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Complex Adaptive Systems Modeling

SHORT REPORT

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On the role of evangelism in consensus formation: a simulation approach

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Abstract

Purpose: Opinions continuously evolve in society. While conservative ideas may get replaced by a new one, some views remain immutable. Opinion formation and innovation diffusion have witnessed lots of attention in the last decade due to its widespread applicability in the diverse domain of science and technology. We analyse these scenarios in which interactions at the micro level results in the changes in opinions at the macro level in a population of predefined ideological groups.

Methods: We use the Bass model, otherwise well known for understanding innovation diffusion phenomena, to compute adoption probabilities of three opinion states-zealot, extremists and moderates. Thereafter, we employ cellular automata to explore the emergence of opinions through local and overlapped interactions between agents (people). NetLogo environment has been used to develop an agent-based model, simulating different ideological scenarios.

Results: Simulation results validate a critical proportion of committed individuals as a plausible basis for ideological shifts in societies. The analysis elucidates upon the role of moderates in the population and emergence of varying opinions. The results further delineate the role of evangelism through social and non-social methods in propagating views.

Conclusion: The results obtained from these simulations endorse the conclusions reported in previous studies regarding the role of a critical zealot population, and the preponderance of non-social influence. We, however, use two-phase opinion model with different experimental settings. Additionally, we examine global observable, such as entropy of the system to reveal common patterns of adoption in the views and evenness of population after reaching a consensus.

Keywords: Opinion formation, Bass model, Cellular automata, Agent based simulations

Background

Civilizations change over the time, and so does its ideologies. Over a period, new beliefs are introduced in the society, which at times sharply contradict the previous convictions. In a society, diverse opinions exist in the competitive state with an original opinion at a prospect of being replaced by new one. Fashion fad, cultural trends, ideological conversions, product adoption, are examples of opinion formation. Moreover, adoption of views also depends on various intrinsic and extrinsic factors (Young 2009).

In this study, we conceive society as the population of extremists, moderates and zealots to analyse some important viewpoints of the opinion formation mechanism. A community of extremists is a fraction of the society who are either in strong favor or against a particular belief system, and zealots are the fanatical supporters of this belief. Moderates are the ideologically right-of-center and perceive the unbiased views of extremists. Extremists are the staunch believers of their opinions with zero tolerance for other's beliefs, thereby provoking conflicting groups with clashes and disputes. On the other hand, moderates are not ideological blinders and tend to see both sides of the issues.

This study is motivated by the prior work of Marvel et al. (2012) wherein they described opinion formation among three different ideological groups using deterministic, continuous mean-field equations. The work presented here, however, use stochastic and discrete model settings to investigate the various aspects of opinion formation as discussed in subsequent sections of this exposition.

In this work, we use the Bass diffusion model to comprehend evangelistic factors like the role of media influence and word of mouth dissemination (Bass 1969, 1980; Fibich et al. 2010). Further, we employ cellular automata (CA) to explore the emergence of opinions in a diverse ideological society, CA approach enhances the robustness of model as a whole by taking the local and overlapping structure of interactions between agents into consideration. This flexibility to reproduce complex behaviour by CA generates an artificial world similar to real world processes (Hegselmann 1996).

In furtherance of this, we analyse the causative factors affecting moderates population. These factors include the influence of extremists and co-existence of moderates with them in the society.

For simulation purpose, we use NetLogo environment to develop an Agent-based model (Tisue and Wilensky 2004). Agent-based modelling (ABM) is a widely endeavoured simulation and modelling technique to realise the interaction between autonomous agents and the situated environment, facilitating the analysis of the effect of their interactions in the system as a whole (Wooldridge 2009).

The results derived through simulations support an enhanced deradicalization to establish evenness in a society having different extremists views. Increasing external control or the role of non-social factors shifts the significant threshold population needed for an opinion agreement.

