How Identity and Uncertainty Affect Online Social Influence
An Agent-Based Approach

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Abstract. Computer simulations have been used to model psychological and sociological phenomena in order to provide insight into how they affect human behavior and population-wide systems. In this study, three agent-based simulations (ABSs) were developed to model opinion dynamics in an online social media context. The main focus was to test the effects of 'social identity' and 'certainty' on social influence. When humans interact, they influence each other's opinions and behavior. It was hypothesized that the influence of other agents based on ingroup/outgroup perceptions can lead to extremism and polarization under conditions of uncertainty. The first two simulations isolated social identity and certainty respectively to see how social influence would shape the attitude formation of the agents, and the opinion distribution by extension. Problems with previous models were remedied to some extent, but not fully resolved. The third combined the two to see if the limitations of both designs would be ameliorated with added complexity. The combination proved to be moderating, and while stable opinion clusters form, extremism and polarization do not develop in the system without added forces.

Keywords: Social influence · Social identity · Certainty · Opinion dynamics · Online social networks · Facebook · Agent-based models · Attitude formation · Abelson diversity problem · Polarization · Extremism · Misinformation

1 Introduction

On social media websites like Facebook, information is disseminated differently from traditional media outlets, as it is negotiated by a network of "friends". This means that users' personal social networks affect what information they are exposed to. As a consequence, social influence has become a major factor in how information is distributed in this context, affecting societal and political opinions.

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Social influence is the process by which people adjust their opinions based on their interactions with other people [1]. This study aims to explore social influence insofar as social identity and uncertainty contribute to it. This is conceptually driven by the idea that attitudes[1] are embedded in a social context, and that people base them around their social ties [2]. Furthermore, their susceptibility to influence is mediated by how certain they feel about their own views, with less certain agents being more vulnerable to changing their opinion [3]. The key aim of this study is to see if these two factors in a social media communication structure will affect the extent to which agents are socially influenced in their attitude formation. Attitude formation is the process by which an individual goes from unstable, ambivalent or ambiguous attitudes about a certain subject to a stable opinion. Once an attitude is formed, it becomes the standard by which an individual uses to evaluate the attitudes of others [4].

Humans form groups based on their social identity. In this study, social identity is operationalized as the set of groups an individual subscribes to, and includes demographic traits like gender, race, and nationality but also cultural traits such as ethnicity, religion, and political affiliation (cf. [5]). It is assumed that group structures affect how information is distributed. Therefore social identity is used as a variable to see what effect it has on system-wide opinion dynamics. Uncertainty refers to the confidence with which an agent holds an opinion, and it is shown to be affected by group membership [2,6]. Group membership is an important concept driving social influence, because people are more likely to be influenced by those who they consider to have the same group membership as themselves, or their ingroup. Conversely, those who identify as a different social category are considered outgroup members and are less influential [7].

While some models have combined uncertainty and social identity [8], the context of their social interactions are dyadic (an interaction between two agents), unlike online social networks. Multiadic communication (one agent communicating to many other agents at once), which is how information is shared on Facebook, has not been extensively studied. While fewer studies have modeled online social networks [9,10], they have not taken into account the specific factors studied here. Furthermore, simulations of extremism and polarization often insert extremist agents into the population, suggesting that extremism does not arise from the same cognitive motivations held by the rest of the population [10,11]. In this study, it is assumed that this is not necessarily the case: it is tested if extremism can arise from these models without inserting a few agents who perpetuate it with unique behaviors.

An important motivation for studying social influence is that it can add to our understanding of the problem of 'fake news' and potentially inform future counter strategies. If agents are vulnerable to social influence, injecting misinformation into a social network can lead to large-scale information disorders, such as the emergence and persistence of polarization and extremism [12,13]. It is estimated that the average American encountered between one and three fake

[1] In the literature, 'attitude' and 'opinion' are often used interchangeably.

