicators and Statistical analysis:

(a) Interaction frequency: To measure interaction frequency for each participant, we extracted the logged data from the bookmarking system (SemanticScuttle), then we used R language to read and clean it. We then calculated the interaction frequency score by the number of times a user clicked on aspects, both pro or contra, to quantify the extent to which she or he interacted with others' bookmarks.

(b) Familiarity: To measure a participant's familiarity with the topic aspects, I made use of a technique already applied in Seitlinger et al. (2017). Specifically, participants had to perform an association test at three points in time: at the beginning (t0), after one week (t1), and by the end of the study (t2). In a Web-based association task, the five aspects were presented separately at the top of five consecutively presented pages (see Figure 2.5). For each aspect, i.e., on every page, the participant had 60 seconds to type as many associations as possible into a text field below. Figure 2.4 shows the instruction initially presented to the participants.

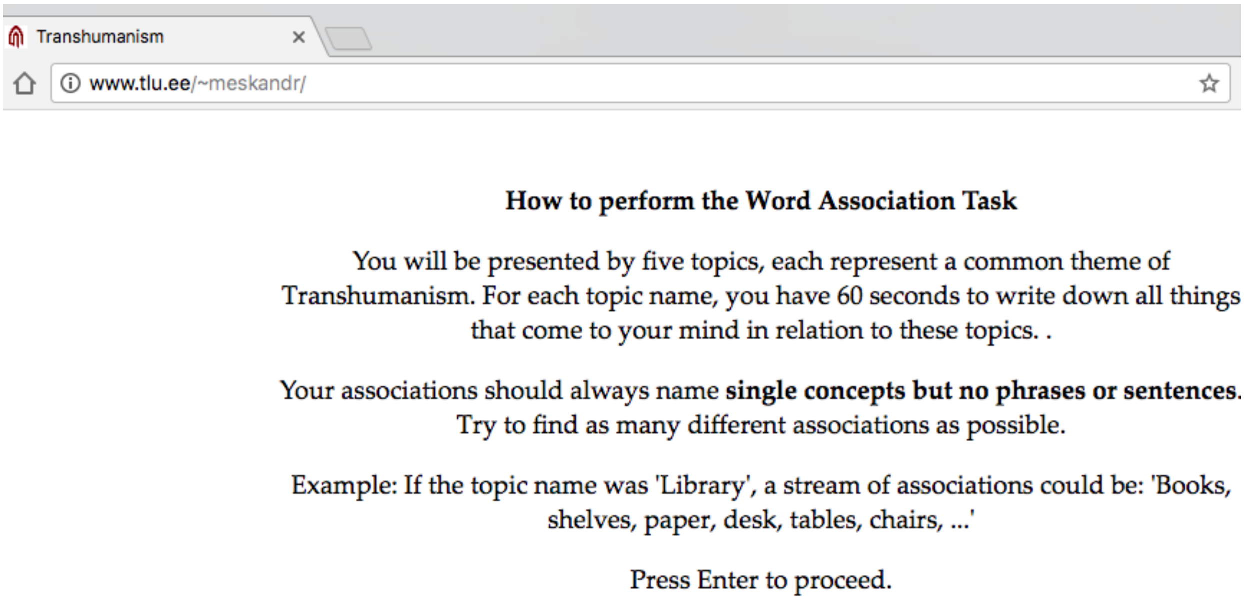

Figure 2.4. Word association task: Instructions

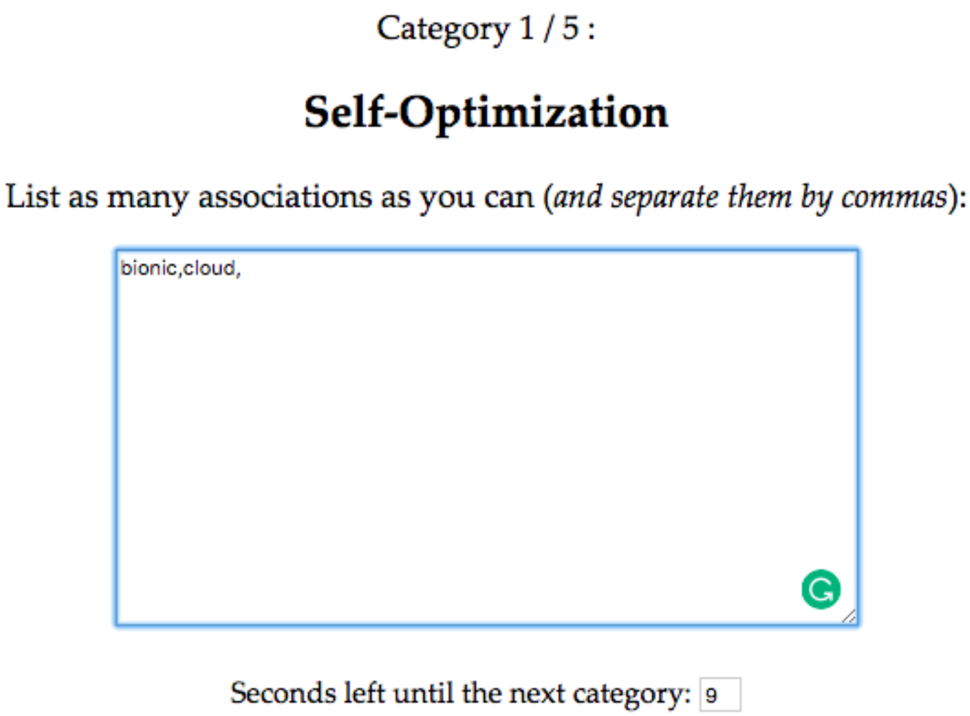

Figure 2.5. Word association task: Adding associations

To derive the familiarity score, the number of associations were counted, denoted nAsso, generated by a given participant to each of the five aspects at t0 and t2, and then, quantified the increase of familiarity by subtracting nAsso(t2) from nAsso(t0). The final familiarity score for a given participant was calculated by averaging these differences in nAsso across all five aspects.

(C) Confirmatory search; To get the confirmatory search bias score for a participant in a given aspect *i*, I determined the distance *D* (absolute value) between the participant's personal stance (PS) towards a given aspect *i* at bookmark *t*, denoted $PS_{i,t}$, and the rated stance of the author (AS) of the resource on the same aspect *i* at the next bookmark *t*+1, denoted $AS_{i,t+1}$. Second, to get an aggregated score of the participant's confirmatory search bias, I first inverted the distance into a similarity score *S* according to

$$S = 1/\left|PS_{i,t} - AS_{i,t+1}\right| \qquad \text{Equation (1),}$$

then, averaged S across all consecutive bookmarks – resulting in a mean S per aspect i, denoted S_i –, and finally, averaged S_i across all five aspects.

(D) Polarisation, this index recorded the polarisation for a participants in a certain aspect, measured by the drift towards +/-3 along consecutive bookmarks.

$$\frac{|\,0 - Sp1\; end\,|}{|\,0 - Sp1\; start\,|+1} \qquad \text{Equation (2),}$$

where *Sp1 end* and *Sp1 start* represent the first personal stance registered by a participant on a topic aspect and the last recorded personal stance on the same aspect respectively.

These four measures that were just mentioned relate to the four concepts mentioned in the model in Figure 1.5.

2.4 Design

To examine my four hypotheses on systematic associations among the four variables of "interaction frequency", "increase in familiarity", "confirmatory search bias", and "polarization", I decided to realize a correlational design. Specifically, for every hypothesis, each specifying a particular, i.e., positive or negative, association between two variables x and y, a bivariate Pearson correlation coefficient, denoted $r(x,y)$, was computed and tested on a significance level of 5%.

Chapter 3

Results:

The just described research design aimed to test the hypotheses of a positive correlation between interaction frequency and familiarity (H1), of a negative correlation between familiarity and confirmatory search (H2), of a positive correlation between confirmatory search and polarisation (H3), and finally, of a negative correlation between polarisation and interaction frequency (H4). Before reporting the results on these four hypotheses, the following provides a descriptive overview of participants' search and annotation activities within the social bookmarking system SemanticScuttle.

In the course of the two weeks, the 13 participants collected a total of 141 bookmarks (M =10.8, SD = 4.0). The bar diagram of Figure 3.1 shows that the average number of bookmarks collected by a participant was not equally distributed across the five aspects. Though the error bars (representing standard deviations) indicate a large variance among participants, they appeared to show a preference for the aspects of "Self-Optimization" and "Artificial Intelligence", followed by "Cyborgization", "Faith in Progress" and "Intervene in Evolution".

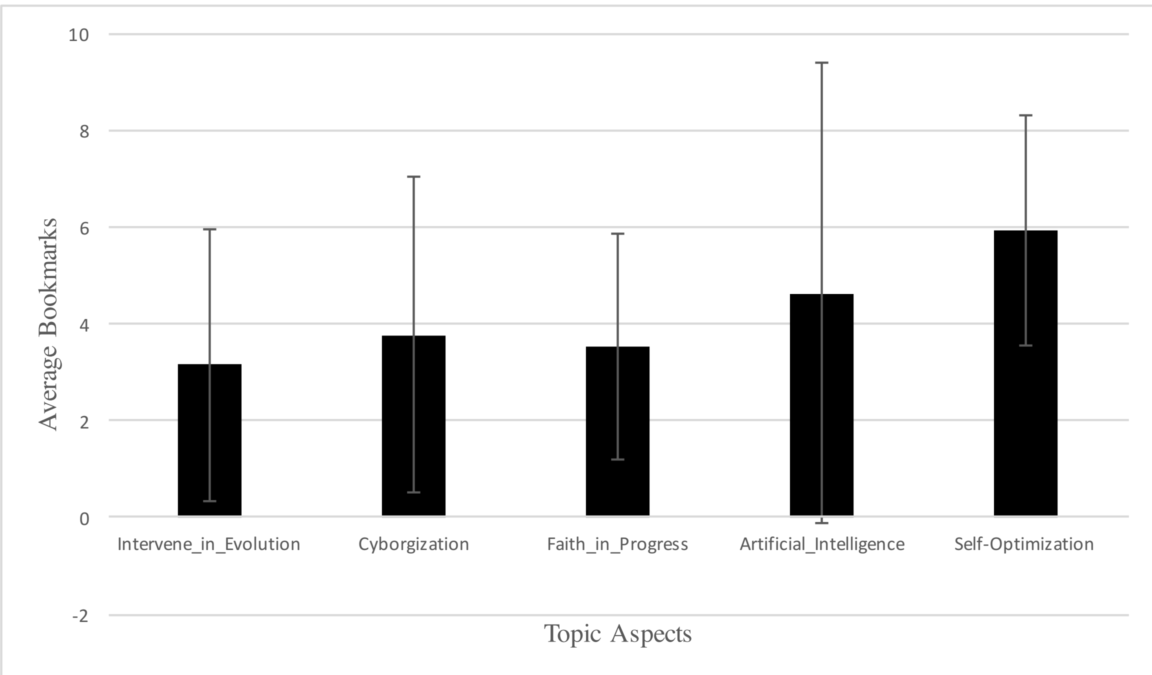

Figure 3.1. Average number of bookmarks per aspect (Error bars represent standard deviations)

Participants had to annotate their bookmarks when adding them to the system by means of social tags: by the end of the study, there were 267 tags logged in the system (M = 1.9 per bookmark, SD = 2.6) .

In order to investigate the way participants explored SemanticScuttle, we logged their clicks on joint artifacts, i.e., the social tags as well as the aspects (see number 2 of Figure 2.2). A frequency analysis revealed that while the aspects made up a popular feature to navigate the shared bookmark collection (301 clicks in total; M=4.6 clicks per participant, SD=3.4), the tags were more or less neglected as a search aid, resulting in not more than a total of 42 clicks. As a consequence, I decided not to include tag clicks into further statistical analyses and to calculate the index of "interaction frequency" solely based on participants' aspect clicks.

To further my understanding of participants' aspect click behavior, I also examined the extent to which the number of pro and contra clicks was balanced and whether this extent varied across the aspects. Except for the aspect of "Faith in progress", Figure 3:1 suggests a strong tendency to explore pro arguments, where this disbalance was most strongly pronounced for the aspect of "Faith in progress".

