Towards an Understanding of Opinion Formation on the Internet

Using a Latent Process Model to Understand the Spread of Information on Social Media

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Abstract. Understanding what drives the process of opinion formation has been studied since the 1960s. With the advent of the social web, this process has drastically changed, as everyone can easily reach out to the global public. However, not everyone expresses their opinion on social media. Understanding what governs this process is crucial to understanding the spread of information on the Internet. We use a latent process model to simulate opinion formation using agent-based modeling. By creating an artificial social network with artificial users and content, we simulate the reaction of users to content and the resulting spread of information. We inform our model from a questionnaire survey study that indicates that actual sharing is rare for a large proportion of users. Our findings indicate that deep network penetration can not be explained by user behavior alone and that "minority effects" might require large scale simulations to be seen. Future research should thus incorporate simulated algorithms and larger populations.

Keywords: Social networks · Agent based model · Opinion formation · Polarization · Attitude.
This preprint was published by Springer under the DOI: 10.1007/978-3-030-61503-1_13

1 Introduction

Facebook, Instagram, Twitter, and WhatsApp are integrated into everyday life. More and more people use social networks to look for information, to form opinions, but also to disseminate opinions [3,6]. However, what information is shown to whom, depends largely on the users' interactions with content.

In the past, social networks also played a major role in debates about how opinions were deliberately influenced to manipulate political outcomes. It is therefore important to better understand and predict opinion-forming processes.

Research is concerned with how the use of social networks influences user behaviour [13]. An example for such effects is the so-called "minority effect", where a small determined fringe minority changes the opinion discourse of an entire group [4,8].

In our research, we try to apply the *Latent-Process Model* of opinion formation in an agent-based model to understand how users react to different types of content. We inform our model using a questionnaire survey. We then use the model to simulate how agreement with content yields different interaction strategies, which in turn yields different network penetrations. Overall, we try to understand whether a complex model such as the latent-process helps to determine the spread of information in social networks.

2 Related Work

We look at the attitude of users of online social networks. Therefore, we first define the term *attitude*. As a person's attitudes and actions are closely interrelated, we then present the *Latent Process Model* that is used to explain the construction and components of attitudes. From these attitudes behavior is derived using social response theory (see Fig. 1).

2.1 Attitude

Several understandings of *attitude* exist. For some, *opinion* and *attitude* are synonymous and interchangeable, whereas others regard them as different aspects of a related process. So far, there is no uniform definition of attitudes [12,10]. Nevertheless, attempts to define *attitude* have showed similarities. Using these and following the definition of Oskamp and Schultz, we understand the term as a tendency to evaluate an object of attitude positively or negatively and to react to it if necessary.

Attitude research. Research on attitudes assumes that attitudes consist of a cognitive, affective, and behavioral component [12]. The cognitive component is a person's thought about an attitude object, often referred to as *beliefs*. The affective component relates to the *feelings* or emotions towards the adjustment object. The behavioural component refers to concrete intentions and an actual behaviour towards an object [12,2,5]. The affective component is important, as emotions are usually motivating and drive behaviour more strongly [12] than cognition.

There is also criticism of this rather established three-component model [2,9]. It is unclear how the components are interconnected and whether the components actually say the same thing or whether they differ enough to be divided into three different entities. It is also doubted whether an attitude always consists of all three components [12]. Here, two views have emerged: On the one hand the proponents of the so-called *Consistency Theorem*, on the other hand those who reject this theorem (*Separate Entities Model*).