Methods

Agent based modelling

Simulations help to identify the cause-effect relationships, underlying hidden processes and lead to the formalisation of theory. The outcomes of the simulation are particularly useful when analytical tools cannot cope up with increased complexity of the system. Agent-based modelling (ABM) has its roots in the modeling of systems where complex behaviors arise from simple rules (interactions). Its widespread applicability in the diversified areas like complex systems analysis, management, economics and social sciences makes ABM a popular technique with the availability of various simulation environments to model dynamic systems (North et al. 2013).

ABM has been reported to analyze forest fires, spread of epidemics, visual surveillance amongst other critical scenarios (Niazi and Hussain 2013). The ease of defining each agent (in our case a person), with adaptive behavior, has led us to choose this approach. Model developed in this study simulates a subpopulation of agents interacting with one another to spread and form their opinion.

Cellular automata

Johann Louis Von Neumann and Stanislaw Marcin Ulam (Von Neumann et al. 1966; Mazoyer and Delorme 1998) introduced the concept of cellular automata (CA) in the form of a grid of cells to study biological systems. Each cell can either have an on or off state. The system evolves due to change in the state of a cell and its neighbours forming a complex grid patterns (Gardner 1970).

CA charter the role of spatial structures in the spread of information. Different rules define the switching between these states depending upon the underlying mechanism of the system (Durrett and Levin 1994).

Each cell has a neighbourhood consisting of adjacent cells. An expansion in the dimensionality of the lattice increases the possible combinations of neighbourhoods. For a cell of radius 1, Von Neumann neighbourhood of a cell is defined as the cell itself along with four of its adjacent cells in north-east-south-west direction. whereas in Moore neighbourhood, the cell along with its four adjacent cells and adjacent diagonal cells are taken into consideration (Fig. 1).

Stephen Wolfram in his pioneering work classified various rules of a self-organizing statistical system (Wolfram 1983). In his book (Wolfram 2002), he gave an exhaustive study of these rules associating cellular automata and its applicability in distinct domains like biology, physics, sociology. The asserted rules act upon the cells and change the state of the cell at every discrete time step. The rules can be deterministic, i.e., state change for all cells in parallel or stochastic, i.e., state change depending upon a probabilistic value. In our model, we use a stochastic approach to induce uncertainty in the opinion of an individual.

Bass model

The Bass model (Bass diffusion model) describes the process of the rate of adoption of a product over a period by the population Bass (1969, 1980).

Following are the categories of adopters in Bass model based on the timing of adoption by various groups (stake holders);

1. Innovators
2. Early adopters

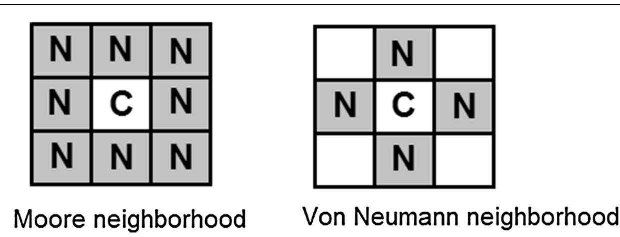

Fig. 1 Two types of neighborhood based on cell radius 1

3. Early majority
4. Laggards.

Innovators adopt an innovation independent of the decision of other people in a social system. Categories 2–4, collectively, are called imitators who adopt innovation in later stages and affected by the decision of others.

Bass model is defined as follows:

$$f(t)/(1-F(t)) = p + (q/M)[A(t)] \tag{1}$$

Alternatively, following is the algebraic simplification of Eq. 1:

$$a(t) = Mp + [q-p]A(t) - (q/M)A^2(t) \tag{2}$$

where $M =$ the potential market (the ultimate number of adopters),
$f(t)$ – the portion of M that adopts at time t,
$F(t)$ – the portion of M that have adopted by time t,
p – coefficient of innovation,
q – coefficient of imitation,
$a(t)$ – adopters (or adoptions) at t and,
$A(t)$ – cumulative adopters (or adoptions) at t.