articles daily in the month before the 2016 presidential election, with the vast majority reported being seen on Facebook [12]. The fact that Russia has used Facebook as a propaganda tool for political influence demonstrates the severity of the problem and the great need for research into helping to understand the dynamics of how information influences peoples' attitudes. Furthermore, Facebook networks, like real-world networks, can be highly segregated [14], contributing to the formation of small groups who communicate among each other with little or no exposure to contrasting opinions (so-called echo chambers), which compound the problem of the spread and circulation of misinformation. The models discussed in this paper are based on the communication structure of such online social media sites. Section 2 will discuss previous agent-based models of opinion dynamics. Subsequently, Sect. 3 will give an overview of the present study while Sects. 4, 5 and 6 will describe the three models developed for this study in detail, with the results of each model following their description. Finally, Sect. 7 provides a discussion of the findings from all three models. It is beyond the scope of this paper to compare the conclusions drawn based on the models with real-world data. However, in the final section various leads for future research along such lines are discussed.

2 Background

2.1 Modelling Opinion Dynamics

The typical way of modelling opinion dynamics in ABMs is using a continuous opinion model, where opinions are represented on a continuous scale (say, between 0 and 1), and the similarity between any two opinions is defined by how close they are on the continuum. This allows for social influence by agent's pulling (or pushing) each others opinions along the spectrum through interaction according to the rules of the model. This continuum represents moderate opinions in the center, and extremist views on either end [15,16]. When combining social influence and opinion dynamics, these models have four potentials for distributing opinions: consensus, polarization, strong diversity or weak diversity. Consensus is agreement on one opinion, and polarization on two opposing opinions. Strong diversity refers to the representation of many opinions along the spectrum, and weak diversity is so-called "opinion clustering", where only several opinions are represented [15].

The fundamental problem with this type of representation is the so-called Abelson's Diversity Puzzle, which says that social influence represented on a spectrum with opinions being pulled towards each other will always lead to consensus unless there are perfectly separate agents who enact zero influence on one another [17,18]. In a highly connected world it is unreasonable to assume that there are entirely isolated groups of individuals who receive no influence from other groups [19], so there must be another explanation for the persistence of a diversity of attitudes in connected networks like Facebook.

2.2 Solutions in Modelling

The most prominent and perhaps successful solution to this problem is the bounded confidence model [20,21]. Bounded confidence models assign 'boundaries' between what agents can be influenced by who and in what direction. Agents have an opinion and a threshold (the 'bound of confidence') on either side of their opinion, where if another agent's opinion is within this threshold, then it can be influenced, if it is outside, it can no longer be influenced. Relative Agreement Models are an augmentation on this, where the amount of agreement between agents will determine the extent of the influence, and agents with lower thresholds (equated with less "uncertainty" surrounding their opinion) will proportionately have more influence in the model [21,22]. This is taken to be a more faithful representation of real influence, because influence is proportional to the certainty of that agent (and not a binary only taking account the distance of opinion), so that confident agents can be more convincing despite how different their opinion is from a less certain agent [22].

There are two major issues with these models. Firstly, if there is even a slight probability that an agent will influence another agent outside of its bound of confidence, the system degrades to consensus (Fig. 1) [23]. Secondly, the clustering of agents are a mathematical necessity determined by their initialized distance from each other and agents only interact on the basis of this distance, which is unrealistically oversimplified even for a reductive model of human behavior.

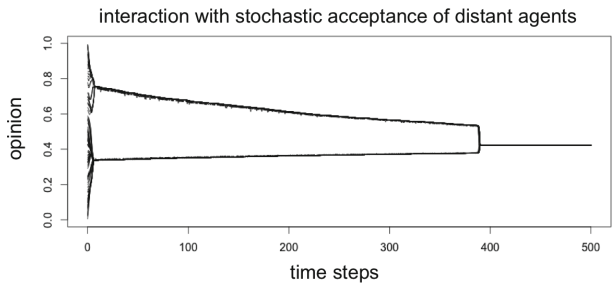

Fig. 1. Probability of acceptance outside of bounds of confidence of .0001 will eventually lead to consensus (from [23]).

3 Present Study

The models described here are also models of social influence, but social influence is mediated by social identity and certainty. Three models were developed for experimentation. In the first model, instead of agents forming groups because of attitude proximity (as with the BC model), they will form groups based on similarity of social identity, following the identity repertoire construct [24]. The second model takes the BC model as is, but uses certainty as a negotiator for group formation as well as stochastic noise, to see if this affects the mathematical rigidity of the original model. Finally, the two models are combined to see if a combination of them creates a more faithful representation of attitude formation, and see what tweaking the parameters of this system results in. If it is possible for stable opinion clustering to form (that is, a heterogeneous distribution) given the Abelson Diversity Problem, can extremism or polarization be modelled by the design of these models given the variables in question?