2.2 Latent-Process-Model

The *latent process model* [7] arose from criticism of the *Consistency Theorem* and the *Separate Entities Model*. All models try to explain the emergence of attitudes. DeFleur and Westie criticize that the models assume a consistency between action and attitude. Still, they believe that an inner process mediates between external stimulus and behaviour. The other two models try to explain this inner process, which cannot be observed through visible behavior, but—according to DeFleur and Westie—behavior cannot be equated with this inner process. They further believe that behaviour is influenced by other factors such as social desirability, not only attitude. For them, attitude is a theoretical construct that must be considered as unknown. The theoretical construct is a link to describe the relationship between object and action. For the attitude itself, there is the antecedent unobservable process of attitude formation and a subsequent reaction. However, they assume that there is a stimulus that triggers cognitive and affective processing and the process of behavioral intentions. The three processes then together or individually form the latent attitude, which manifest through a cognitive or affective reaction or behavior. Here, DeFleur and Westie speak of a probability conception, i.e., how probable it is that a person behaves towards an object in a similar way as in the past. An advantage of the model is that the attitude does not have to be seen as an explanation for a person's behaviour, but rather as the regularity of certain behaviour patterns. A further advantage of the *Latent Process Model* is that no connection between the individual components within the model is assumed, but they can arise in the model from one to three process types [7,12].

Another model of social interaction is the diamond model or four-dimensions of social response by Nail et al. [11]. This model states that the actual opinion voicing of a person in a social setting of majorities and minorities can be of four types. Behavior can be *congruent*, which means that their external attitude (or voiced opinion) matches that of the majority. *Conforming* individuals show an external attitude that also matches the majority, but is opposing the internal attitude. Anticonforming individuals share the minority opinion (internally) and voice it (externally). And independent individuals may or may not share the majority opinion (internally), but refrain from sharing in either case—they stay externally neutral. Which behavior is shown depends on the strength of internal attitudes and the strength of the externally perceived majority opinion. Different thresholds induce different behaviors.

2.3 Research Aim

The goal of our research is thus to utilize the latent-process model and the four dimensions of social response to understand how opinion formation—and even hidden opinion change—spread in social network structures. Different from previous research (e.g. Brousmiche et al. [1]), we include a theory of social response.

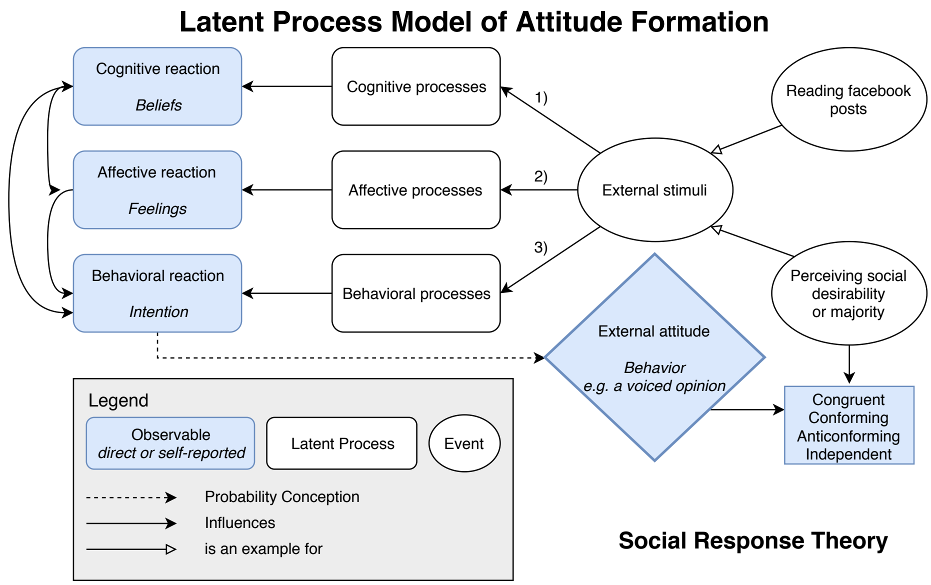

Fig. 1. Latent Process Model of Attitude Formation. Individual Events can have different influences on each processes (see 1, 2, and 3). The external behavior (opinion voicing) is then guided by social response theory.

3 Method

To achieve this aim, we build an agent-based model that simulates opinion formation using a *latent process model* based on three pillars. First, our model uses message sending. Our messages are of different types, addressing either cognitive or affective processes in the agents. Second, the agents opinion formation is simulated using cognitive, affective, and also behavioral processes. Lastly, each agent may behave in accordance to the four-dimensions of social response. Since such a model has a plethora of possible parameter configurations, we limit the simulation experiments by informing the model using data from a survey.