The Bass model is widely used as a utility to provides decision-making assistance to the managers in making pre-launch, launch and post-launch strategic choices. The following factors influence the decision making of potential adopters:

1. External influences: these influences do not have direct social interaction with an individual such as advertisement campaigns and different form of mass media technologies. An individual gets influenced by an external influence with a probability (p) in an iteration (t).
2. Internal influences: these influences cause direct interaction and a person is affected by the interaction with others having different opinions with some probability (q).

Consequently, an iteration-dependent likelihood of adoption (PA (t)), provided a person has not yet adopted, is defined as follows (Goldenberg et al. 2001):

$$PA(t) = \left[1-(1-p)(1-q)^{k(t)}\right] \tag{3}$$

where p represents the effect of external influences, i.e., advertising; q is the effect of internal influence coming from previous adopters and $k(t)$ is the number of previous adopters during time period t.

Scientific community view opinion formation and information diffusion as two different and independent processes. However, these are often intertwined with each other, and a correlation exists. Agents develop and exchange their opinions during diffusion and their opinions also affect their diffusion actions (Xiong et al. 2014). Shen et al. characterized opinions evolution as a chain of contacting and interaction processes.

Whereby, contact process determines opinion diffusion and interaction process transfer information from one agent to another (Shen and Liu 2007).

Even though Bass model effectively models opinion diffusion process, it does not permit the participating entity (agent) to return to the previous state (ideology) once adopted (Young 2009). Therefore, we use the Bass model to calculate adoption probabilities of opinions only. An agent's opinion may change in the presence of its neighbours. Moreover, an agent may find similar or dissimilar opinionated neighbours and updates its opinion depending upon the neighbourhood majority. To allow agents to change their beliefs during opinion formation, we use cellular automata (CA).

We employ the combination of Bass model (Eq. 3) and stochastic cellular automata to investigate the impact of p (external influence) and q (internal influence) in altering the opinion of population (Fig. 2).

Model procedures

In the model developed, we analyse, how the interactions between the agents lead to various ideological scenarios. Model execution begins with an adequate population of 10,000 persons (agents) with different opinions. Previous studies have also experimented with similar population size to manifest conclusion stability (Sznajd-Weron and Sznajd 2000).

The initial population consists of five sub population categories-B (extremists of old ideology), A (extremists of new ideology), AB (moderates with the neutral opinion), ZA (zealots of ideology A) and ZB (zealots of ideology B) (Marvel et al. 2012).

Two extremists views can only be affected by the presence of opposing groups. Zealots of B (ZB) and A (ZA) are fanatic supporters of the old and new ideologies respectively. Zealots will never change their current opinion, whereas, moderates are neutrally opinionated faction that can change their beliefs through interaction with other opinionated subpopulation (Fig. 3). In the real world interpersonal communication (like in artificial society), an individual may confront other people with diverse opinions. We use random-neighbour interaction rule to model such interaction among agents dependent on spatial location; wherein each agent randomly moves to a cell site with equal probability (Liu and Wang 2013; Gündüç 2015).

In each iteration, adoption probabilities of ideologies are calculated for population types-A, B, and AB with and without external influences. The internal (word-of-mouth opinion) and external influence (media, advertising) parameters are determined randomly from a defined range. Agents having greater adoption probabilities than a chosen random-threshold, participate in opinion formation because the influence of opinions varies with time and also depends on its adopter's population size. During an interaction, individual opinion changes, if one opinionated neighbouring group is in the majority. Further, for each agent, its Von Neumann neighbourhood is compared by considering neighbors as speakers and the agent itself at the centre cell as a listener (Fig. 3).