4 Model 1: Social Identity

This model relies conceptually on the idea of ingroup/outgroup perceptions, where an agent can only be influenced by another agent if they are perceived of as their ingroup. What is being manipulated here is how many identity dimensions agents are comparing themselves on, and how many possible identities exist within these dimensions. The combination of these two factors determines the composition of the population, and therefore how diverse it is. The goal here is to see if there is some combination where ingroup sizes will facilitate clustering, but not into groups of agents who share all traits.

4.1 Design

Each agent has a set of identity traits referred to here (and in the literature) as their 'identity repertoire' [24]. In this experiment, this repertoire is a set of arbitrary length, which is the same for all agents, and the length of the set affects the composition of the population. Larger identity repertoires, and more options within each identity dimension will lead to a more diverse population. If the identity repertoire length is 3, this could theoretically correspond to gender, race, and religion. Within each identity an agent has a corresponding category (e.g.. Christian/Muslim/Jewish), which is indicated as a discrete integer. This means that if two agents share an integer on one dimension, they are of the same category on this dimension. The larger the repertoire, the more possible 'types' and the more possible combinations for an individual agent. For example, consider a population which has an identity repertoire of 2 (they compare themselves on 2 dimensions) and each dimension has 2 categories (0 or 1). This basic combination means that there are 4 possible types: 00, 01, 10, 11. Agents in this construct may share no traits in common (00 and 11), one trait in common (00 and 01), or all traits in common (00 and 00). Whether or not an agent considers another agent their ingroup is defined by how many traits they share in common, which is also a variable named the 'similarity threshold'.

The model is fully connected to the extent that each agent is exposed to the attitude of any other, so that it can be considered an unbiased system. On each time step, a random agent is chosen to 'broadcast' it's opinion, which is then received by all agents in the network. If this agent is in a particular agent's ingroup, it will be influenced by this agent to some degree, k_u, the 'influence factor'. If x is an agents attitude and x' is the influencing agents attitude, the change in the agents attitude, Δx, is calculated as follows:

$$\Delta x = x + k_u|x' - x| \tag{1}$$

Where x moves towards x' by the difference between x and x' times k_u. The influence factor k_u is a modified version of Deffuant et al. [11] which includes the uncertainty of the influencing agent (which will be used in Model 2) and is calculated as follows:

$$k_u(x, x', u, u') = (1 - u')(e^{-(x - x'u)^2}) \tag{2}$$

Where u is the agents uncertainty and u' is the influencing agent's uncertainty. This equation moderates the degree to which an agent will go towards another agent's opinion. If the agent is very certain, k_u will be smaller, and the more quickly the graph of possible influence given the difference between the two attitudes will go to zero. Also, the larger the distance between the two agent's attitudes, the faster the equation goes to 0 generally.

This basic formula will be used throughout the models, however as mentioned this particular model does not take uncertainty into account. For these simulations, both u and u' will be set to .5 for all agents and will not vary as a result of influence. The equation (graphed in Fig. 2) is as follows:

$$k_u(x, x') = .5(e^{-(x - x'.5)^2}) \tag{3}$$

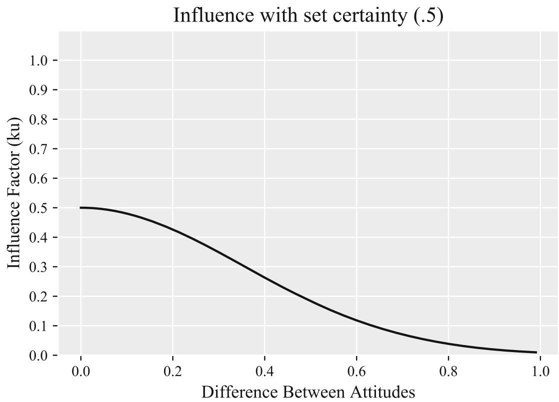

Fig. 2. Influence when certainty is set to .5.