In this survey we measure both the distribution of different agent-types and different content-types. This means two things. First, it means that we determine if users react differently to cognitive and affective stimuli. From this, we determine the distribution of different reaction of our agents. Second, it means that we ask users about their reactions to different contents, using real life social media posts, to determine what processes in the latent-process model are addressed.

3.1 Online questionnaire

As mentioned before, expressing one's opinion on social media depends on unobservable antecedent processes. Therefore, we concentrate on the observable external opinion or behavioural reaction. The survey was sent via individual social networks (i.e., Facebook, Twitter, etc.) between December 2018 and February 2019 using convenience sampling.

Survey Materials. The survey consisted of two parts. In the first part, we asked for gender and age as demographics. We further looked at the experience with and the knowledge about online social networks. we asked, how large their biggest chat-group was and with how many users they were connected.

For part two, we first introduced a scenario: Here, the participants should think of an online social network with a similar structure and functionality as Facebook. Then, we presented four different *contents* and asked questions about each of them (more details in the following paragraph). These questions measured the cognitive and affective *value* of these example news posts using a semantic differential (more details in the next paragraph). We further asked the users, how they would react to this content (more details in the last paragraph of this section). Lastly, we asked whether the content helped them form an opinion, whether it supported their opinion, and whether they perceived it as polarizing.

Contents used in our study. To cover a breath of different affective and cognitive values we used four different content variations: first, a serious article (1. *Zeit Online article*) and second, a polarizing article (2. *Bild Online article*). For these two, we used a report on an EU survey on anti-Semitism, which was published on both websites. We further used an emotional promotional item (3. *Instagram post*) and an unemotional promotional item (4. *online evaluation*). Both contents advertise for a Berlin bar (BRYK).

Measuring cognitive and affective value. After the presentation of each content, we asked the participants to evaluate the content with 12 adjectives on a semantic differential. This was done to capture the affective and cognitive value for the latent process model presented in section 2.2.

Measuring behavioral value. Afterwards, we presented the same content again (to see a possible influence on opinion formation) to the participants and asked them how much they would agree with the content and how they would react (share, comment, like, ignore), if they were to encounter it in a social network. These questions deal with the *behavioral dimension* of the latent process model and were also be integrated into the agent-based model.

4 Results of the online survey

As a first step of this study, we analyzed the data of the online survey using SPSS. As a second step, building on these results, we created an agent-based model (see section 5) and analyzed the data using SPSS and Netlogo. Following, we present the results of the online survey, starting with a short sample description.

Sample Description. Of the 105 participants 63 were female and 42 were male. The participants were on average 31.7 years old (SD = 11.5). From the four different social networks/messaging-apps most participants use WhatsApp (97%), followed by Facebook (87%) and Instagram (52%), the least participants use Twitter (13%). The largest chat group for most participants consists of *10 to 20* (34%), *more than 20* (34%) or *5 to 10* (26%) people. In social networks, many participants are connected with *more than 300* (34%) users. On the other hand, many also stated that they are connected with *less than 50* (16%) users.

Four different contents Following, regarding the *contents*, we look at the correlations of the *cognitive*, *affective* and *behavior-reaction* and their influence in the *opinion formation*, the support readiness (*support*), the reinforcement of the conviction (*conviction*) through other people and the polarizing overall impression (*polarizing*).

For *Zeit online* the *cognitive reaction* showed a positive influence on the *willingness to share the content* and an negative influence on the *intention to ignore* the content. The *cognitive reaction* further correlated positively with the *opinion formation* and *support*, but negatively with the evaluation how *polarizing* a content is. As can be seen in table 1, calculated linear regressions with the *cognitive reaction* as independent variable confirmed the influence on the dependent variables.

Table 1. Regression results for Zeit online with the cognitive reaction

Dependent variable	Regression results	Corr. r^2
Sharing:	$F(1, 103) = 19.07, p < .001.$	r^2=.15
Ignoring:	$F(1, 103) = 13.31, p < .001.$	r^2=.11
Opinion formation:	$F(1, 103) = 90.05, p < .001.$	r^2=.46
Support:	$F(1, 103) = 52.12, p < .001.$	r^2=.33
Polarizing:	$F(1, 103) = 18.58, p < .001.$	r^2=.15

Comparison of the four different contents Comparing the contents (see Fig. 2), the participants perceive *Bild online* as most polarizing. Further, less participants would include the *Instagram post* in their opinion formation. In contrast, most participants would include the *online evaluation.* Matching, the most participants share the *online evaluation* to support a person in their network.