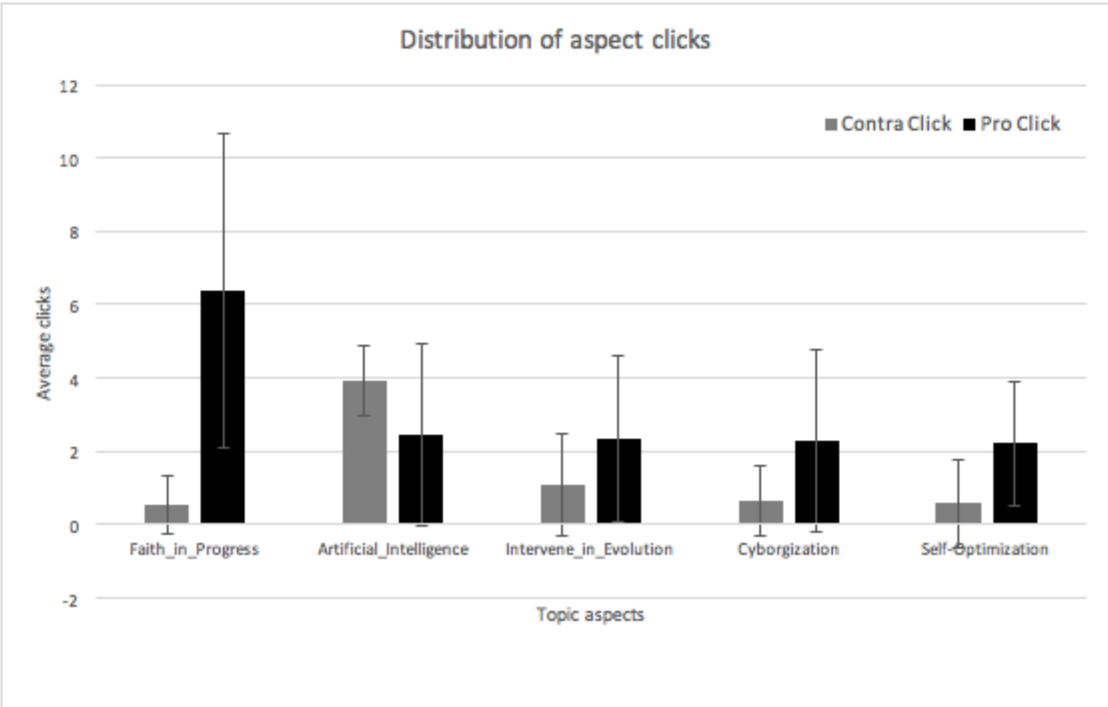

Figure 3.2. Average number of pro and contra clicks per aspect.

Note. Error bars represent standard deviations.

Derived from their change of stance from the start to the end of the study period, when adding bookmarks on each aspect, participants scored almost a similar polarisation score on the different topic aspects, showing the highest score on Artificial intelligence, indicating that it could be the most controversial (Figure 3.3). Note that the scores are in absolute values and do not indicate the direction of polarisation, and that a positive value does not mean that participants changed on average to positive side, but rather that they shifted slightly to either more positive or more negative.

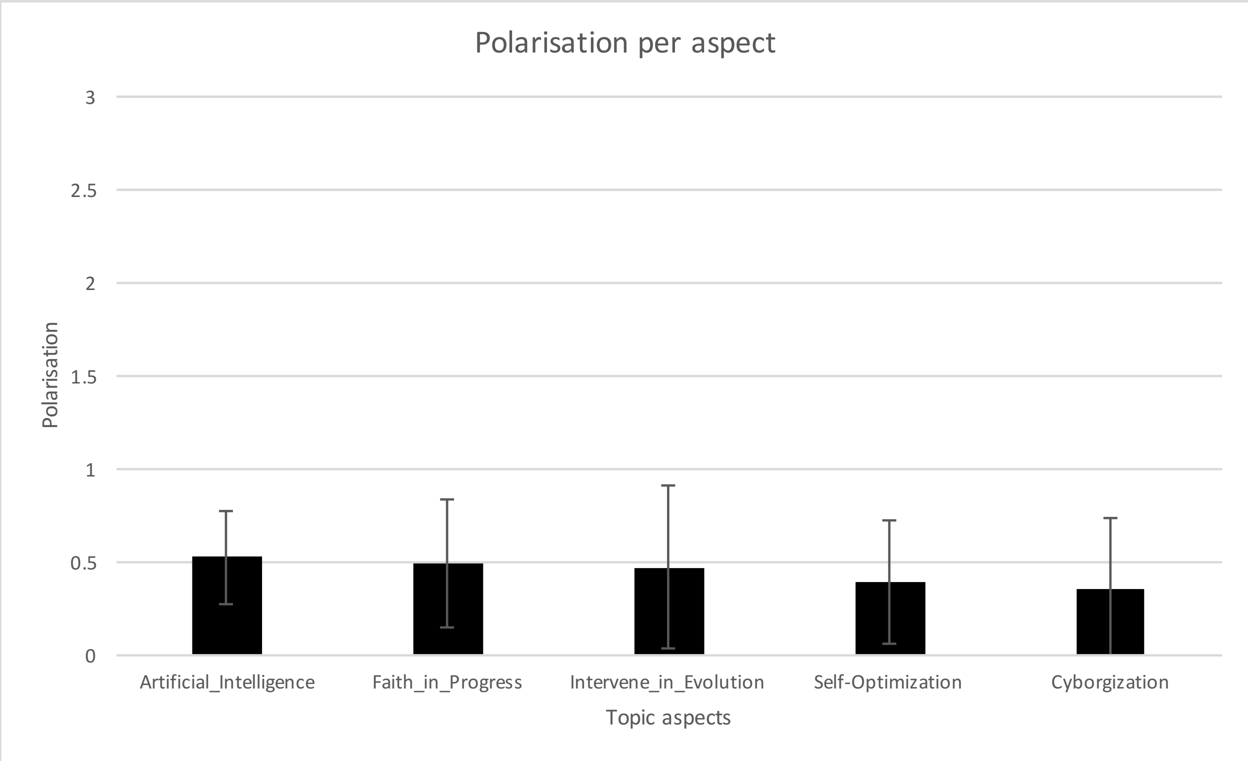

Figure 3.3. Average Polarisation score per aspect.

Note. Error bars represent standard deviations.

3.1 Hypothesis H1:

Our first hypothesis was that **the more people interact with joint artifacts, the more familiar with different aspects of a search topic they will get, i.e., the more (mental) associations to the topic they will forge.**

The variables included in this hypothesis are Interaction Frequency and Familiarity. Based on the just described descriptive analysis, the index of Interaction Frequency was calculated per participant by first counting the number of pro and contra clicks on each aspect and then, averaging these counts across all five aspects. The index of Familiarity, on the other hand, was not based on log-file recordings but the free association task. Specifically, per participant and aspect, I determined the difference between the number of associations at the beginning and at the end of the study and then, aggregated these differences across all five aspects. The first and second row of Table 3.1 presents the mean, standard deviation and range of the Interaction Frequency and Familiarity index, respectively.

	Measured by	***M***	***SD***	**Min:Max**
Interaction Frequency	Number of clicks on aspects	4.63	2.08	1 : 9.4
Familiarity	The increase in mental associations	0.97	1.99	-1.4 : 5.4
Confirmation Bias	Distance between personal stance and author stance	0.53	0.20	0.28 : 0.97
Polarisation	The shift in personal stance	0.44	0.25	0 : 0.75

Table 3.1. Mean, Standard Deviation and Range for each of the four variables included in the study's hypotheses.

Figure 3.4 presents the scatter plot drawing each participant's Familiarity score against the corresponding Interaction Frequency score. In accordance with hypothesis H1, the best-fitting regression line indicates a positive relationship between the two measures: the more frequently a participant had clicked on a given aspect (to search for associated bookmarks), the higher was the increase of her or his associations to that aspect.

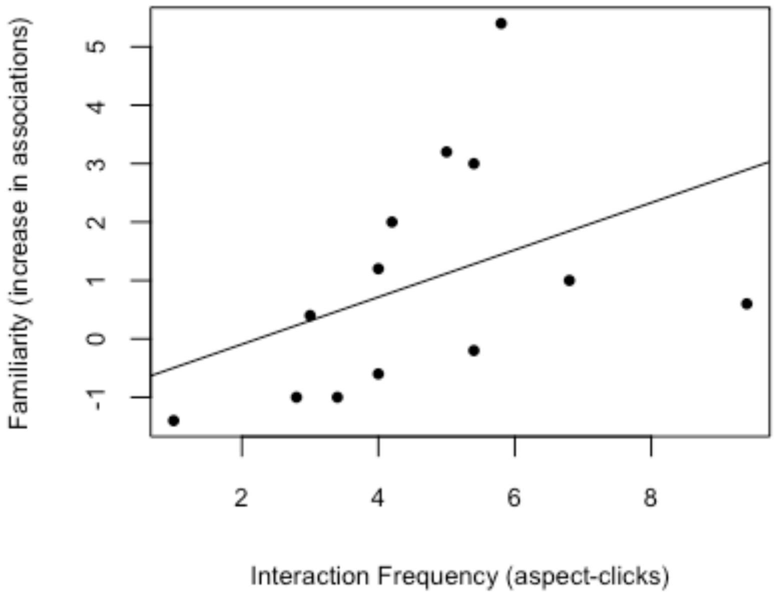

Figure 3.4. Familiarity score against Interaction Frequency score per participant.

Note. Each point represents one of the N=13 participants. Solid line represents best-fit regression line.

A Pearson's product-moment correlation coefficient was computed to further quantify this relationship. While pointing towards a moderate strength, the coefficient of r=.42 did not reach significance (see also Table 3.1).

3.2 Hypothesis H2:

My second hypothesis was that **the more familiar a person is with a given topic, the weaker is her/his confirmatory search bias.** We examined the relationship between Familiarity and Confirmatory bias score. To measure the Confirmation bias score for each user, I first calculated the score per aspect and participant according to Equation (1), then aggregated across aspects. The descriptive statistics on this confirmatory bias score are presented in the third row of Table 3.1.

Figure 3.5 depicts the scatterplot that draws each participant's Familiarity score against the corresponding Confirmatory Bias score. A glance at this plot reveals that, contrary to hypothesis H2, no systematic relationship seems to exist: A weak positive correlation coefficient of r=0.12, which is also represented by the small positive slope of the best-fitting regression line, in no way reaches significance (p=.69; see also Table 3.2). Thus, these results do not support the assumption that an increase of familiarity with different aspects of a topic helps mitigate people's confirmatory search bias.

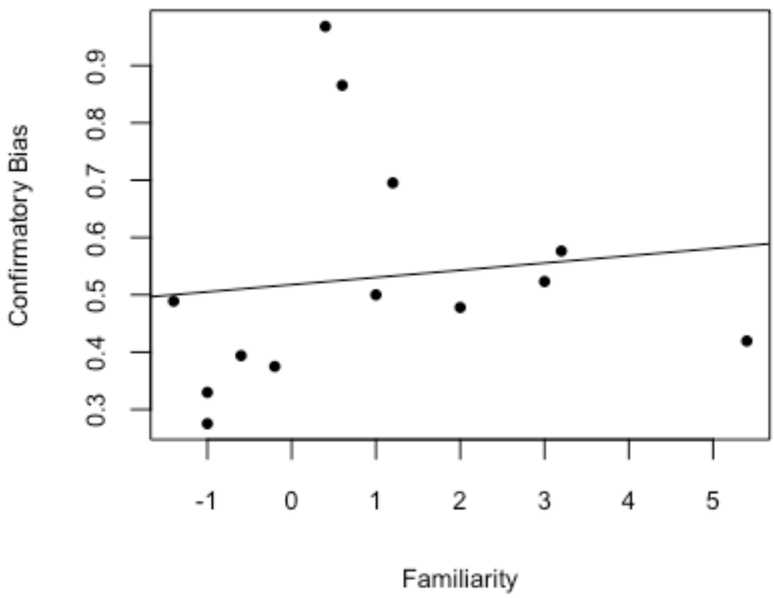

Figure 3.5. Scatter plot drawing Confirmatory Search Bias against Familiarity.
Note. Each point represents one of the *N*=13 participants. Solid line represents best-fit regression line.

3.3 Hypothesis H3:

My third hypothesis concerns the relationship between Confirmatory search and a person's tendency to be polarised on a search topic, stating that **the weaker a person's confirmatory search bias is, the more balanced (i.e., the less polarized) her or his view on the topic is**.

Polarisation index was calculated per aspect and participant using Equation (2) and then, aggregating across all aspect to get an average score per participant. The descriptive statistics on this index are presented in the fourth row of Table 3.1. The scatterplot in Figure 3.6, which draws the Confirmatory Search scores against the corresponding Polarisation scores, suggests a strong and negative relationship between the two measures. The correlation coefficient was r=-.79 and highly significant ($p < .01$) – as also indicated by the steep slope of the best-fitting regression line. Thus, in stark contrast to hypothesis H3, I observed an increase of confirmatory search on a given aspect to be accompanied by a less polarized stance towards that aspect.

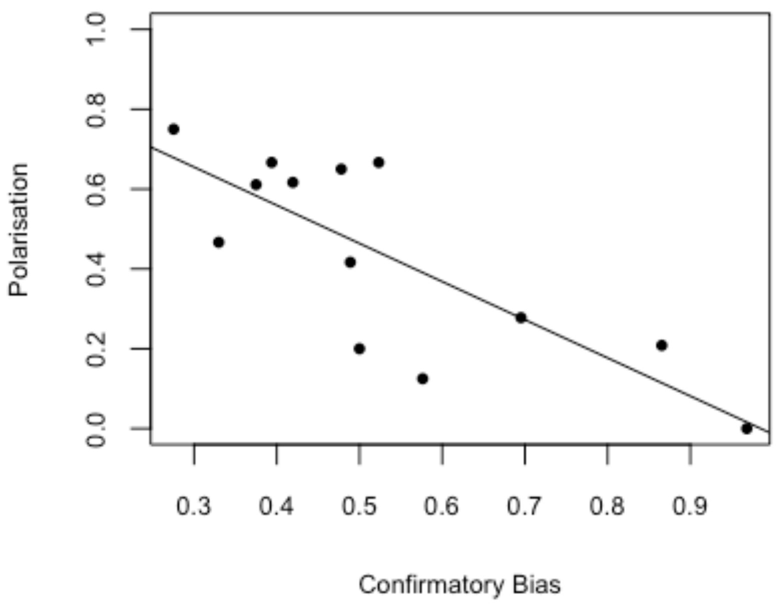

Figure 3.6. Scatter plot drawing Confirmatory Search Bias against Polarisation.