In order to maintain the integrity of the model conceptually (in terms of the Abelson Diversity Puzzle), agents who are under no chance of influence are altered. That is, if an agent does not share enough similarities with any agent to consider them the ingroup (and therefore are immune to social influence), their similarity threshold is lowered until they are ensured to have at least one ingroup member.

4.2 Results

When agents must share all traits in common to be considered an ingroup, stable opinion clusters occur. They are essentially small consensus islands whereby each type of agent is excluded from influence from any agent who does not share all of their traits. However, as with the Abelson Diversity Problem, in populations which are not sufficiently diverse, if agents consider anything less than sharing all traits in common, the population will converge to consensus (Fig. 3). The solution to this, then, is to increase the identity repertoire and the complexity of each dimension, and to find the optimum number of traits by which agents compare each other and see what the resulting opinion clusters are. There are only a few scenarios which create any semblance of a reasonable amount of clustering, or a balance between consensus and complete anomie (Fig. 3). The diversity has to be large enough whereby there are no 'types' for agents to separate into, so that they form groups with others based on overlapping, uncorrelated traits.

The problem with this system is that it is not realistic. Having one similarity threshold for basically the entire population is not how people identify their ingroups, some people are more or less open than others. There are no strict rules as to how people choose to identify with each other, and on what grounds. If the amount of similarities is loosened in either direction, or the threshold is randomized, the result is either anomie if it is too constrained, or consensus if it is too open or random. There are many other factors which could affect how influence works are not taken into account in this model, therefore, it is encouraging that at least under very limited circumstances, identity and affiliation itself can have some effect on stable opinion clusters.

5 Model 2: Certainty

This model is based directly on the bounded confidence model, but this study does not claim to resolve the problems with the BC system, where small random amounts of acceptance outside the threshold creates consensus, as with the Abelson problem. Instead, it is to modify the Bounded Confidence construct, which by design deterministically has agents cluster by nearest 'acceptable' neighbors, creating stable opinion clusters as a mathematical necessity. By introducing certainty, it is hoped that the diversity of sources of information circulating in the system will affect the quality of these clusters to create a more realistic set of opinion dynamics. "More realistic" means specifically:

- A system where the diversity of information being circulated affects the overall certainty of the system, and the length of time for the system to stabilize.
- A system which agents do not cluster according to their "uniform" distribution as with BC models.

The certainties of the agents will be negotiated by the source of the information being broadcast (whether it is from their ingroup or their outgroup), so

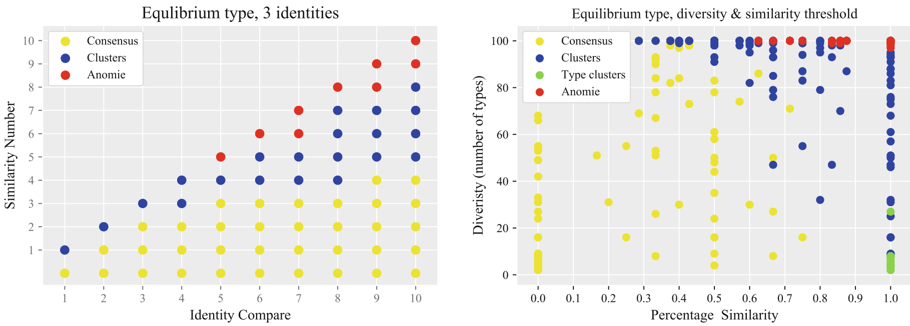

Fig. 3. (Left) Depending on the amount of identities, the similarity number must be a bit higher than 50% to avoid consensus. (Right) Clustering occurs when the diversity is higher, and the requirement for similarities is relatively high. Type clusters occur at strict similarity requirements (100%), with low levels of diversity. Typically, similarity requirements below 50% will lead to consensus, although requirements as high as 75% can lead to consensus in low diversity populations.

that it is the exposure to information which makes an agent more or less certain [25]. The reason this is important in studying social influence in identity is that in moments of uncertainty, people default to the opinions of others [6].[2] This tendency facilitates misinformation, because when an individual defaults without question, their beliefs can be reinforced by others regardless of the validity of that attitude, or the consequences of believing it [1].