5 Method: Agent-based model

Using the online survey results, we have developed an agent-based simulation, which we from now on call the *o-formation model*[1]. For the methodical implemen-

[1] As in opinion formation.

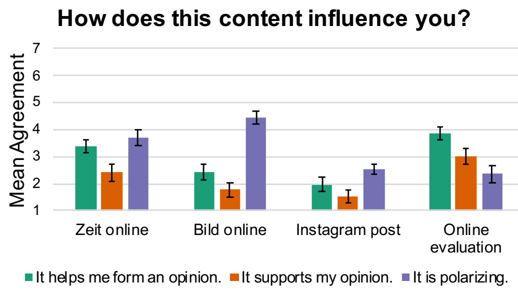

Fig. 2. Means for the comparison of the four different contents. Error bars denote 95% confidence interval.

tation we used the multi-agent programming language Netlogo in version 6.0.1, developed by Uri Wilensky [16]. NetLogo provides a user interface to agent-based modeling and allows to run several hundreds of simulations using a batch mode.

5.1 O-formation model: Before the simulation starts

Based on the reported average size of a network we set the network size for all simulation runs to 100 agents. To reduce the complexity of the model and to enable a comparability of the results, we fixed some settings from the beginning, that we describe following and are visible in Table 2.

Table 2. Initially adjusted parameter settings for the agents of the model

parameter	value	parameter	value	parameter	value
agent count	100	positive proportion	10%	negative proportion	10%
proportion seen	10%	clustering-coefficient	0.14	initial opinion	100%
conformity rate	50%	congruence rate	50%	anticonformity rate	50%
independence rate	50 %				

Modelling attitude As mentioned earlier, each agent has an *internal* and *external attitude* on a certain topic. Each agent can have a positive or negative *internal attitude* or have **not yet formed** an attitude (see Table 2 positive and negative proportion). The attitude is stored as a number.

Initially 10% of the 100 agents in the network see the content (*proportion seen*). Of all agents, 10% each have a *positive* or a *negative* internal attitude towards the content (see Table 2 *positive proportion* and *negative proportion*).

The *internal attitude* is only known by the agent itself. In contrast, the *external attitude* or external opinion is a public disclosure of the opinion. It therefore describes whether an agent has already made a positive or negative statement on the topic by sharing the message. Neutral agents have not yet shared the message.

An agent may also have an *external attitude* different from their *internal* one. How internal and external attitude relate to each other is governed by social response theory. Depending on the direction and strength of the attitude as well as the attitude of other agents different thresholds apply for determining the external attitude. We fixed the rates of the different *social response types* (congruence, anticonformity, conformity, independence) to 50%. For example, if an agent has the same attitude as the majority—thus *a congruent social response*—it decreases the threshold to share the content by 50%. Inversely, if an agent hold the minority attitude—thus *an anticongruent social response*—the threshold is increased by 50% (see Table 2 *rates*).

The *internal attitude* and *external opinion* of an agent can change through the exchange with other contents or other agents.

5.2 Generating the artificial network

Since we looked at user behavior on Facebook in the survey, we also wanted to look at a network similar to Facebook in agent-based modeling. We opted for a easy to generate but classical small world network, the Watts-Strogatz model [15]. In this network, agents can see and share content from friends connected to them. There are close friendships or more distant acquaintances. Therefore, we weighted the connections between the agents by assigning a random value between 0 and 3 to each edge.

In their study, Ugander et al. analyzed the structure of Facebook and found that with a circle of friends of 100, the clustering coefficient is 0.14 on average. We used the results of this study as a basis for our model, and therefore adjusted the *neighborhood-size* to 2 and the parameter *rewire-probability* to 35%, what generates a *clustering coefficient* of 0.14 [14]. We then performed 1800 simulation runs to verify that the parameter settings lead to the desired average *clustering coefficient* ($M = 0.14, SD = 0.23$).