Note. Each point represents one of the N=13 participants. Solid line represents best-fit regression line.

3.4 Hypothesis H4:

The fourth and last hypothesis was that **the more balanced a person's view of a given topic is, the more likely she/he is to interact with joint artifacts.**

Again, we start presenting the results with a corresponding scatter plot depicting the two variables' relationship (Figur 3.7), which, descriptively, appears to be in accordance with hypothesis H4: The regression line and correlation coefficient suggest a negative association of both variables, which, however, is weak and does not reach significance (r=-.16, *n.s.*).

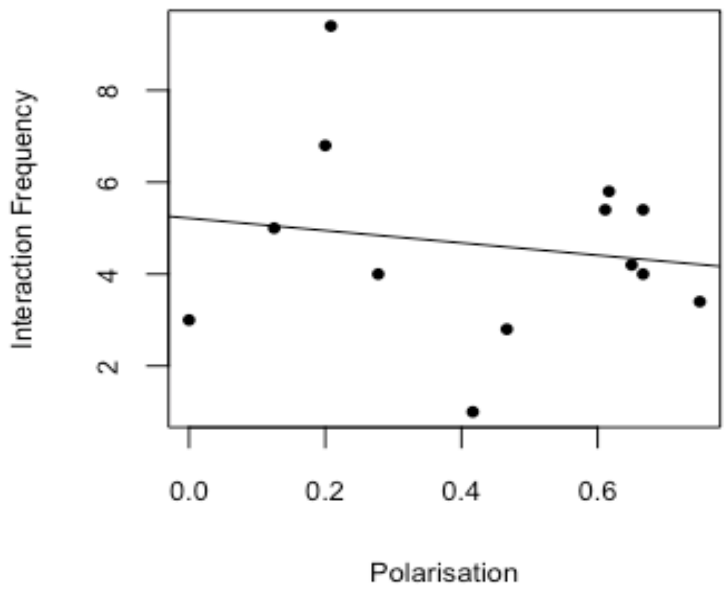

Figure 3.7. Scatter plot drawing Polarisation score against Interaction Frequency score.

Note. Each point represents one of the N=13 participants. Solid line represents best-fit regression line.

		Interaction Frequency	Familiarity	Confirmatory search	Polarisation
Interaction Frequency	*r*	1	0.42	0.28	-0.16
	p	.	0.15	0.30	0.60
Familiarity	*r*		1	0.12	-0.02
	p			0.69	0.95
Confirmatory search	*r*			1	-0.79**
	p			.	0.001
Polarisation	*r*				1
	p				.

N=13; **Significant at the .01 level

Table 3.2. Pearson correlations among investigated variables.

Chapter 4

Discussion

The goal of this study was to get a better understanding of the socio-cognitive dynamics when people form opinions in online environments. In particular, the goal was to further our understanding of the relationship between confirmatory search and polarisation that previous studies had already demonstrated.

Based on results of previous studies (e.g., Seitlinger et al., 2017), I expected that when collecting bookmarks in a shared search system, participants who interact with joint artifacts get more familiar with particular aspects of a search topic, i.e., exhibit an increase in mental associations (H1). Our results indicated a positive correlation between Interaction frequency and Familiarity, yet the correlation was moderate and showed no significance. But nonetheless the results are similar to the findings of Seitlinger and colleagues (2017) that under collaborative search conditions, participants show an increase of mental associations (i.e., familiarity with a topic). This increase in familiarity then was assumed to be coupled with a reduced confirmatory search bias (H2). The results, however, did not indicate a systematic relationship between the two corresponding measures. The third hypothesis (H3) assumed that when a person's confirmatory search bias was reduced, this person should show a more balanced and less polarised opinion in a topic, i.e., that there should be a positive correlation between confirmatory search bias and polarisation. Interestingly enough, the results showed the exact opposite, with a significant negative correlation between the two measures indicating that an increase in confirmatory search bias on a search topic is accompanied by a less polarised stance towards the aspect. Similar to the second hypothesis (H2), the results on the fourth hypothesis (H4) did not show a systematic relationship between the scores representing Polarisation and the frequency of interaction with joint artifacts. Nevertheless, the relationship's direction was in accordance with the initial assumption that a decrease in the polarisation score should be correlated with an increased tendency to interact with joint artifacts.

Based on these results, I revisited the socio-cognitive model of polarisation (Figure 1.5), and annotated on it to illustrate the results (see Figure 4.1).

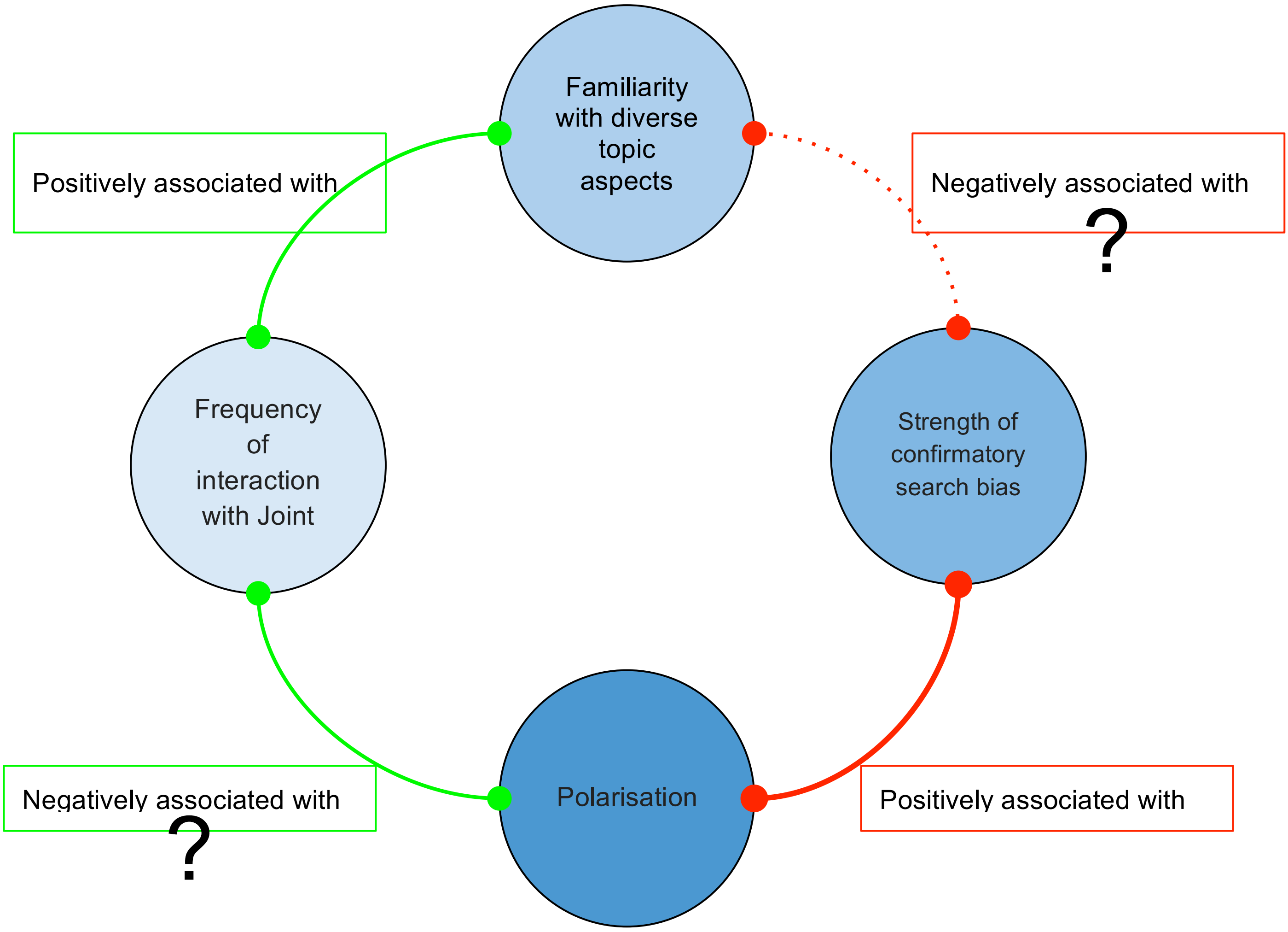

Figure 4.1. Results based annotated Cyclical model of socio-cognitive dynamics around the phenomenon of polarisation

Though the results contradict H3, further descriptive analyses imply that, in the end, these results might fit into the theoretical framework of this thesis. Figure 4.2 shows the average stance of the participants towards the different topic aspects at the beginning of the study, i.e., when collecting the first bookmark, and reveals a slightly positive but rather balanced stance (M = 1.1, SD = 0.38, with a range of 0.8:1.75).

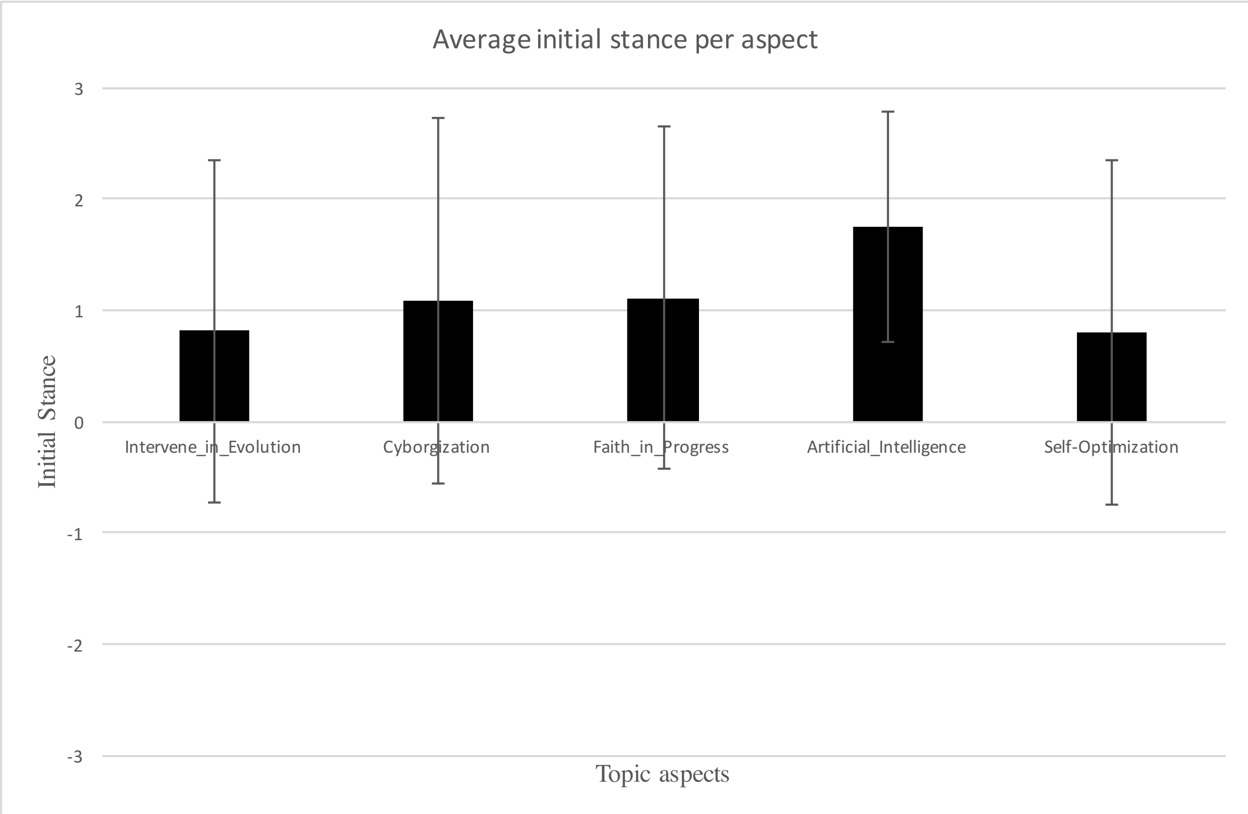

Figure 4.2: Initial Stance per aspect

Note. Error bars represent standard deviations.

From this it follows that participants exhibiting a confirmatory search bias, i.e., a small average distance between personal and author stance, had searched for resources representing balanced viewpoints. And given their search for such resources had further enhanced their initially balanced stances and thus, decreased their polarization scores, their behavior gave rise to a co-occurrence of confirmatory search and depolarization.

And the answer to the first research questions (RQ1) based on this argument would be that, when starting from a balanced initial stance a confirmatory search bias would have a negative relationship with polarisation.