5.1 Design

In this model, agents still broadcast their opinion at random, but their opinions can change randomly based on their certainty. Certainty is a number between 0 and 1 which describes how committed the agent is to the opinion it holds. Low certainties allow for a greater likelihood of random opinion change, or noise.

Two principles are borrowed from Grow [8] which are drawn from psychological research and used in their model on certainty and social influence:

1. Certainty is inversely related to the ability to be influenced.
2. Certainty is directly related to the amount of agreement among peers (social cohesion).

Equation 1 ensures that agents who are more certain will be less influenced by agents whose opinion is farther from them on the spectrum, thereby fulfilling principle 1 (Fig. 4).

Principle 2 describes the process of certainty changing as a result of the (non-linear) interactions among agents. Therefore, it was fulfilled using a series

[2] Classical studies in psychology have also long confirmed this tendency. See [26] for social norms, [27] for social comparison theory, [28] for conformity, [29] for affiliation and [30] for social categorization theory. For a summary see [6] pg 770.

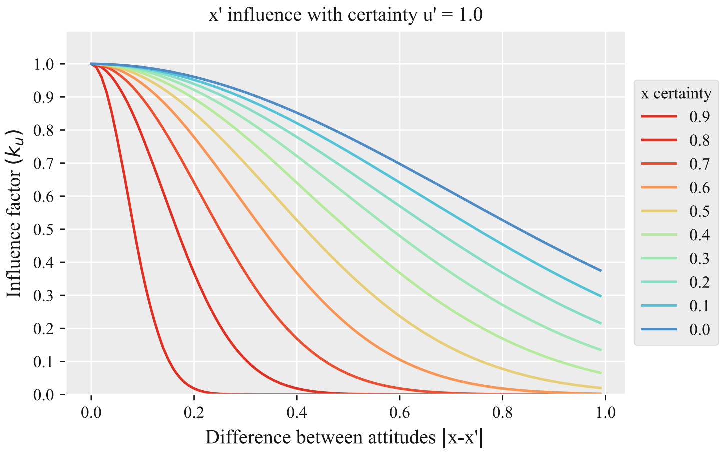

Fig. 4. As the certainty of x increases, the influence factor drops quickly to zero as the difference between their opinions ($|x - x'|$) increases.

of coefficients which change the certainty of the agent depending which agent is broadcasting at a particular time step.

Table 1. Receiving broadcast weights

	Ingroup		Outgroup
Change attitude	$(1)\mu = +1$		$(2)\mu = -.01$
	Agree	Disagree	$(5)\mu = -.01$
	$(3)\mu = +1$	$(4)\mu = -1$	

Values of μ for each possible scenario of receiving information. (1) If an agent changes its mind it can only do so if the broadcast is from the ingroup. (2) (5) A small change happens from not agreeing with your outgroup which makes the system less stable the more opinions are broadcasted. (3), (4) The weight of not changing an attitude is equal but opposite whether you agree or disagree. Groups are punished if they do not agree, so the larger majority is dismantled if there are more opinions within the ingroup (4).

All of these results have a population of 100 agents and are measured first with a uniform starting certainty of .5. The reason for this is twofold: first, if agents all begin with the same certainty the resulting groupings will not be affected by the initial state and second, .5 certainty will ensure the system begins in a state of enough certainty that noise will not take over and equilibrium can be reached. To adjust certainty as described above, agent x with uncertainty u adjusts its certainty at each time step as follows:

$$u_{(t+1)} = u + \varepsilon\mu \tag{4}$$

Table 2. Broadcast weights

Change attitude	$\mu = 1$
Do not change attitude	$\mu = .01$

Broadcasting has a higher weight when the agent changes their mind. Attitudes which are expressed generally get a small change, meaning certainty increases over time.

Where $\varepsilon = .01$, and μ varies depending on the communication (Table 1). ε is a measure of the speed of certainty change, and has been chosen as .01 for practical purposes of simulation duration (ε varies with the number of agents and is calculated by the percent of the population of a single agent, with a population of 100, this is 1% or .01). μ is a weight value that when varied promotes different dynamics in the simulation (Tables 1 and 2).