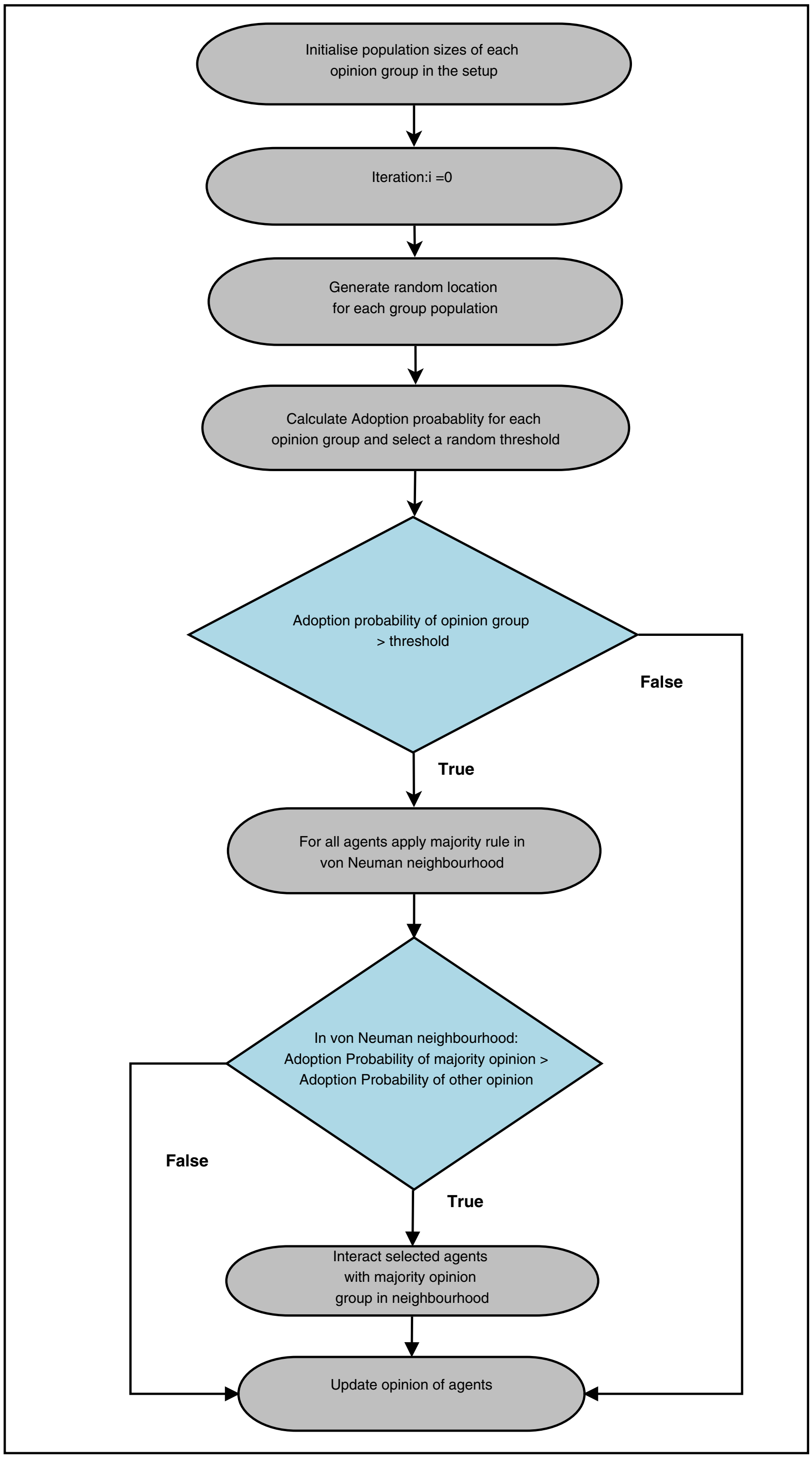

Fig. 2 Process flow diagram of the model

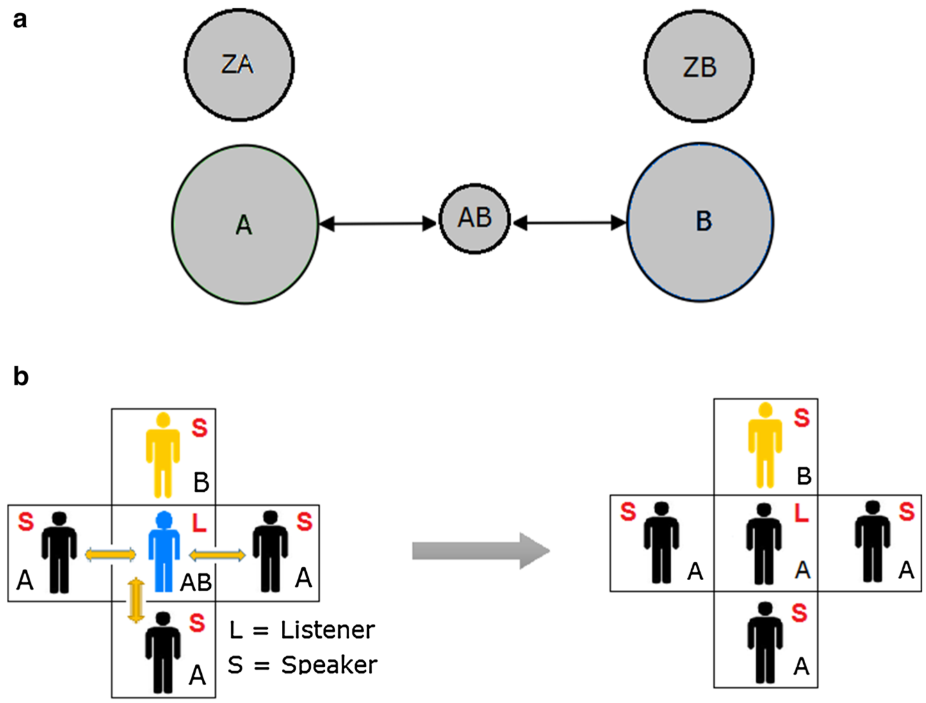

Fig. 3 **a** Transition between different opinion states in the model. **b** Speakers communicating opinions to listeners in their Von Neumann neighborhood. Hereby, the listener (*blue*) adopts majority opinion of the speakers (*black*). Adapted from Marvel et al. (2012)

Table 1 defines the interaction rules to accept majority opinion by a listener. An agent (listener) changes his currently held opinion only when the adoption probability of the majority group is larger than a randomly chosen threshold value and the adoption probabilities of the other neighbouring ideologies as well (Fig. 2).

At the end of each iteration, all agents are moved to a new random location in the environment. Interaction with other agents at new locations helps in the diffusion of opinions (Algorithm 1).

Table 1 Rules for interactions between agents (adapted from Marvel et al. 2012)

Listener	Speaker	Listener (post-interaction)
AB	A, ZA	A
AB	B, ZB	B
A	B, ZB	AB
B	A, ZA	AB

Algorithm 1 Pseudo code of the adopted algorithm to spread ideologies

```
Setup population size for each ideology
Set x, y ∈ (Extremists = A/B , Zealots = ZA/ZB and Moderates = AB )
iteration = 0
k = 700   #k = number of ticks
while iteration ≤ k do
    Generate population (Agents) at random location.
    Calculate PA_i using Bass Model , i ∈ A, B and AB
    threshold = random float number ∈ (0, 1)
    if PA_x(t),PA_y(t) > threshold then
        for all agents check neighbors4 (Cellular Automata) do
            if no. of agents x > no. of agents y and PA_x(t) > PA_y(t) then
                Interact with agent x and change opinion
            end if
        end for
    end if
    update agent population for each group
end while
```

The term **"Tick"** refers to the discrete time step during which agents of subpopulation interact.

Results and discussion

All simulations in this paper were performed in parallel with Behavior Space and OpenMP on High Computing Performance facility (Dagum and Enon 1998).

Without external influence and zealots of new ideology

Population size

Initially, we investigate the effect of varying the initial population of $A(A + ZA)$ and B on the model dynamics. Table 2 represents the parameters and their ranges to initialise the model functioning.

Figure 4 depicts the change in fractional population of ideologies for initial $ZA = 2100$. Simulations conducted for population lesser than this also exhibited similar variation in the population, wherein ideology B in majority prevails beyond a particular population of B.