Furthermore, when participants were searching for resources that had balanced views, new mental associations were being made based on these views (i.e familiarity with a topic aspect). So in fact when doing a confirmatory search for more balanced views, these associations are being reinforced, increasing the familiarity of the participants.
In this case an increase in familiarity should correlate positively with an increase in confirmatory search, as person's information goal is constituted by currently available memory units (Fu & Pirolli, 2007).

Yet the study results did not find any systematic relationship between familiarity and confirmation bias, and the answer to our second research question (RQ2), would be that although the interaction with joint artifacts helps to increase the familiarity with a search topic, this familiarity may or may not be coupled with a decrease in the person’s confirmatory search, based on her initial stance towards this topic, and in the case that this stance was a balanced one, the confirmatory search then correlates negatively with the polarisation of her opinion, leading to more interaction with others’ joint artifact.

After discussing the results of the study, and answering the research questions, following is the conclusion and design implications derived from the study results.

Chapter 5

Conclusion and practical design implications:

In this study, we tested the relationship between confirmatory search bias and polarisation, and tried to investigate the impact joint artifact and familiarity has on this relationship.

While the findings on the positive role of joint artifacts in the level of familiarity - people experience when doing an online search task - are not novel, they support previous findings on the same topic (e.g., Seitlinger et al., 2017). This suggest to give a value and consideration for the role of joint artifacts when designing for online environments, as an example, consider designing tools and services within platforms where people interact while forming opinions on certain topics, that can measure people's familiarity with the topic being discussed then offer ways to view resources from the same or other environments, which can play a role in increasing their familiarity with the topic (e.g using the concept of nudges to show the users, other resources on a topic while sharing an opinion about) similar concept was discussed by Wang et.al (2014), studying the role of nudges to raise users' awareness about the impact of their post before posting them.

Another design related concept, would be to measure users interactions, and when a user shows low score in interaction frequency, the system nudges can get more intensive. In another case if a user interacted only with whom who share the same views, those nudges can then serve to help her interact with others who share more diverse opinions about the topic in hand, which can give the raise for new mental associations to be made with the issue on discussion (Benedek & Neubauer, 2013).

Furthermore, and based on H3 results, negative relationship between confirmatory search bias and polarisation, and post-hoc interpretation allow to derive a dynamic design principle for a depolarizing discourse service, which does not counteract confirmatory search on principle but takes into account a user's current stance and which might even stimulate a confirmation bias, if the current stance is balanced.

Each of these design concepts can be studied in future work, to measure their effects and study their role in opinion formation in online discussions. Moreover, this work has faced multiple challenges that caused numerous limitations, which will be discussed in the following section.

Chapter 6

Limitations and Future work:

One limitation of this work is the small sample size (N=15), due to the long period of engagement the study required from the participants, even though there was an extrinsic incentive (in the form of a gift card when finishing the study), some participants lost motivation and did not finish their tasks. To face this issue, we only took in regard the active participants (N=13) when doing the statistical analysis, whom they finished the tasks assigned to them.

In future studies, this work can be conducted as a lab study, instead of a home-based one, to increase the participants' engagement and to have a more controllable environment.

Another limitation is the lack of a body of knowledge, that can be used to derive the indices that were used as the behavioral indicators (see section 2.3 Behavioural indicators and statistical analysis). To face this issue, multiple versions of the indices were debated and tried (see Appendix-C, R code).
The methodology that was followed in calculating each index can be reintroduced in new ways to bring about validation of the results, as part of a future work.

Overall this work can be considered as a pilot study, which next ones can use in order to examine the findings, either by changing the topic to a one which participants are well acquainted with, work to increase the sample size, redo the calculations of indices or introduce new and alternative ones.

Chapter 7

Kokkuvõte:
Üldiselt on viimastel aastatel interneti ja *onlaine* sotsiaalvõrgustike (kus lahatakse erinevaid teemasid) kasutamine pidevalt kasvanud. Ühelt poolt on see inimestele andnud võimaluse osaleda aruteludes ja jagada oma mõtteid nende füüsilisest asukohast sõltumata. Ent teisalt on selle taustal saanud oluliseks ka viisid, kuidas infot internetis jagatakse ja kasutatakse, kuna neil lehtedel võivad esineda kallutatud ja vastandlikud arvamused.

Selles töös uuriti veebis aset leidvate grupivestluste dünaamikat. Töö keskendub kahele peamisele aspektile: Eelduslik otsingu kõrvalekalle ja vastandumine. Lisaks pööratakse tähelepanu ka teistele, näiteks kuidas mõjutab arvamuste tekkimist kasutajate vahelise suhtluse käigus inimeste varasem kokkupuude teemaga.
Uurimise läbiviimiseks määratakse neli tegurit: “suhtluse tihedus”, “tutvuse kasv”, “Eelduslik otsingu kõrvalekalle” ja “vastandumine”.

Uurimus viidi läbi *online* keskkonnas, kus osalejatele anti ülesanne otsida informatsiooni konkreetse teema kohta kahe nädala jooksul. Selle aja vältel jälgiti nende suhtlust kaaslastega ning pandi kirja, kuidas nende arvamused selle tagajärjel muutusid.

Tulemused näitasid, et suhtlus teiste osalejatega parandab teemast arusaamist. Lisaks selgus, et kui inimesed lähenevad teemale algusest peale neutraalselt, siis neil püsib Eelduslik otsingu kõrvalekalle, mis vähendab vastandumist teema erinevate arvamuste vahel - ehk siis sellisel juhul polariseerumist ei toimu.

Nendele tulemustele toetudes pakuti töös välja ka viise, kuidas kujundada erinevaid teenuseid, mis saaksid mõõta ja vajadusel tõsta inimeste teadlikkust erinevates valdkondades.

References

B

Benedek, M., & Neubauer, A. (2013). Revisiting Mednick's model on creativity-related differences in associative hierarchies. Evidence for a common path to uncommon thought. The Journal of Creative Behavior, 47(4), 273–289. doi:10.1002/jocb.35 Bousfield.

Bryan C. Semaan , Scott P. Robertson , Sara Douglas , Misa Maruyama, Social media supporting political deliberation across multiple public spheres: towards depolarization, Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing, February 15-19, 2014, Baltimore, Maryland, USA doi:10.1145/2531602.2531605

D

Danescu-Niculescu-Mizil, West, Jurafsky, Leskovec & Potts (2013). No country for old members: User lifecycle and linguistic change in online communities. In Proceedings of the 22nd international conference on World Wide Web, pages 307–318

Danah m. boyd, Nicole B. Ellison (2007) Social Network Sites: Definition, History, and Scholarship.doi: 10.1111/j.1083-6101.2007.00393.x.

Dennerlein S., Seitlinger P., Lex E., Ley T. (2016) Take up My Tags: Exploring Benefits of Meaning Making in a Collaborative Learning Task at the Workplace. In: Verbert K., Sharples M., Klobučar T. (eds) Adaptive and Adaptable Learning. EC-TEL 2016. Lecture Notes in Computer Science, vol 9891. Springer, Cham.

De Liddo, Anna and Buckingham Shum, Simon (2013). The Evidence Hub: harnessing the collective intelligence of communities to build evidence-based knowledge. In: Large Scale Ideation and Deliberation Workshop, 29 June - 02 July 2013, Munich, Germany.

Diana C. Mutz, Paul S. Martin, Facilitating Communication Across Lines of Political Difference:
The Role of Mass Media. American Political Science Review, March 2001, 95 (1): 97-114.

Dimitar Nikolov, Diego F.M. Oliveira, Alessandro Flammini, Filippo Menczer (2015). Measuring online social bubbles. DOI: 10.7717/peerj-cs.38

F

Festinger, L. (1954). A theory of social comparison processes. *Human Relations, 7*, 117-140.
Fu, W.-T., & Pirolli, P. (2007). SNIF-ACT: a cognitive model of user navigation on the World Wide Web. *Human Computer Interaction, 22*, 355-412.

Fu, W.-T., & Dong, W. (2012). Collaborative indexing and knowledge exploration: A social learning model. IEEE Intelligent Systems, 27(1), 39–46. doi:10.1109/MIS.2010.131

H

Huckfeldt, R., Mendez, J., & Osborn, T. (2004). Disagreement, ambivalence, and engagement: the political consequences of heterogeneous networks. *Political Psychology, 25*, 65-95.

J

Jennifer Brundidge, Encountering ‘‘Difference’’ in the Contemporary Public Sphere: The Contribution of the Internet to the Heterogeneity of Political Discussion Networks (2010).DOI:10.1111/j.1460-2466.2010.01509.x

K

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media? In M. Rappa & P. Jones (Eds.), *Proceedings of the 19th International Conference on World Wide Web* (pp. 591-600). New York: ACM press.

M

Markant, D., & Gureckis, T. (2014). Is it better to select or to receive? Learning via active vs. passive hypothesis testing. *Journal of Experimental Psychology: General*, 143, 94-122.

Mutz, D., & Martin, P. (2001). Facilitating communication across lines of political difference: the role of mass media. *American Political Science Review, 95*, 97-114.

Michael MacKuen,Jennifer Wolak,Luke Keele,George E. Marcus (2010), Civic Engagements:

Resolute Partisanship or Reflective Deliberation. DOI: 10.1111/j.1540-5907.2010.00440.x

Markant, D. B., & Gureckis, T. M. (2014). Is it better to select or to receive? Learning via active

and passive hypothesis testing. Journal of Experimental Psychology: General, 143(1), 94-122. http://dx.doi.org/10.1037/a0032108

N

Nikolov, Dimitar Oliveira, Diego F. M. Flammini, Alessandro Menczer, Filippo (2015). Measuring Online Social Bubbles. DOI:10.7717/peerj-cs.38

MacKuen, Wolak, Keele & Marcus, 2010, Civic engagements: Resolute partisanship or reflective deliberation. American Journal of Political Science, 54(2):440–458

P

Peter Dahlgren (2005) The Internet, Public Spheres, and Political Communication: Dispersion and Deliberation. DOI: 10.1080/10584600590933160

Paul Seitlinger,Tobias Ley,Dietrich Albert (2015), Verbatim and Semantic Imitation in Indexing
Resources on the Web: A Fuzzy-trace Account of Social Tagging. DOI: 10.1002/acp.3067

Paul Seitlinger, Tobias Ley, Dominik Kowald, Dieter Theiler, Ilire Hasani-Mavriqi, Sebastian Dennerlein, Elisabeth Lex, Dietrich Albert (2017), Balancing the fluency-consistency tradeoff in collaborative information search with a recommender approach. DOI: 10.1080/10447318.2017.1379240

R

Rick Thomas, Michael R. Dougherty, Daniel R. Buttaccio (2014), Memory Constraints on Hypothesis Generation and Decision Making. DOI: 10.1177/0963721414534853

S

Schweiger, S., Oeberst, A., & Cress, U. (2014). Confirmation bias in web- based search: A randomized online study on the effects of expert information and social tags on information search and evaluation. Journal of Medical Internet Research, 16(3), e94. doi:10.2196/jmir.3044

Stroud, N. (2010). Polarization and partisan selective exposure. *Journal of Communication, 60*, 556-576.

Sunstein, C. (2001). Echo chambers: Bush v. Gore, Impeachment, and Beyond. Princeton, Oxford: Princeton University Press.

T

Thomas, R., Dougherty, M., & Buttaccio, D. (2014). Memory constraints on hypothesis generation and decision making. *Psychological Science, 23*, 264-270.

W

Wai-Tat Fu, Peter Pirolli.SNIF-ACT: a cognitive model of user navigation on the world wide web. Journal Human-Computer Interaction archive Volume 22 Issue 4, November 2007 Pages 355-412

Y

Yu Wang, Jiebo Luo, Richard Niemi, Yuncheng Li (201) To Follow or Not to Follow: Analyzing

the Growth Patterns of the Trumpists on Twitter, , Workshop Proceedings of the 10th International AAAI Conference on Web and Social Media, 2016.

Yang Wang , Pedro Giovanni Leon , Alessandro Acquisti , Lorrie Faith Cranor , Alain Forget ,

Norman Sadeh, A field trial of privacy nudges for facebook, Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, April 26-May 01, 2014, Toronto, Ontario, Canada [doi:10.1145/2556288.2557413]

Appendixes:

Appendix A - Task instructions

Instructions and demographic surveys were sent to participants view their emails, using google forms.

1- Introduction to the study and gathering of demographic data:

Link:

https://goo.gl/forms/pVPwtfiFt6HT0fwa2

Text:

Thank you for your interest in participating in the study.

In this form, you will get info about the study, answer basic questions about you, then sign an electronic informed consent to confirm your understanding and willingness to participate in the study.

You have until Monday 21 August to fill this form.

Info:

The study is about digital curation that is, how people collect and annotate resources in shared Web environments.

How long? Two Weeks

Where the work will be? in SemanticScuttle an online platform (link will be provided with a user guide once you fill the form).

When? Any time of the day as long as you log in once per day.

What are we collecting resources about?

The umbrella term is Transhumanism, but we will be collecting resources about its aspects, which are:
-Cyborgization: Enhancement of human cognitive and physical abilities by blending organic and synthetic substance.