Finally, agents with low certainty can change their opinion at random with a probability defined by the following equation, which is a function of the agent's uncertainty u:

$$p(u) = (ue^{-(1-u)})^2 \tag{5}$$

5.2 Results

The resulting system is one where the "pressure to conform" is high enough that extremism, and indeed small groups in general, can only persist in situations which have a diverse enough opinion cluster that majority pressures do not overcome small ingroup stability. That is, since large groups of agents are consistently confirming each others opinions, if they are large enough they will destabilize small groupings. The stability of cluster formation, then, is related to the number and population of each opinion group, which is consistent with the literature on social groups and attitude certainty [31].

First, an information space where certainty (on average) is less given the amount of information being circulated is demonstrated in Fig. 5. To start, Fig. 5 (left) shows simply the more clusters the longer the system takes to stabilize, with a Pearson's correlation of .49. Figure 5 (right) shows that average certainty after 100 stable runs is significantly smaller given a larger amount of clusters, which demonstrates that more information in the system leads to less certain agents overall (more clusters = more attitudes). This trend diminishes after longer runs, but this is because for a cluster to be stable, the average certainty is always increasing, if the average certainty were always decreasing, the cluster would be vulnerable to random opinion change and would no longer remain stable. Furthermore, the certainty increasing over time when unchallenged is considered a feature of certainty under normal conditions [31,32].

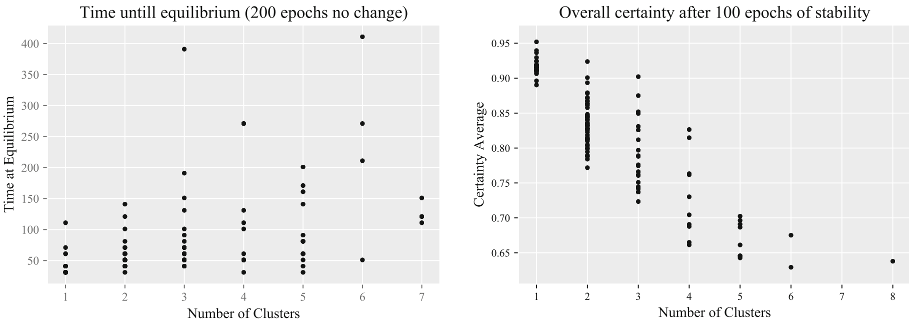

Fig. 5. (Left) Time until equilibrium is reached and number of clusters at equilibrium. Each dot represents one simulation run. (Right) Average certainty of clusters over the course of the simulation. Each dot represents one simulation run.

6 Model 3: Combination

This model is a combination of the two former models. It is hoped that combining both can resolve issues with the previous by virtue of its complexity, and produce a more flexible model by employing both certainty and identity.

6.1 Design

This model uses all of the former methods, running essentially in parallel. Here, however, the similarity threshold was able to be lowered to less than 50% similarities, and the difference tolerance (essentially the 'bound of confidence'), will also be randomized between 0 and 1. This creates a heterogeneous population of more and less 'open' agents who nevertheless operate by the same basic rules as the previous implementations. Heterogeneity is a desirable feature in agent-based models generally in that it is more reflective of human populations [33]. Also, 'relaxing' the strict parameters required in the first models addresses the limitations of those models in hopes that this simulation will produce clustering with less rigid restrictions.

6.2 Results

As was hoped, the relaxation of the parameters from the first two models allows for stable clusters in this iteration. Namely, the amount of similarities required for agents to be considered ingroup members could be lowered to less than half of the repertoire length. Formerly, this would lead to consensus inevitably, however, because of the added difference threshold, this would be resisted. The difference threshold can also be flexible, and is initialized at random between 0 and 1 for each agent, which would have lead to consensus in Model 2. This combination of these two models, then, successfully allows for a relatively more realistic representation of identity and certainty, while still maintaining stable clusters over time. This is significant, because it suggests that adding variables on top of each other can provide solutions to the Abelson Diversity Problem without adding a disintegrating force.

The simulation gives rise to extremism, but by and large only if there are agents which are initialized as extreme. This would imply that a system can become extreme when an extremist is inserted, but does not say anything about the system being able to produce extremism. In order to test this, agents were initialized with attitudes considered moderate (between .2 and .8), and the resulting population of extremists was found once the system arrived at equilibrium (Table 3).