Table 2 Initialisation parameters for simulation setup

Variables	Range
Population A	0
Population AB	100
Population ZA	1000–5000
Population ZB	0
Population B	4900–8900
Random-threshold	0–1
Internal influence parameter for ideology A	0.0008–0.004
Internal influence parameter for ideology B	0.0008–0.004
Internal influence parameter for ideology AB	0.0008–0.004

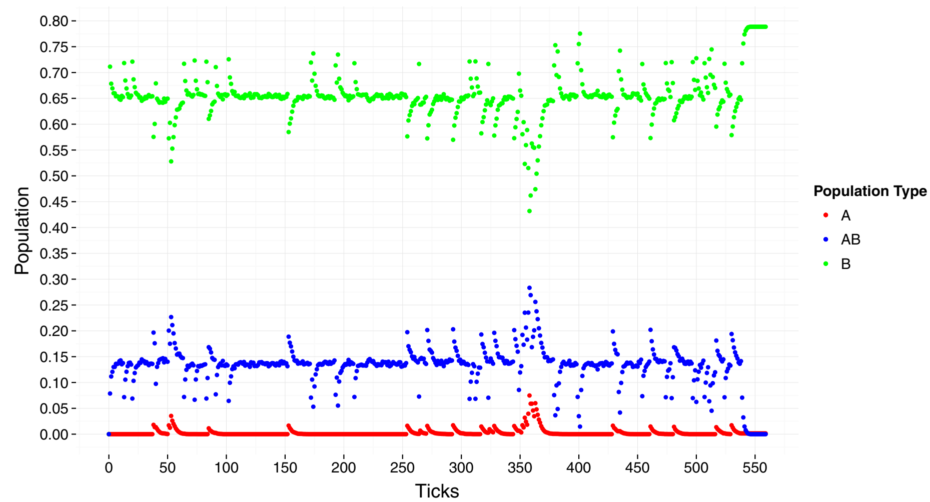

Fig. 4 Fractional population size of ideologies with respect to ticks for initial $ZA = 2100$

However, as soon as the initial population of ZA reaches 2180 ± 10, ideology A starts predominating, resulting in the decimation of ideology B as well as of moderates. Henceforth, this initial critical population of ZA is referred A_c in this study. Figure 5 illustrate population variation for $ZA = 2250$. AB grows to a peak point of 0.3162 (as a population fraction) at $t = 226$, and quickly diminishes. With the growth of AB, competition for the conversion into either of the extremist ideology increases. When A becomes slightly greater than B, more AB are converted to A as compared to B, and the opinion transition toward new ideology starts to occur. The existence of A_c to shift the opinion towards minority validates the results reported by Marvel et al. (2012).

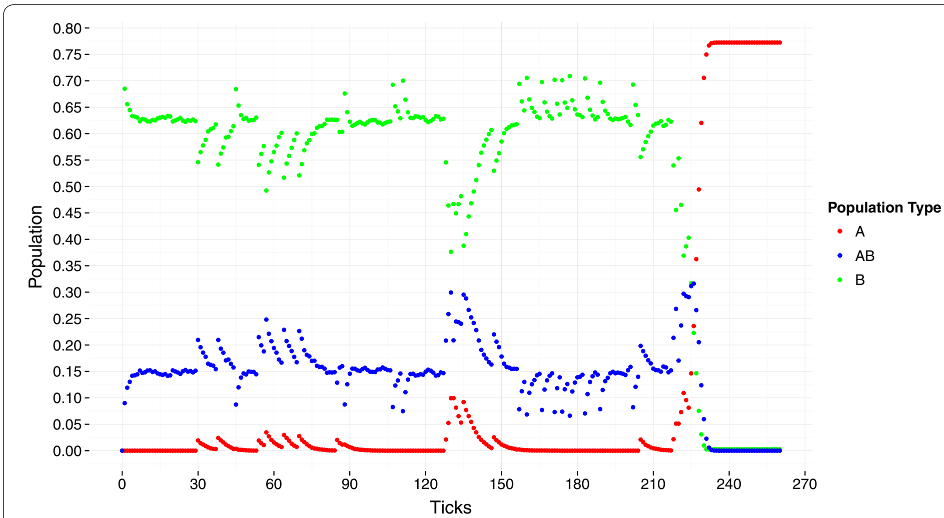

Fig. 5 Fractional Population size of ideologies with respect to *ticks* for $ZA = 2250 > A_c$