-Self-optimization: efforts of an individual to improve different aspects of life, such as diet, sleep pattern, sportive and
cognitive activities, to increase well-being and health, enhance mental abilities and extend life expectancy.

-Belief in progress: Strong affirmation of scientific progress and technical development.

-Intervene in evolution: Accelerating the evolution of human beings by means of e.g. genetic engineering or prenatal diagnostics and prenatal interventions.

-Artificial Intelligence: Modeling human consciousness in terms of self-awareness, intelligence/creativity and emotional/motivational states.

Tasks:

What exactly we will be doing?

1- Collecting resources on a daily basis (15 to 30 minutes per day):

Search for resources (articles, papers, videos, images, books..) on any of the topic aspects listed above and add the link of this resource to the online platform (the process will be explained in another document).
- You need to add at least 1 resource per day (you are welcome to add more).
- You should read at least 1 resource from another participant (you are welcome to read more)

2-Association task (5 minutes, at the beginning, in the middle and end of the study):

Is a 5 minutes task, where you will be presented with a term and you have a minute to write down all the associations you can think of that are related to this it.

for example I present you with the word "Table" and you have 60 seconds to write down associations to it, like.. chair, wood, dinner, coffee ...etc)

3-Opinion piece (10 to 20 minutes, at the end of the study):
After the two weeks you will be invited to write 100 words about the topic (Transhumanism) to share your opinion.

N.B: Once you complete the study you will be gifted with a 30 EUR Amazon gift card, sent to your email.

Time table:

Saturday 19/08: sending out the Demographic form + Informed consent

Monday 21/08: Association task 1

Tuesday 22/08: Registration to the online tool /start to collect resources.

Tuesday 29/08: Association task 2

Tuesday 05/09: Association task 3 + stop collecting resources

Wednesday 06/09: Opinion Piece and end of the study.

Monday 18/09: sending out Amazon gifts.

Informed consent:
Participation in the study is voluntary:
You may revoke your consent to participate at any time and without stating reasons, but you will lose the compensation.
You can revoke your consent to store your data until the end of data collection. This will not cause you any disadvantages.

Protection of data privacy:
No personal data is recorded, what will be recorded is your activity on the platform (resources, tags, logs, clicks).
After the study all links to your username or email will be deleted.

Usage of anonymised data:
The results and data from this study will be used for a scientific publication.
The anonymity of the participants will be ensured in this process, that is data cannot be related to specific persons.

2- Association Task:
Link:
https://goo.gl/forms/Z9FZdPKPGPBfCFkJ3

Content:
Thank you for filling the introductory form and signing the informed consent.
If you have not done that, please do before performing this task (like to the introductory form is: https://goo.gl/forms/lgfVWr3xyjNI8vjx2)

Next step is to perform the first association test.

Instructions will be found in the link below, please take your time reading them.

Please try to relax and be natural in your responses.
Once done, you will get a txt output copy it and past it in the form below or send the downloaded file to eskandar.almonzer@gmail.com

The link to the association test is: http://www.tlu.ee/~meskandr/#g=1&p=home

If you had any questions do not hesitate to email me.
You have till tomorrow Tuesday 21, August to complete the task.

3- SemanticScuttle introduction:

Link:

https://goo.gl/forms/XEIa7uhwnZh23D7C3

Content:

Hi there!

Thank you for filling the introductory form and doing the association test.

*Please if you have not done them yet, make sure to do so before proceeding.
1st- The introductory form: https://goo.gl/forms/YLwZGfxWe2uqlQTD2
2nd- The association task: https://goo.gl/forms/lsv6LTs2EtnZPihz1

The 3rd step will be *only* to create an account in the platform that we will be using for the following two weeks to collect resources and annotate them.

Please make sure to follow the User Guid, you can find it next to the log in.

Link: http://css-kti.tugraz.at/tools/SemanticScuttle/

In the corner you have User Guide, please read the guide carefully and get to know the platform.

When done, please fill the form below with both the username and the email, you used to create the account.

Please try to finish this task by tomorrow Wednesday, 23 of August.

Once everyone made an account I will give the go to start the resource collecting.

4- Resource collection:
Link:
https://goo.gl/forms/jZ1CU1Oyz80BNxD62
Content:
Hello everyone,

Thank you for creating accounts on the tool.

For the next two weeks we MUST use the platform on a daily basis to do two things:

1- Searching online:
Add one resource at least related to one of the 5 aspects (Self-Optimization, Cyborgization, Intervene in Evolution,
Faith in Progress, Artificial Intelligence). Hover over these words in the tool to get more info.

Note: Please follow the process as it was explained in the User Guide (can be found next to the login/logout button).
Following the instructions is as important as doing the task.

2- Searching in the platform:
Discover what others added and read one or more of their added resources.

Please remember that the resources should all be in English.

FAQ:

Can I do all of that in one day only?
No, the study is highly dependant on you visiting the site on a daily basis (weekend included) and doing the 2 steps above.

My cat is sick and will not be able to enter the site will I be disqualified?
No, failing to login for a day is not a big issue, you all have your personal life.

How would you know if we did not log in every day?
I have a crystal ball to monitor your clicks and logs on daily basis.
(please refer to the informed consent regarding data privacy and usage of usage of anonymised data)

What will happen if I failed to participate for four days in a row?
I will have to remove your data from the study and you will not be able to buy that thing on Amazon using the gift card.

I want to withdraw from the study, is it OK?
You are welcome to withdraw at any point, but failing to complete the study will cause you to lose the gift and I really want to give you the gift so please stay!.
(please refer to the informed consent)

For any other questions now or during the study please send me an email any time you want, I will make sure to give you all the support you need.

Incase you did not bookmark it yet!
http://css-kti.tugraz.at/tools/SemanticScuttle/login.php

Next task will be the second association test next Thursday 31st of August!

Until then I wish you enjoy, have fun and learn new things!

Appendix B - Collected data:

Association task:

The collected data can be found as in excel in the acompanied driver, due to the large table it could not be added to this file.

Following is a just sample of the AssocationTest results file.

Code	**Group (IC, CI)**	**Measurement point**	**Stimulus**	**Responses**	**RTs**
AE1979	CI	t0	InterveneInEvolution	stop, stagnation	52200,54880,60009
AE1979	CI	t0	Cyborgization	power, uncontrollable	55383,60007
AE1979	CI	t0	FaithInProgress	positivity, energy, sun, bright future, movement, trust	12606,17706,21520,30943,49792,60008
AE1979	CI	t0	AI	wisdom, effectiveness, distrust, future, role change, progress, inhuman	7779,14468,20801,29240,40935,49063,56164,60009
AE1979	CI	t0	SelfOptimization	drive, energy, spirit, evolution, mindfulness, reading	13169,14940,16984,20473,28534,51907,60008

Search task:

The collected data can be found as in excel in the acompanied driver, due to the large table it could not be added to this file.

Following is a just sample of the SemanticScuttleData:

user	timestamp	id	event	typeOfEvent	itemTitle	userResponse	
19	Fri Aug 25 19:50:06 CEST 2017	71da71a2-3f	AddUrl	BENEFITS & RISKS OF ARTIFICIAL INTELLIGEN	[link:https://futureoflife.org/background/benefits-risks-of-art	bookmarkid:	content:{tags
20	Thu Aug 24 21:17:36 CEST 2017	7ec780c0-5b	AddUrl	Can we build AI without losing control over it	[link:https://www.youtube.com/watch?v=8nt3edWLglg	bookmarkid:	content:{tags
20	Fri Aug 25 22:11:54 CEST 2017	f1cfe1a3-15c	AddUrl	Artificial Intelligence Is Changing the World			
20	Sat Aug 26 21:49:36 CEST 2017	e4c5c53c-cd	AddUrl	Humans 'will become God-like cyborgs withir	[link:http://www.telegraph.co.uk/culture/hay-festival/11627	bookmarkid:	content:{tags
20	Sun Aug 27 18:05:44 CEST 2017	3abb33eb-58	AddUrl	Making machines clever and whether robots	[link:http://www.telegraph.co.uk/technology/2017/08/26/gc	bookmarkid:	content:{tags
20	Mon Aug 28 10:08:10 CEST 2017	5f4ead44-32	AddUrl	The Ethics of Human Enhancement	[link:https://www.bbvaopenmind.com/en/article/ethics-issu	bookmarkid:	content:{tags
20	Tue Aug 29 12:38:42 CEST 2017	76882514-54	AddUrl	Human Genetic Engineering	[link:http://humangenetic.org/human-genetic-engineering-pı	bookmarkid:	content:{tags
20	Fri Sep 01 02:42:29 CEST 2017	6a85b0f1-21	AddUrl	Google's Deep Mind			
20	Sun Sep 03 21:49:16 CEST 2017	4b7e53f9-62	AddUrl	Misuse of artificial intelligence 'could do harr	[link:http://www.bbc.com/news/business-34266425	bookmarkid:	content:{tags