Modelling messages In the model, a topic (or message) is one configuration randomly chosen from the four contents of the online questionnaire.

Table 3. Initial parameter settings of the four different contents

parameter	Zeit	Bild	Instagram	Evaluation
cognitive-impact	0.4	0.3	0.22	0.23
affective-impact	0.06	0	0	0
influence-likelihood on agents if it agrees	0.69	0.39	0.34	0.72
influence-likelihood on agent if rejects	0.14	0.26	0.09	0.26
sharing threshold	16	14	14	11

Additionally to the initial adjustment of the parameters, we have created templates for the four *contents* of the online survey. Here, we defined the influence of the *cognitive* and *affective component* of the *latent process model* (see section 2.2). We designed the parameter settings of the four *contents* according to the results of the online survey, as can be seen in Table 3.

5.3 Opinion distributions at the beginning

At the beginning of the simulation we adjusted four *different opinion distributions*. In the beginning of the *first distribution* (*Neutral*), only 10% of the agents have a positive and 10% a negative attitude towards the topic of the content. In contrast, in the *second distribution* (*Polarized*) every person has an attitude towards the topic of the content. Here, 50% of the agents have a positive and 50% a negative attitude. The *third distribution* considers an already widely accepted issue. The content proponents are in the majority (*proponents*). Here 60% of the agents have a positive and 10% of the agents have a negative attitude towards the content. Mirror-inverted in the *last distribution* (*Opposition*) are 60% agents with a negative and 10% agents with a positive attitude towards the content.

5.4 Transfer of the results to the o-formation model

The linear regression results described in chapter 4 form the basis of our *o-formation model*. The *opinion formation* by agents is influenced by how important the cognitive or affective aspect of the subject is to them. It is also possible that an agent is affectively/emotionally convinced of a topic, but cognitively or logically rejects it. The importance of the *affective* and *cognitive component* is initially determined on a scale of -3 to 3 (to match the survey data). The distribution of values depends on the *type of person*. Agents with a *public point of view* randomly receive a value between 2 and 3 for positive attitude and -3 and -2 for negative attitude, agents with a *hidden point of view* randomly receive a value between 1 and 3 for positive attitude and -3 and -1 for negative attitude and zero for agents with a *neutral* attitude.

In addition to the agent, a content and the relative stance of the content (positive or negative) are defined at the beginning. The content also has a cognitive (range: -3 to 3) and affective (range: -3 to 3) component. In addition, we have determined how strongly an agent evaluates the content according to the *affective-impact* and *cognitive-impact* components. The content remains the same in the network, whereas the agents can change their internal and external attitude through exposure to content.

In addition, we variate in the model how many people include content corresponding to their attitude in their *opinion formation* and, based on the results of the survey, how many include content contradicting their attitude in their opinion formation (see also rows 3 and 4 in Table 3).

Decision algorithms. When the simulation starts, the agents form their internal attitude by comparing their own *cognitive component* with the *cognitive component* of the content they see. The calculation depends on the *type of person* the agent belongs to. If the cognitive value for the agent and the content is positive and the cognitive value of the content is higher than that of the agent, a 3 is returned as the value. The value is smaller if the cognitive content is equal to or smaller than the value of the agent. The value indicates how much the agent matches the *cognitive component* of the content. The content can thus convince the agent more convincingly than its own logical arguments or less convincingly. For agents with a negative cognitive value, the calculation is analogous. Agents with a cognitive value of 0 can only be flipped by very convincing contents ($>$1.99 or negative). Analogously, each agent also compares his own *affective component* with the *affective component* of the content.

Following the model of DeFleur and Westie, the cognitive and affective value together form the *latent attitude* [7] by multiplying the *cognitive component* by the *cognitive-impact*. Here, it is calculated to what extent the content convinces a person cognitively, i.e., with logical arguments, and how much importance he attaches to the aspect of opinion formation. The same calculation is performed for the *affective component* and multiplied by 2, since the *affective component* is considered to be more important [12]. The *affective* and *cognitive components* thus form the *latent attitude* in the model. If the *latent attitude* is positive, the person agrees with the opinion of the content. If the latent attitude is negative, the person rejects the content.