Adoption probabilities and opinion strength

We analyse variation in adoption probability and opinion strength to better comprehend the phenomena of opinion shift towards new ideology beyond Ac.

Without external influence, adoption probabilities of ideologies are defined by Eqs. 4, 5 and 6 (Moldovan and Goldenberg 2004)

$$PA_A(t) = 1 - (1 - q_A)^{k(t)_A}(1 - q_{ZA})^{k(t)_{ZA}} \tag{4}$$

$$PA_B(t) = 1 - (1 - q_B)^{k(t)_B} \tag{5}$$

$$PA_{AB}(t) = 1 - (1 - q_{AB})^{k(t)_{AB}} \tag{6}$$

where $q_A =$ internal influence of extremists (A)
$q_B =$ internal influence of extremists (B)
$q_{ZA} =$ internal influence of zealots A
$q_{AB} =$ internal influence of moderates (AB)
$k(t)_A =$ population of extremists (A) at iteration t
$k(t)_B =$ population of extremists (B) at iteration t
$k(t)_{ZA} =$ population of zealots (A) at iteration t
$k(t)_{AB} =$ population of moderates (AB) at iteration t

As soon as the population of A becomes greater than that of B, PA_A increases, while PA_B and P_{AB} decreases. Eventually, PA_{AB} becomes zero whereas PA_A attains a stable value. This endorses the effect of adoption probability on opinion transition in a society (Fig. 6).

Opinion strength measures how strongly or weakly a person is for/against an opinion (Chong and Druckman 2007). Opinion strength of an agent is the ratio of total number of speakers with same ideology of listener to the total number of speakers in listener's Moore neighbourhood (Eq. 13).

$$OpinionStrength(x) = n_x/8 \tag{7}$$

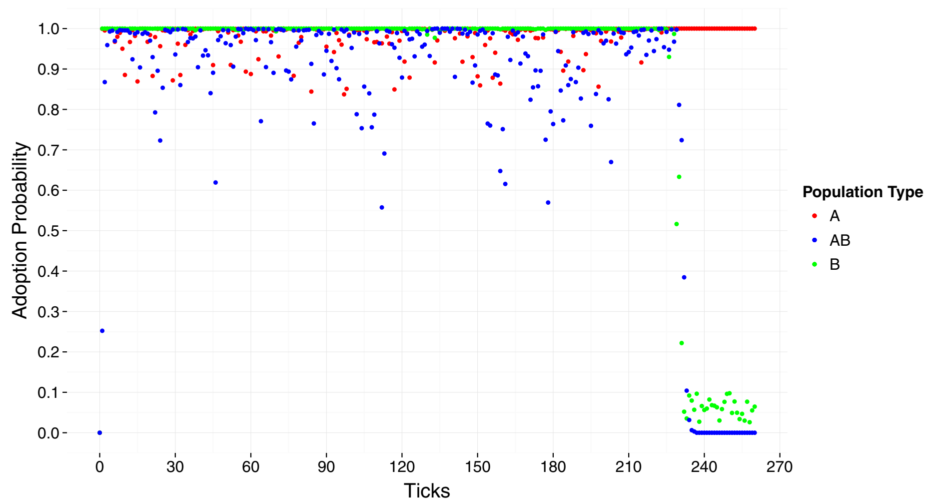

Fig. 6 Adoption probabilities of ideologies with respect to *ticks*. *Figure* shows the transition in adoption probabilities for initial *ZA* population = 2250

where n_x = Number of neighbors of ideology x and $x \in (A, B, AB)$

Mean opinion strength (MOS) is the arithmetic mean of opinion strength of each ideology (Eq. 8). MOS depends upon opinion of neighborhood population.