Appendix C - R Code

```
rm(list=ls())

library ( doBy )

### Reading in data
setwd("~/Dropbox/MT_Almonzer")
## Association Task AT
AT_data <- read.table ( "AT_MT_Almonzer.txt" , sep="\t" , fill=T , head=T , quote="" )
AT_data [ , "Code" ] <- tolower ( AT_data [ , "Code" ] )
names ( AT_data ) <- c ("Code","Group","Measurement.point","Stimulus","Responses","RTs")
AT_codes <- unique ( AT_data [ , "Code" ] )
## Search environment Semantic Scuttle
ScuttleData <- read.table ( "SemScuttleData.txt" , sep="\t" , fill=T , head=T , quote="" )
allParticipants <- sort ( unique ( ScuttleData [ , "user" ] ) )
## Mapping AT and Semantic Scuttle codes
MappingTable <- read.table ( "MT_AE_Mapping.txt" , sep="\t" , fill=T , head=T , quote="" )
MappingTable [ , "AT.Username" ] <- tolower ( MappingTable [ , "AT.Username" ] )

## AT
## Aspect names in AT
#[1] "InterveneInEvolution" "Cyborgization"      "FaithInProgress"     "AI"
#[5] "SelfOptimization"
## Aspect names in Scuttle
#[1] "Artificial_Intelligence" "Faith_in_Progress"      "Cyborgization"
"Intervene_in_Evolution"
#[5] "Self-Optimization"

for ( i in 1 : nrow ( AT_data ) ) {
 #for ( i in 207 : 208 ) {

 if ( i ==1 ) {
  AT_RT_df <- NULL
  summary_df <- NULL
```

```
}

i_code <- c ( as.matrix ( AT_data [ i , "Code" ] ) )
i_mPoint <- c ( as.matrix ( AT_data [ i , "Measurement.point" ] ) )
i_stimulus <- c ( as.matrix ( AT_data [ i , "Stimulus" ] ) )
i_responses <- c ( as.matrix ( AT_data [ i , "Responses" ] ) )
i_RTs <- c ( as.matrix ( AT_data [ i , "RTs" ] ) )
i_Group <- c ( as.matrix ( AT_data [ i , "Group" ] ) )
if ( i_stimulus == "InterveneInEvolution" ) { i_stimulus <- "Intervene_in_Evolution" }
if ( i_stimulus == "Cyborgization" ) { i_stimulus <- "Cyborgization" }
if ( i_stimulus == "FaithInProgress" ) { i_stimulus <- "Faith_in_Progress" }
if ( i_stimulus == "AI" ) { i_stimulus <- "Artificial_Intelligence" }
if ( i_stimulus == "SelfOptimization" ) { i_stimulus <- "Self-Optimization" }
#if ( i_mPoint == "t0" ) { SocSet <- "BeforeStudy" }
#if ( i_mPoint == "t1" ) {
#  if ( i_Group == "CI" ) { SocSet <- "Collaborative" } else {
#    SocSet <- "Individual"
#  }
#}
#if ( i_mPoint == "t2" ) {
#  if ( i_Group == "CI" ) { SocSet <- "Individual" } else {
#    SocSet <- "Collaborative"
#  }
#}

timeLimit <- 60
ints <- 13
if ( length ( i_responses) > 0 ) {

  producedSomething <- 1
  i_responses <- unlist ( strsplit ( i_responses , "," ) )
  seconds <- seq ( 0 , timeLimit , length = ints )

  if ( length ( i_RTs ) > 0 ) {

    RTsAvailable <- 1
```

```
    i_RTs <- round ( as.numeric ( unlist ( strsplit ( i_RTs , "," ) ) ) / 1000 )
    i_RTs <- i_RTs [ 1 : length (i_responses) ]
    if ( length ( which ( ( i_RTs > timeLimit ) == T ) ) > 0 ) {
      i_RTs <- i_RTs [ - which ( ( i_RTs > timeLimit ) == T ) ]
    }
    i_sVec <- rep ( 0 , timeLimit )
    i_sVec [ i_RTs ] <- 1
    i_sVec <- cumsum ( i_sVec )
    seqi <- seconds
    i_sVec <- c ( 0 , i_sVec [ seqi ] )

   } else {

    i_sVec <- rep ( NA , ints )
    RTsAvailable <- 0

   }

   #i_df <- data.frame ( i_code , i_mPoint , i_stimulus , seconds , i_sVec , i_Group , SocSet )
   i_df <- data.frame ( i_code , i_mPoint , i_stimulus , seconds , i_sVec )
   AT_RT_df <- rbind ( AT_RT_df , i_df )

  } else {

   producedSomething <- 0

  }

  # i_summary <- data.frame ( i_code , i_mPoint , i_stimulus , producedSomething , RTsAvailable ,
i_Group , SocSet )
  i_summary <- data.frame ( i_code , i_mPoint , i_stimulus , producedSomething , RTsAvailable )
  summary_df <- rbind ( summary_df , i_summary )

}
aspects <- c ( as.matrix ( unique ( AT_RT_df [ , "i_stimulus" ] ) ) )
```

```
## Semantic Scuttle

#unique ( c ( as.matrix ( ScuttleData [ c ( which ( ScuttleData [ , "event"] == "ClickAspectCon" ) ,
#         which ( ScuttleData [ , "event"] == "ClickAspectPro" ) ) , "typeOfEvent" ] ) ) )

commitmentFx <- function ( p ) {
  lUser <- which ( ScuttleData [ , "user" ] == p )
  nResCollected <- length ( which ( ScuttleData [ lUser , "event" ] == "AddUrl" ) )
  nAspectsClicked <- length ( c ( which ( ScuttleData [ lUser , "event" ] == "ClickAspectCon" ) ,
                              which ( ScuttleData [ lUser , "event" ] == "ClickAspectPro" ) ) )
  return ( c ( nResCollected , nAspectsClicked ) )
}

AT_Participants <- MappingTable [ , "User.ID" ]
stats_commitment <- sapply ( AT_Participants , commitmentFx )
colnames ( stats_commitment ) <- AT_Participants

activePartis <- intersect ( which ( stats_commitment [ 1 , ] >= 5 ) , # whether they have collected at
least 5 resources
                        which ( stats_commitment [ 2 , ] >= 5 ) ) # and performed an aspect-based search at
least 5 times
activePartis <- AT_Participants [ activePartis ]

## Function for creating analysis-friendly list of participant's data
px_list_fx <- function ( px ) {

  px_data <- ScuttleData [ which ( ScuttleData [ , "user" ] == px ) , ]
  px_uniqueEvents <-  unique ( px_data [ , "id" ] )

  for ( ID_i in 1 : length ( px_uniqueEvents ) ) {

    if ( ID_i == 1 ) { px_eventList <- NULL }
    l_event <- which ( px_data [ , "id" ] == c ( as.matrix ( px_uniqueEvents [ ID_i ] ) ) )
    eventData <- px_data [ l_event , ]

    if ( length ( l_event ) == 1 ) {
```

```
i_event <- c ( as.matrix ( eventData [ , "event" ] ) )

if ( ( i_event == "ClickAspectCon" ) | ( i_event == "ClickAspectPro" ) ) {

  if ( tail ( unlist ( strsplit ( i_event , "" ) ) , n = 1 ) == "n" ) {
    proOrCon <- "Contra"
  } else { proOrCon <- "Pro" }
  clickedAspect <- c ( as.matrix ( eventData [ , "typeOfEvent" ] ) )
  i_listElement <- c ( clickedAspect , proOrCon )
  names ( i_listElement ) <- c ( "Aspect" , "ProOrCon" )
  i_listElement <- list ( i_listElement )
  names ( i_listElement ) <- "AspectClicked"
  px_eventList <- c ( px_eventList , i_listElement )

}

if ( i_event == "ClickOnLink" ) {

  Link <- c ( as.matrix ( eventData [ , "itemTitle" ] ) )
  Link <- gsub ( "\\[|\\]|link:", "", Link)
  i_listElement <- Link
  names ( i_listElement ) <- c ( "Link" )
  i_listElement <- list ( i_listElement )
  names ( i_listElement ) <- "LinkClicked"
  px_eventList <- c ( px_eventList , i_listElement )

}

if ( i_event == "Search" ) {

  SearchTerm <- c ( as.matrix ( eventData [ , "typeOfEvent" ] ) )
  i_listElement <- SearchTerm
  names ( i_listElement ) <- c ( "SearchTerm" )
  i_listElement <- list ( i_listElement )
  names ( i_listElement ) <- "KW_based_Search"
```

```
      px_eventList <- c ( px_eventList , i_listElement )

    }

    if ( i_event == "tags" ) {

      clickedTag <- c ( as.matrix ( eventData [ , "typeOfEvent" ] ) )
      i_listElement <- clickedTag
      names ( i_listElement ) <- c ( "Tag" )
      i_listElement <- list ( i_listElement )
      names ( i_listElement ) <- "TagClicked"
      px_eventList <- c ( px_eventList , i_listElement )

    }

  } else {

    Link <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] == "AddUrl" ) , "itemTitle" ] ) )
    Link <- gsub ( "\\[|\\]|link:", "", Link )
    Link_ID <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] == "AddUrl" ) ,
"userResponse" ] ) )
    Link_ID <- as.numeric ( gsub ( "bookmarkid:", "", Link_ID ) )

    TAS <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] == "AddUrl" ) , "X" ] ) )
    TAS <- gsub ( "\\[|\\]|\\{|\\}|content:|tags:", "", TAS )
    if ( length ( unlist ( strsplit ( TAS , "" ) ) ) == 0 ) { TAS <- NA }
    Trust <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] == "RateTrustworthiness" ) ,
"X" ] ) )
    Trust <- as.numeric ( gsub ( "\\]|content:|trust:|\\{|\\}", "", Trust ) )

    PersonalStanceString <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] ==
"JudgePersonalStance" ) , "X" ] ) )
    PersonalStanceString <- gsub ( "\\[|\\]|content:|personalStance:|\\{|\\}", "", PersonalStanceString )
    PersonalStanceString <- unlist ( strsplit ( PersonalStanceString , "," ) )
    PersonalStanceNumeric <- as.numeric ( gsub ( "NA" , "" , PersonalStanceString ) )
    ChosenAspects <- which ( is.na ( PersonalStanceNumeric ) == F )
```

```
      ChosenAspects <- aspects [ ChosenAspects ]
      if ( length ( ChosenAspects ) > 1 ) { ChosenAspects <- paste ( ChosenAspects , collapse = ", " ) }
      if ( length ( unlist ( strsplit ( ChosenAspects , "" ) ) ) == 0 ) { ChosenAspects <- NA }
      PersonalStance <- toString ( PersonalStanceNumeric )
      if ( length ( unlist ( strsplit ( PersonalStance , "" ) ) ) == 0 ) { PersonalStance <- NA }

      AuthorStanceString <- c ( as.matrix ( eventData [ which ( eventData [ , "event" ] ==
"JudgeAuthorStance" ) , "X" ] ) )
      AuthorStance <- gsub ( "\\[|\\]|content:|authorStance:|\\{|\\}", "", AuthorStanceString )
      if ( length ( unlist ( strsplit ( AuthorStance , "" ) ) ) == 0 ) { AuthorStance <- NA }

      i_listElement <- c ( Link , Link_ID , TAS , Trust , ChosenAspects , PersonalStance , AuthorStance
)
      names ( i_listElement ) <- c ( "Link" , "Link_ID" , "TAS" , "Trust" , "ChosenAspects" ,
"PersonalStance" , "AuthorStance" )
      i_listElement <- list ( i_listElement )
      names ( i_listElement ) <- "BookmarkAdded"
      px_eventList <- c ( px_eventList , i_listElement )

    }

  }

  return ( px_eventList )

}
## Creating data frame including different search indices per participant
for ( pxx in 1 : length ( activePartis ) ) {

  if ( pxx == 1 ) { PersonByAspect_df <- NULL }

  px <- activePartis [pxx]

  StanceDevFx <- function ( px ) {

    px_df <- NULL
```

```
px_list <- px_list_fx ( px )
px_events <- names ( px_list )
l_BookmarkAdded <- which ( px_events == "BookmarkAdded" )

AspectsOfBmks <- lapply ( px_list [ l_BookmarkAdded ] , function ( i ) { i [ "ChosenAspects" ] } )
allTappedAspects <- unlist ( strsplit (  unlist ( AspectsOfBmks ) , "," ) )
allTappedAspects <- c ( as.matrix ( gsub ( " ", "" , allTappedAspects ) ) )
if ( length (which ( is.na ( allTappedAspects ) ) ) > 0 ) {
 allTappedAspects <- allTappedAspects [ - which ( is.na ( allTappedAspects ) ) ]
}

for ( x in 1 : length ( aspects ) ) {

 aspect_x <- aspects [ x ]
 BmksIncludingAspect_x <- lapply ( AspectsOfBmks , function ( i ) {
  bmkAspects <- c ( as.matrix ( unlist ( strsplit ( i , "," ) ) ) )
  is.element ( aspect_x , bmkAspects )
 } )
 BmksIncludingAspect_x <- c ( as.matrix ( which ( BmksIncludingAspect_x == T ) ) )

 if ( length ( BmksIncludingAspect_x ) > 0 ) {

  l_BookmarkAdded_aspect_x <- l_BookmarkAdded [ BmksIncludingAspect_x ]
  consecStances_Aspect_x <- unlist (
   lapply ( px_list [ l_BookmarkAdded_aspect_x ] , function ( i ) {
    i_aspect <- gsub ( " " , "" , unlist ( strsplit ( i [ "ChosenAspects" ] , "," ) ) )
    i_aspect <- i_aspect [ which ( i_aspect == aspect_x ) ]
    i_stance <- i [ "PersonalStance" ]
    i_stance <- unlist ( strsplit ( i_stance , "," ) ) [ match ( i_aspect , aspects ) ]
    i_stance <- as.numeric ( i_stance )
   } ) )
  consecAStances_Aspect_x <- unlist (
   lapply ( px_list [ l_BookmarkAdded_aspect_x ] , function ( i ) {
    i_aspect <- gsub ( " " , "" , unlist ( strsplit ( i [ "ChosenAspects" ] , "," ) ) )
    i_aspect <- i_aspect [ which ( i_aspect == aspect_x ) ]
    i_stance <- i [ "AuthorStance" ]
```

```
      i_stance <- unlist ( strsplit ( i_stance , "," ) ) [ match ( i_aspect , aspects ) ]