Table 3. 10 run averages for different attitude ranges

Initial attitude range	Initial extremist population	Final extremist population	Difference	Final average extremist certainty	Initial mean/ standard deviation	Final Mean/ standard deviation	Difference
(1) 0–1	38.3	23.8	−14.5	0.80	0.495/0.281	0.510/0.215	+.015/−.066
(2) .2−.8	0.0	2.3	+2.3	0.27	0.493/0.169	0.496/ 0.124	+.003/−.045

(1) With initial extremists and (2) Without initial extremists (extremists as being defined by attitudes $< .2$ or $> .8$).

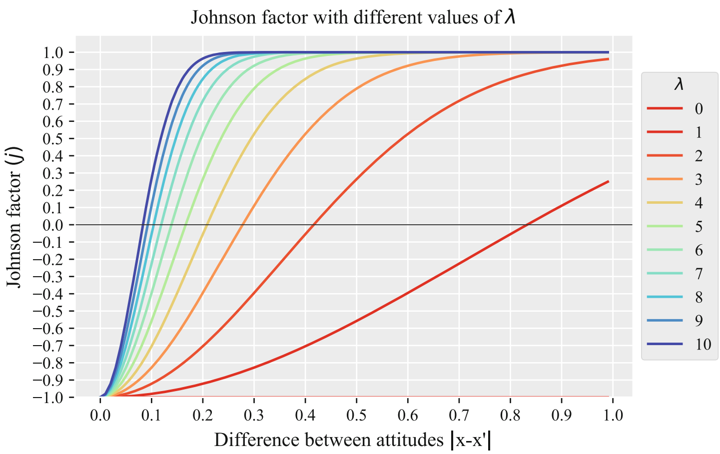

Fig. 6. Johnson factor for different values of λ ($\beta = 1$).

The system in itself, then, does not lead to extremism in any meaningful way due to large pressures towards moderation by the majority of agents. To push the system to its limits and determine if there are conditions whereby polarization or extremism can be produced with an initially moderate population, another parameter was experimented with. Named the Johnson factor, it is based on a theory by Donald Johnson in his 1940 paper *Confidence and the Expression of Opinion* [34], postulating that extreme attitudes tend to become confident because they are able to reject more opinions which are farther away from their own than those who hold more moderate opinions. The Johnson factor moderates the certainty of agents on any broadcast (see (2) (5) Table 1). Instead of the confidence decreasing by $\varepsilon\mu$ (μ is negative here) in the event of an outgroup broadcast, certainty will decrease by the Johnson factor j, which is defined by the following equation:

$$j(x, x') = \beta(2 * e^{-\lambda(x-x')^2} - 1) \tag{6}$$

Where x is the agent's attitude and x' is the broadcasting agent's attitude, β is a scaling factor determining the magnitude of j and λ is a variable describing at what threshold of attitude difference there will be zero change in certainty (the x-intercept in Fig. 6).

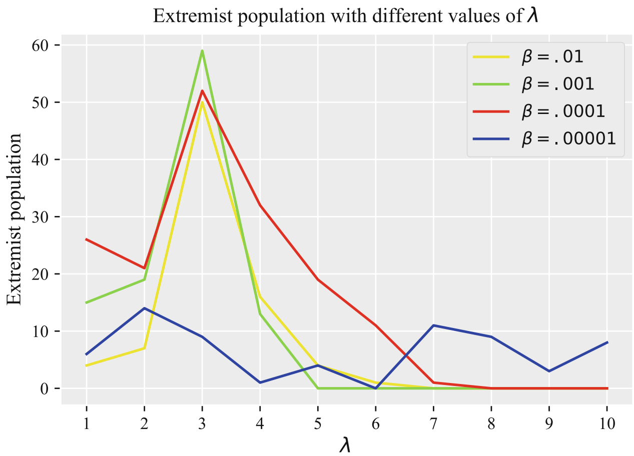

Fig. 7. Extremist population for values of λ. $\lambda = 3$ is the ideal value for producing large amounts of extremists given $\beta > \mu$.