However, not all agents include the content in their own opinion forming. The *internal opinion* is important for the selection of agents who include the content in the opinion forming process. At this point, the model filters for agents who see the content for the first time and for a percentage of agents with a positive *internal opinion*, the content is included in the opinion forming process. These agents then adopt the content as their own *internal opinion*, provided the opinions differ. Agents with a negative *internal opinion* also go through the same process, albeit with a lower likelihood.

After the agents have formed their *internal opinion*, the agents who see the content for the first time are again filtered out and assigned a behavior. Agents who have the same opinion as the content and who exceed the *sharing threshold* (set at the beginning) share the content.

5.5 How do starting conditions affect the model?

We exemplary show the results for *Zeit online* and all initial opinion distributions. We see that almost no user behaves *anticonforming* during the simulation runs(see Fig. 3). The biggest change occurred for users, that themselves *conform*. In the *proponents* distribution only three users adapt themselves to the opinion ($M = 2.96, SD = 2.3$). Further, we see that external attitude changes are larger than internal opinion changes (see Fig. 3), although changes remain small.

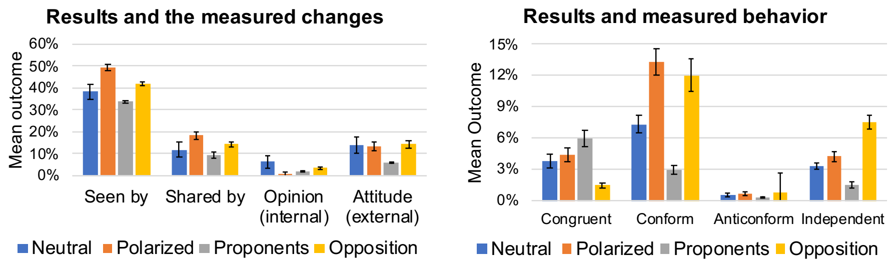

Fig. 3. Averaged outcomes at the end of the simulations for the four initial opinion distributions and the respective measured changes for the example content Zeit online over all simulations (left) and behavior classification (right). Error bars denote 95% confidence interval.

6 Discussion

Using the agent-based simulation we found four main results. First, the network penetration of the four contents is small for all four initial distributions and in no simulation do all agents see the contents at the end. It can therefore be assumed that users who agree with the opinion of the content do not see any incentive to share the content. Secondly, the content has only a minor influence on the formation of attitudes and the expression of opinions. This reflects the passivity of the participants reported in the questionnaire. Thirdly, the social influence has only a small influence on the behaviour of the agents. An oppositional distribution increases the conformity of the persons, which could be due to the fact that persons receive particularly little social support in this distribution and would therefore rather adapt to the opinions of others. Fourthly, the content was mainly shared when a person acted in conformity with the opinion and influence of their friends.

7 Conclusion and Outlook

First of all, we can argue that the differences in using social networks influences how people react to online content. Our results have shown that the cognitive response, i.e., the logical evaluation, has an influence on the type of reaction, opinion-forming, and willingness to support others. The affective reaction, i.e., the emotional evaluation, also has a partial influence on the formation of opinion and willingness to support and strongly influences conviction.

Although sharing is considered to be the strongest form of participation, overall most users, regardless of the type of content, are passive and unwilling to promote opinion-forming by sharing contributions. Due to the low activity, over a third of users, at least in our model, do not see the contributions and the social impact has almost no impact. Users seem most likely to share content in order to conform to their friends. Given that users actually do see content that intends to shape opinions, large network effects seem to be at play, that require additional investigation. Our small 100 agent simulation might underestimate the effect of the determined minority in social networks. Furthermore, other malicious types of content were not simulated (e.g., click-bait, spam, fake news). These could have resulted in different outcomes as well. Lastly, a large component of the spread of information in social networks are algorithms. They determine how the behavior of individuals leads to actual exposure. In our simulation, we assumed that sharing equates exposure. This is not the case in real social networks. The research could be extended be integrating evaluations and simulations of recommender systems and their effects of opinion formation.

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