      i_stance <- as.numeric ( i_stance )
     } ) )
   DevZeroA <- sapply ( consecAStances_Aspect_x , function ( i ) { sqrt ( ( 0 - i ) ^ 2 ) } )

   DevZero <- sapply ( consecStances_Aspect_x , function ( i ) { sqrt ( ( 0 - i ) ^ 2 ) } )
   if ( length ( DevZero ) >= 1 ) {
    last <- DevZero [ length ( DevZero ) ]
    first <- DevZero [ 1 ]
    PolQuot <- last / ( first + 1 )
    initStance <- consecStances_Aspect_x [ 1 ]
    endStance <- consecStances_Aspect_x [ length ( DevZero ) ]
    extremityRes <- mean(DevZeroA,na.rm=T)
   } else {
    PolQuot <- DevZero
    initStance <- NA
    endStance <- NA
    extremityRes <- NA
   }
   i_df <- data.frame ( px , aspect_x , PolQuot , initStance , endStance , extremityRes )
   px_df <- rbind ( px_df , i_df )

  } else {

   DevZero <- NA
   PolQuot <- NA
   initStance <- NA
   endStance <- NA
   extremityRes <- NA
   i_df <- data.frame ( px , aspect_x , PolQuot , initStance , endStance , extremityRes )
   px_df <- rbind ( px_df , i_df )

  }

} # iterating through aspects
return ( px_df )
```

```
  }
  px_df_StanceDev <- StanceDevFx ( px )
  px_df_compiled <- px_df_StanceDev
  ## potential artifact-mediated interaction indices

  aspectsClickedFx <- function ( px ) {

    px_df <- NULL
    px_list <- px_list_fx ( px )
    px_events <- names ( px_list )
    l_AspectsClicked <- which ( px_events == "AspectClicked" )

    px_AspectClicks <- lapply ( px_list [ l_AspectsClicked ] , function ( i ) { i [ 1 ] } )
    px_clickedAspects <- c ( as.matrix ( unlist ( px_AspectClicks ) ) )
    nClicksPerAspect <- t ( sapply ( aspects , function ( i ) {
      iClicks <- px_list [ l_AspectsClicked [ which ( px_clickedAspects == i )  ] ]
      niClicks <- length ( iClicks )
      nContra <- length ( which ( unlist ( lapply ( iClicks , function ( i ) { i [ 2 ] } ) ) == "Contra" ) )
      nPro <- length ( which ( unlist ( lapply ( iClicks , function ( i ) { i [ 2 ] } ) ) == "Pro" ) )
      data.frame ( niClicks , nPro , nContra )
    }
    ) )
    px_df <- data.frame ( px , aspects , nClicksPerAspect )

    return ( px_df )

  }
  px_df_AspectsClicked <- aspectsClickedFx ( px )
  px_df_compiled <- cbind ( px_df_compiled , px_df_AspectsClicked [ , c
("niClicks","nPro","nContra") ] )

  ## potential confirmatory search indeces
  # Variant 1: Personal stance --> Valence of subsequent aspect click
  ConfirmedByAspectFx <- function ( px ) {
```

```
px_df <- NULL
px_list <- px_list_fx ( px )
px_events <- names ( px_list )
l_BookmarkAdded <- which ( px_events == "BookmarkAdded" )

AspectsOfBmks <- lapply ( px_list [ l_BookmarkAdded ] , function ( i ) { i [ "ChosenAspects" ] } )
allTappedAspects <- unlist ( strsplit (  unlist ( AspectsOfBmks ) , "," ) )
allTappedAspects <- c ( as.matrix ( gsub ( " ", "" , allTappedAspects ) ) )
if ( length (which ( is.na ( allTappedAspects ) ) ) > 0 ) {
  allTappedAspects <- allTappedAspects [ - which ( is.na ( allTappedAspects ) ) ]
}

allTappedAspects_unique <- unique ( allTappedAspects )

for ( x in 1 : length ( allTappedAspects_unique ) ) {

  aspect_x <- allTappedAspects_unique [ x ]

  l_Aspect_x_Clicked <- c ( as.matrix ( which ( unlist ( lapply ( px_list , function ( i ) {

    is.element ( aspect_x , c ( as.matrix ( i ["Aspect"] ) ) )

  } ) ) == T ) ) )

  BmksIncludingAspect_x <- lapply ( AspectsOfBmks , function ( i ) {
    bmkAspects <- c ( as.matrix ( unlist ( strsplit ( i , "," ) ) ) )
    is.element ( aspect_x , bmkAspects )
  } )
  BmksIncludingAspect_x <- c ( as.matrix ( which ( BmksIncludingAspect_x == T ) ) )

  if ( length ( BmksIncludingAspect_x ) > 0 ) {
    l_BookmarkAdded_aspect_x <- l_BookmarkAdded [ BmksIncludingAspect_x ]

    for ( i in 1 : length ( l_BookmarkAdded_aspect_x ) ) {

      positionInUserStream <- l_BookmarkAdded_aspect_x [ i ]
```

```
        iBookmarkEvent <- px_list [[ positionInUserStream ]]
        iChosenAspect <- unlist ( strsplit ( c ( as.matrix ( iBookmarkEvent [ "ChosenAspects" ] ) ) , ","
) )
        iChosenAspect <- gsub ( " " , "" , iChosenAspect )
        iChosenAspect <- iChosenAspect [ iChosenAspect == aspect_x ]
        iAspect_ProOrCon <- c ( as.matrix ( iBookmarkEvent [ "PersonalStance" ] ) )
        iAspect_ProOrCon <- unlist ( strsplit ( iAspect_ProOrCon , "," ) ) [ match ( iChosenAspect ,
aspects ) ]
        iAspect_ProOrCon <- as.numeric ( iAspect_ProOrCon )

        # check whether bookmark has actually been assigned to an aspect
        NAs <- which ( is.na ( iChosenAspect ) == T )
        if (  length ( NAs ) == 0 ) {

          # for ( j in 1 : length ( iChosenAspects ) ) {

          if ( iAspect_ProOrCon > 0 ) { i_stance <- "Pro" }
          if ( iAspect_ProOrCon == 0 ) { i_stance <- "Balanced" }
          if ( iAspect_ProOrCon < 0 ) { i_stance <- "Contra" }

          # check whether there was at least one further bookmark in participant's future history
          nBookmarks <- length ( l_BookmarkAdded_aspect_x )

          if ( nBookmarks > i ) {

            nextBookmarksPosition <- l_BookmarkAdded_aspect_x [ i + 1 ]
            # check whether an aspect has been clicked in between the current bookmark i and the next
one i+1
            interimStream <- ( positionInUserStream + 1 ) : ( nextBookmarksPosition - 1 )

            if ( length ( intersect ( l_Aspect_x_Clicked , interimStream ) ) > 0 ) { # aspect_x has been
clicked at least one time

              InterimAspectsClicked <- px_list [ intersect ( l_Aspect_x_Clicked , interimStream ) ]

              for ( k in 1 : length ( InterimAspectsClicked ) ) {
```

```
        clicked_aspect <- c ( as.matrix ( InterimAspectsClicked [[ k ]] [ "Aspect" ] ) )
        clicked_aspect_stance <- c ( as.matrix ( InterimAspectsClicked [[ k ]] [ "ProOrCon" ] ) )

        if ( i_stance == "Balanced" ) { ConfirmationClick <- NA } else {
          if ( clicked_aspect_stance == i_stance ) { ConfirmationClick <- 1 } else {
            ConfirmationClick <- 0 }
        }

        i_df <- data.frame ( px , aspect_x , iChosenAspect , i_stance , clicked_aspect ,
                        clicked_aspect_stance , ConfirmationClick )
        names ( i_df ) <- c ( "participant" , "aspect" , "BookmarkAspect" , "CurrentStance" ,
                        "ClickedAspect" , "ClickedAspectStance" , "ConfirmationByClick?" )
        px_df <- rbind ( px_df , i_df )

      } # iterating through aspects clicked between two bookmarks

    } else {

      clicked_aspect <- NA
      clicked_aspect_stance <- NA
      ConfirmationClick <- NA
      i_df <- data.frame ( px , aspect_x , iChosenAspect , i_stance , clicked_aspect ,
                      clicked_aspect_stance , ConfirmationClick )
      names ( i_df ) <- c ( "participant" , "aspect" , "BookmarkAspect" , "CurrentStance" ,
                      "ClickedAspect" , "ClickedAspectStance" , "ConfirmationByClick?" )
      px_df <- rbind ( px_df , i_df )

    }

  } else {
    # check whether aspects have been clicked after last bookmark
    nAspectClicksAfterLastBmk <- length ( which ( l_Aspect_x_Clicked > positionInUserStream
) )

    if ( nAspectClicksAfterLastBmk == 0 ) {
```

```
          clicked_aspect <- NA
          clicked_aspect_stance <- NA
          ConfirmationClick <- NA
          i_df <- data.frame ( px , aspect_x , iChosenAspect , i_stance , clicked_aspect ,
                    clicked_aspect_stance , ConfirmationClick )
          names ( i_df ) <- c ( "participant" , "aspect" , "BookmarkAspect" , "CurrentStance" ,
                    "ClickedAspect" , "ClickedAspectStance" , "ConfirmationByClick?" )
          px_df <- rbind ( px_df , i_df )

        } else {

          LastAspectsClicked <- px_list [ l_Aspect_x_Clicked [ which ( l_Aspect_x_Clicked >
positionInUserStream ) ] ]

          for ( k in 1 : length ( LastAspectsClicked ) ) {

            clicked_aspect <- c ( as.matrix ( LastAspectsClicked [[ k ]] [ "Aspect" ] ) )
            clicked_aspect_stance <- c ( as.matrix ( LastAspectsClicked [[ k ]] [ "ProOrCon" ] ) )

            if ( i_stance == "Balanced" ) { ConfirmationClick <- NA } else {
              if ( clicked_aspect_stance == i_stance ) { ConfirmationClick <- 1 } else {
                ConfirmationClick <- 0 }
            }

            i_df <- data.frame ( px , aspect_x , iChosenAspect , i_stance , clicked_aspect ,
                      clicked_aspect_stance , ConfirmationClick )
            names ( i_df ) <- c ( "participant" , "aspect" , "BookmarkAspect" , "CurrentStance" ,
                      "ClickedAspect" , "ClickedAspectStance" , "ConfirmationByClick?" )
            px_df <- rbind ( px_df , i_df )

          } # iterating through aspects clicked after last bookmark

        }

      }
```

```
        # } # iterating through aspects of bookmark

      } else {

        iChosenAspect <- NA
        i_stance <- NA
        clicked_aspect <- NA
        clicked_aspect_stance <- NA
        ConfirmationClick <- NA
        i_df <- data.frame ( px , aspect_x , iChosenAspect , i_stance , clicked_aspect ,
                    clicked_aspect_stance , ConfirmationClick )
        names ( i_df ) <- c ( "participant" , "aspect" , "BookmarkAspect" , "CurrentStance" ,
                    "ClickedAspect" , "ClickedAspectStance" , "ConfirmationByClick?" )
        px_df <- rbind ( px_df , i_df )

      }

    } # iterating through bookmarks

  }

 } # iterating through aspects clicked by participant

 return ( px_df )

}
px_ConfirmByAspectClicks <- ConfirmedByAspectFx ( px )
px_unique_AspectsClicked <- c ( as.matrix ( unique ( px_ConfirmByAspectClicks [ , "aspect" ] ) ) )
for ( ax in 1 : length ( aspects ) ) {
 if ( ax == 1 ) { px_confBiasI_df <- NULL }
 aspect_ax <- aspects [ ax ]
 lax <- which ( px_ConfirmByAspectClicks [ , "aspect" ] == aspect_ax )
 aspect_confBias <- mean ( px_ConfirmByAspectClicks [ lax , "ConfirmationByClick?" ] , na.rm =
T )
 px_confBiasI_df <- rbind ( px_confBiasI_df , data.frame ( px , aspect_ax , aspect_confBias ) )
```

```
}
px_df_compiled <- cbind ( px_df_compiled , px_confBiasI_df [ , "aspect_confBias" ] )

# Variant 2: Personal stance --> Author stance of subsequent bookmark
ConfirmedByAuthorStanceFx <- function ( px ) {

  px_df <- NULL
  px_list <- px_list_fx ( px )
  px_events <- names ( px_list )
  l_BookmarkAdded <- which ( px_events == "BookmarkAdded" )

  AspectsOfBmks <- lapply ( px_list [ l_BookmarkAdded ] , function ( i ) { i [ "ChosenAspects" ] } )
  allTappedAspects <- unlist ( strsplit (  unlist ( AspectsOfBmks ) , "," ) )
  allTappedAspects <- c ( as.matrix ( gsub ( " ", "" , allTappedAspects ) ) )
  if ( length (which ( is.na ( allTappedAspects ) ) ) > 0 ) {
    allTappedAspects <- allTappedAspects [ - which ( is.na ( allTappedAspects ) ) ]
  }

  allTappedAspects_unique <- unique ( allTappedAspects )

  for ( x in 1 : length ( allTappedAspects_unique ) ) {

    aspect_x <- allTappedAspects_unique [ x ]

    BmksIncludingAspect_x <- lapply ( AspectsOfBmks , function ( i ) {
      iAspects <- unlist ( strsplit ( c ( as.matrix ( i ) ) , "," ) )
      iAspects <- gsub ( " " , "" , iAspects )
      is.element ( aspect_x , iAspects )

    } )
    BmksIncludingAspect_x <- l_BookmarkAdded [ c ( as.matrix ( which ( unlist ( 