Higher values of λ result in smaller differences being required to increase confidence, and reaches a limit of about .1 difference (which is relatively small), in order for confidence to be increased. Where $\lambda = 0$, μ remains unchanged and the simulation runs as before. Figure 7 shows that the extremist population increases until $\lambda = 3$ for all values of β which were tested. As λ gets larger than 3, the difference required to increase certainty is much smaller, and the certainty of the population rises proportionally despite whether the agent's opinion resides in the extremes. For $\lambda >= 5$, this is about a difference of 1.5, meaning that many agents will have a difference of opinion which is larger than this. In these cases, certainty increases for all agents and there is not enough uncertainty to produce the noise required for agents to become extreme. Interestingly, larger values of λ actually safeguard against extremism. As β goes towards .0001 it is approaching the original μ, which means it has a very small effect and results in small amounts of extremists due to slightly lower uncertainty.

7 Discussion and Conclusion

The main questions of this study were, are the variables of social identity and uncertainty able to affect social influence and result in complex opinion dynamics (including extremism and polarization) as observed in online social networks such as Facebook? Furthermore, given the constraints of the Abelson Diversity Puzzle, do stable opinion clusters form?

Model 1 demonstrated that social identity is able to produce stable opinion clusters as long as the amount of connections is limited and the population is somewhat diverse. Model 2 did successfully allow for certainty to be negotiated by ingroup size, and therefore added a level of complexity to the rigidity of the bounded confidence model. This supports the theory that certainty is a negotiator of group dynamics, as is suggested by the literature, and this basis for a model could be used for further investigation of these concepts (see uncertainty identity theory as described in [35] pages 943–45). Model 3 demonstrated that while clustering occurs, moderating forces are strong, and extremism or polarization do not result from the system alone. One option was experimented with to see if extremism resulted, showing the virtues of the design of Model 3 as a testing ground to isolate variables outside of social influence and certainty. The aim of this research is not to systematically test other theories, but it is hoped that the results of this experiment suggests the potentials of the model design.

Ultimately, given the Abelson Problem, these models demonstrate that opinion distributions other than consensus can exist in systems where everyone is connected. That is, since Facebook is not a network where everyone agrees on one opinion, these models are successful to the extent that they were able to reproduce a myriad of opinions on a macro level, while maintaining influence connections between groups of agents. Because of this, social identity and certainty can be considered possible explanations for the formation of social connections, and for how people are influenced by others.

Therefore, these models can tentatively say that if Facebook facilitated an open broadcast of opinions open to all members of the network, it seems to have a moderating effect overall. Encouraging open information exchange, where people are exposed to many diverse opinions, could help to mitigate information disorders, as has been observed in offline social networks [36]. As the messages in these models are all weighted equally, that is, no message is more persuasive than any other, it is hard to extrapolate these results to include things like propaganda. Considering these factors would be a fruitful starting point in future research and could be possible contributors in polarization and extremism, as well as other information disorders.

There are several reasons why the design and results are not completely descriptive of the effects of social influence on Facebook. For example, Model 1 does not allow for similarities between agents which are flexible and less than half of the identity repertoire. This is due to the constraints of opinion dynamic models with regard to the Abelson Diversity Problem. Nevertheless, the attempts to reconcile this problem were somewhat successful. The fact that Model 3 allowed for the relaxation of both the bound of confidence principle and the similarity threshold is very encouraging, and suggests that the interaction of these factors is a fruitful starting point both with regards to agent-based model design, and a possible factor in swaying opinion dynamics in the real world.

A key future challenge for all three models is comparison with real-world data. Indeed, the veracity of the models themselves cannot be confirmed without this, even though on an abstract level it can be concluded that they succeeded to reproduce macro-level trends of opinion diversity (i.e. avoiding consensus). A thorough collection of relevant data, either from mining the Facebook API (which is limited due to privacy restrictions) or by gathering it via an application, was beyond the scope of this present study. Given these results, though, follow up research focusing on empirical data and using the modeling methods outlined in this paper would be beneficial to further examining the results and moving forward with more complex models. Nevertheless, this process of building systems and combining them appears to be a sufficient method for exploring the effects of the factors described here in isolation, and could be used to test other possible interacting variables in the psychology of attitude formation.

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