BmksIncludingAspect_x ) == T ) ) ) ]

    nBmksIncludingAspect_x <- length ( BmksIncludingAspect_x )
    if ( nBmksIncludingAspect_x >= 2 ) {
```

```
for ( Bmk_i in 1 : ( nBmksIncludingAspect_x - 1 ) ) {

  Bmk_i_Aspect <- px_list [[ BmksIncludingAspect_x [ Bmk_i ] ]] [ "ChosenAspects" ]
  Bmk_i_Aspect <- unlist ( strsplit ( Bmk_i_Aspect , "," ) )
  Bmk_i_Aspect <- gsub ( " " , "" , Bmk_i_Aspect )
  Bmk_i_Aspect <- Bmk_i_Aspect [ which ( Bmk_i_Aspect == aspect_x ) ]

  Bmk_i_PersonStance <- px_list [[ BmksIncludingAspect_x [ Bmk_i ] ]] [ "PersonalStance" ]
  Bmk_i_PersonStance <- unlist ( strsplit ( Bmk_i_PersonStance , "," ) ) [ match ( Bmk_i_Aspect , aspects ) ]
  Bmk_i_PersonStance <- as.numeric ( Bmk_i_PersonStance )
  if ( Bmk_i_PersonStance > 0 ) { PStance <- "Pro" }
  if ( Bmk_i_PersonStance == 0 ) { PStance <- "Balanced" }
  if ( Bmk_i_PersonStance < 0 ) { PStance <- "Contra" }

  Bmk_i_AuthorStance <- px_list [[ BmksIncludingAspect_x [ Bmk_i ] ]] [ "AuthorStance" ]
  Bmk_i_AuthorStance <- unlist ( strsplit ( Bmk_i_AuthorStance , "," ) ) [ match ( Bmk_i_Aspect , aspects ) ]
  Bmk_i_AuthorStance <- as.numeric ( Bmk_i_AuthorStance )
  confB_PminusA <-  sqrt ( ( Bmk_i_PersonStance - Bmk_i_AuthorStance ) ^ 2 )

  Bmk_next_Aspect <- px_list [[ BmksIncludingAspect_x [ ( Bmk_i + 1 ) ] ]] [ "ChosenAspects" ]
  Bmk_next_Aspect <- unlist ( strsplit ( Bmk_next_Aspect , "," ) )
  Bmk_next_Aspect <- gsub ( " " , "" , Bmk_next_Aspect )
  Bmk_next_Aspect <- Bmk_next_Aspect [ which ( Bmk_next_Aspect == aspect_x ) ]

  Bmk_next_AuthorStance <- px_list [[ BmksIncludingAspect_x [ ( Bmk_i + 1 ) ] ]] [ "AuthorStance" ]
  Bmk_next_AuthorStance <- unlist ( strsplit ( Bmk_next_AuthorStance , "," ) ) [ match ( Bmk_next_Aspect , aspects ) ]
  Bmk_next_AuthorStance <- as.numeric ( Bmk_next_AuthorStance )
  if ( Bmk_next_AuthorStance > 0 ) { AStance <- "Pro" }
  if ( Bmk_next_AuthorStance == 0 ) { AStance <- "Balanced" }
  if ( Bmk_next_AuthorStance < 0 ) { AStance <- "Contra" }
```

```
        ChangeInStance <- length ( Bmk_i_PersonStance : Bmk_next_AuthorStance )
        confB_continuous <- 1 / ChangeInStance
        #confSearchI <- ChangeInStance
        if ( PStance == AStance ) { confB_dicho <- 1 } else { confB_dicho <- 0 }

        i_df <- data.frame ( px , aspect_x , Bmk_i_Aspect , Bmk_i_PersonStance , Bmk_next_Aspect ,
                    Bmk_next_AuthorStance , confB_continuous , confB_dicho , confB_PminusA )
        px_df <- rbind ( px_df , i_df )

      } # iterating through bookmarks

    } else {

      Bmk_i_Aspect <- NA
      Bmk_i_PersonStance <- NA
      Bmk_next_Aspect <- NA
      Bmk_next_AuthorStance <- NA
      ChangeInStance <- NA
      confB_continuous <- NA
      confB_dicho <- NA
      confB_PminusA <- NA
      i_df <- data.frame ( px , aspect_x , Bmk_i_Aspect , Bmk_i_PersonStance , Bmk_next_Aspect ,
                  Bmk_next_AuthorStance , confB_continuous , confB_dicho , confB_PminusA )
      px_df <- rbind ( px_df , i_df )

    }

  } # iterating through aspects

  return ( px_df )

 }
 px_ConfirmByAuthorStance <- ConfirmedByAuthorStanceFx ( px )
 px_unique_AspectsTapped <- c ( as.matrix ( unique ( px_ConfirmByAuthorStance [ , "aspect_x" ] ) )
)
 for ( ax in 1 : length ( aspects ) ) {
```

```
    if ( ax == 1 ) { px_confBiasII_df <- NULL }
    aspect_ax <- aspects [ ax ]
    lax <- which ( px_ConfirmByAuthorStance [ , "aspect_x" ] == aspect_ax )
    confB_continuous <- mean ( px_ConfirmByAuthorStance [ lax , "confB_continuous" ] , na.rm = T )
    confB_dicho <- mean ( px_ConfirmByAuthorStance [ lax , "confB_dicho" ] , na.rm = T )
    confB_PminusA <- mean ( px_ConfirmByAuthorStance [ lax , "confB_PminusA" ] , na.rm = T )
    px_confBiasII_df <- rbind ( px_confBiasII_df , data.frame ( px , aspect_ax , confB_continuous ,
                                                  confB_dicho , confB_PminusA ) )
  }
  px_df_compiled <- cbind ( px_df_compiled , px_confBiasII_df [ , c ( "confB_continuous" ,
"confB_dicho" , "confB_PminusA" ) ] )
  names ( px_df_compiled ) <- c ( "Participant" , "Aspect" , "Polar" , "InitStance", "EndStance" ,
"extremityRes" , "AspectClick" , "AspectProClick" ,
                            "AspectContraClick" , "confB_AspClick" , "confB_continuous" , "confB_dicho"
, "confB_PminusA" )
  rownames ( px_df_compiled ) <- c ()
  PersonByAspect_df <- rbind ( PersonByAspect_df , px_df_compiled )

  print ( pxx )

}
## Adding AT data to data frame
AT_Index <- rep ( NA , nrow ( PersonByAspect_df ) )
PersonByAspect_df <- cbind ( PersonByAspect_df , AT_Index )
PartisInDf <- unique ( PersonByAspect_df [ , "Participant" ] )
for ( px in 1 : length ( PartisInDf ) ) {
  px_ID <- PartisInDf [ px ]
  l_px_ID <- which ( PersonByAspect_df [ , "Participant" ] == px_ID )
  px_ScuttleData <- PersonByAspect_df [ l_px_ID , ]

  px_ID_PseudoCode <- MappingTable [ which ( MappingTable [ , "User.ID" ] == px_ID ) ,
"AT.Username" ]
  px_ATData <- AT_RT_df [ which ( AT_RT_df [ , "i_code" ] == px_ID_PseudoCode ) , ]
  Increase_nAsso_Fx <- function ( aspect_x ) {
    px_aspect_x_data <- px_ATData [ px_ATData [ , "i_stimulus" ] == aspect_x , ]
    t0_N <- px_aspect_x_data [ px_aspect_x_data [ , "i_mPoint" ] == "t0" , "i_sVec" ]
```

```
    t0_N <- t0_N [ length ( t0_N ) ]
    t2_N <- px_aspect_x_data [ px_aspect_x_data [ , "i_mPoint" ] == "t2" , "i_sVec" ]
    t2_N <- t2_N [ length ( t2_N ) ]
    increase <- t2_N - t0_N
    return ( increase )
  }
  px_Increase_nAsso <- sapply ( px_ScuttleData [ , "Aspect" ] , Increase_nAsso_Fx )
  PersonByAspect_df [ l_px_ID , "AT_Index" ] <- px_Increase_nAsso

}
PersonByAspect_df [ , "AspectClick" ] <- as.numeric ( PersonByAspect_df [ , "AspectClick" ] )
PersonByAspect_df [ , "AspectProClick" ] <- as.numeric ( PersonByAspect_df [ , "AspectProClick" ]
)
PersonByAspect_df [ , "AspectContraClick" ] <- as.numeric ( PersonByAspect_df [ ,
"AspectContraClick" ] )
PersonByAspect_df [ , "Polar" ] <- as.numeric ( PersonByAspect_df [ , "Polar" ] )
PersonByAspect_df [ , "confB_continuous" ] <- as.numeric ( PersonByAspect_df [ ,
"confB_continuous" ] )
PersonByAspect_df [ , "confB_dicho" ] <- as.numeric ( PersonByAspect_df [ , "confB_dicho" ] )
PersonByAspect_df [ , "confB_PminusA" ] <- as.numeric ( PersonByAspect_df [ , "confB_PminusA"
] )
PersonByAspect_df [ , "InitStance" ] <- as.numeric ( PersonByAspect_df [ , "InitStance" ] )
PersonByAspect_df [ , "EndStance" ] <- as.numeric ( PersonByAspect_df [ , "EndStance" ] )
PersonByAspect_df [ , "extremityRes" ] <- as.numeric ( PersonByAspect_df [ , "extremityRes" ] )

### Descriptives
# Polarization index
PolQuotStats <- summaryBy ( Polar ~ Aspect , data = PersonByAspect_df ,
                    FUN = function ( x ) ( c ( mean ( x , na.rm = T ) , sd ( x , na.rm = T ) ) ) )
AspectClickStats <- summaryBy ( AspectClick ~ Aspect , data = PersonByAspect_df ,
                      FUN = function ( x ) ( c ( mean ( x , na.rm = T ) , sd ( x , na.rm = T ) ) ) )
InitStanceStats <- summaryBy ( InitStance ~ Aspect , data = PersonByAspect_df ,
                    FUN = function ( x ) ( c ( mean ( x , na.rm = T ) , sd ( x , na.rm = T ) ) ) )
EndStanceStats <- summaryBy ( EndStance ~ Aspect , data = PersonByAspect_df ,
                     FUN = function ( x ) ( c ( mean ( x , na.rm = T ) , sd ( x , na.rm = T ) ) ) )
mean(InitStanceStats[,2])
```

```
#cor.test ( PersonByAspect_df [ , "AspectClick" ] , PersonByAspect_df [ , "AT_Index" ]  )
#cor.test ( PersonByAspect_df [ , "AT_Index" ] , PersonByAspect_df [ , "confB_dicho" ]  )
#cor.test ( PersonByAspect_df [ , "confB_dicho" ] , PersonByAspect_df [ , "Polar" ]  )
#cor.test ( PersonByAspect_df [ , "Polar" ] , PersonByAspect_df [ , "AspectClick" ]  )

## Aggregate

PartisInDf <- unique ( PersonByAspect_df [ , "Participant" ] )
for ( px in 1 : length ( PartisInDf ) ) {

  if ( px == 1 ) { agg_df <- NULL }
  px_ID <- PartisInDf [ px ]
  l_px_ID <- which ( PersonByAspect_df [ , "Participant" ] == px_ID )
  px_Data <- PersonByAspect_df [ l_px_ID , ]
  proContraMeans <- colMeans(px_Data[,c("AspectProClick","AspectContraClick")],na.rm=T)
  balancedClickBeh <- c(as.matrix(proContraMeans[1]/proContraMeans[2]))
  px_Data_Agg <- c ( px_ID , colMeans ( px_Data [ , c ( "AspectClick" , "AT_Index" ,
"confB_AspClick" ,
                                        "confB_dicho" , "confB_continuous" , "confB_PminusA" ,
                                        "Polar" , "extremityRes" ) ] , na.rm = T ) )
  px_Data_Agg <- c ( px_Data_Agg , balancedClickBeh )
  names ( px_Data_Agg ) <- c ( "Code" , "AspectClick" , "AT_Index" , "confB_AspClick" ,
"confB_dicho" , "confB_continuous",
                        "confB_PminusA" , "Polar" , "ClickBalance" ,"extremityRes" )
  agg_df <- rbind ( agg_df , px_Data_Agg )

}

agg_df [ , "AspectClick" ] <- as.numeric ( agg_df [ , "AspectClick" ] )
agg_df [ , "AT_Index" ] <- as.numeric ( agg_df [ , "AT_Index" ] )
agg_df [ , "confB_continuous" ] <- as.numeric ( agg_df [ , "confB_continuous" ] )
agg_df [ , "confB_dicho" ] <- as.numeric ( agg_df [ , "confB_dicho" ] )
agg_df [ , "confB_AspClick" ] <- as.numeric ( agg_df [ , "confB_AspClick" ] )
agg_df [ , "confB_PminusA" ] <- as.numeric ( agg_df [ , "confB_PminusA" ] )
agg_df [ , "Polar" ] <- as.numeric ( agg_df [ , "Polar" ] )
```

```
agg_df [ , "ClickBalance" ] <- as.numeric ( agg_df [ , "ClickBalance" ] )
agg_df [ , "extremityRes" ] <- as.numeric ( agg_df [ , "extremityRes" ] )
# agg_df <- agg_df [ - which ( agg_df [ , "Code"] == "20") , ] # outlier
## Testing hypotheses
# H1
plot ( agg_df [ , "AspectClick" ] , agg_df [ , "AT_Index" ] , xlab = "Interaction Frequencey (aspect-
click frequency)" ,
      ylab = "Familiraity (increase in associations)" , cex.lab = 0.8 , cex.axis = 0.8 , cex = 0.8 , pch = 16
)
abline ( lm ( agg_df [ , "AT_Index" ] ~ agg_df [ , "AspectClick" ] ) )
cor.test ( agg_df [ , "AspectClick" ] , agg_df [ , "AT_Index" ] )

# H2
plot ( agg_df [ , "AT_Index" ] , agg_df [ , "confB_continuous" ] , xlab = " Familiraity (increase in
associations)" ,
      ylab = "Confirmatroy Bias, cex.lab = 0.8 , cex.axis = 0.8 , cex = 0.8 , pch = 16 )
abline ( lm ( agg_df [ , "confB_continuous" ] ~ agg_df [ , "AT_Index" ] ) )
cor.test ( agg_df [ , " confB_continuous " ] , agg_df [ , "AT_Index" ] )

# H3
plot ( agg_df [ , "confB_continuous" ] , agg_df [ , "Polar" ] , xlab = "Confirmatory Bias" ,
      ylab = "Polarisation" , cex.lab = 0.8 , cex.axis = 0.8 , cex = 0.8 , pch = 16 , ylim = c ( 0 , 1 ) )
abline ( lm ( agg_df [ , "Polar" ] ~ agg_df [ , " confB_continuous " ] ) )
cor.test ( agg_df [ , "confB_continuous" ] , agg_df [ , "Polar" ] )

# H4
plot ( agg_df [ , "Polar" ] , agg_df [ , "AspectClick" ] , xlab = "Polarisation" ,
      ylab = "Interaction Frequencey (aspect-click frequency)" , cex.lab = 0.8 , cex.axis = 0.8 , cex =
0.8 , pch = 16 )
abline ( lm ( agg_df [ , "AspectClick" ] ~ agg_df [ , "Polar" ] ) )
cor.test ( agg_df [ , "Polar" ] , agg_df [ , "AspectClick" ] )

cor ( agg_df [ , c ( "AspectClick" , "AT_Index" , "confB_PminusA" , "Polar" , "ClickBalance" ) ] )
cor.test ( agg_df [ , "confB_PminusA" ] , agg_df [ , "Polar" ] )
rownames(agg_df) <- c()
summary ( lm ( Polar ~ confB_PminusA * AspectClick , data.frame ( agg_df ) ) )
```