Therefore, as one ideological group's size starts increasing its corresponding MOS also increases ,while the MOS of other two ideologies decreases (Fig. 7).

$$MeanOpinionStrength = \sum_{i=1}^{N} OpinionStrength(x)/N \tag{8}$$

where N = Number of agents of ideology x and $x \in (A, B, AB)$.

With external influence and zealots of new ideology

To simulate evangelism using non-social methods, i.e., media campaign, advertising, social media, etc., we use a variable p as a parameter of external influence of an ideology. The range of p is adapted from a published study (Moldovan and Goldenberg 2004) that suits to our experimental settings (Table 3). To enhance the impact of evangelism among moderates, we increased the internal influence of AB with a reduced evangelism capacity (internal influence) of other two ideologies (A and B). Range of the internal and external influence parameters of different sub populations is shown in Table 3.

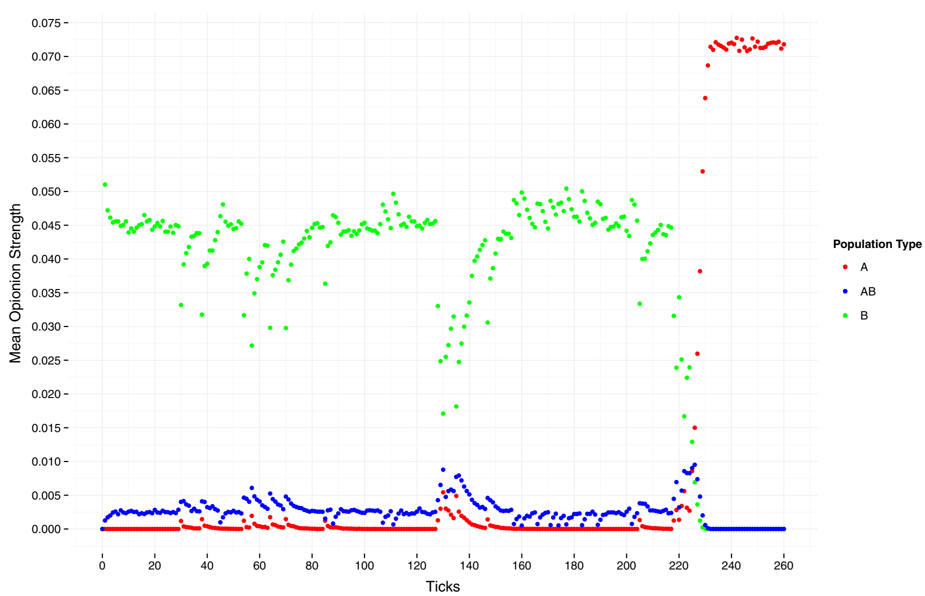

Fig. 7 Variation of mean opinion strength of ideologies with respect to ticks, for $ZA = 2250 > A_c$

Table 3 Range of values considered for influence parameters

Description	Range
External influence parameter (p)	0.001–0.5
Internal influence of ideology A	0.0008–0.001
Internal influence of ideology B	0.0008–0.001
Internal influence of AB	0.001–0.004

Population size

In simulations, we have used an initial population of zealots of A (ZA) varying from 1000–3000, and average of external influence (p) as 0.03. According to an analysis of 213 applications of Bass diffusion model done by Sultan et al., the average external influence parameter was estimated to be 0.03 (Sultan et al. 1990; Lee et al. 2010). With external influence, more AB are generated as the consequence of increased interactions between the two opposing factions A and B. AB survived beyond the critical value of zealot population (A_c). However, for large ZA ($ZA > A_c$), an increased values (in comparison to other two factions) of the internal and external influence of AB is required to ascertain their survival. Though, minor perturbations exist between the populations B and AB, these are not sufficient for an opinion transition (Fig. 8).

Adoption probabilities

The adoption probabilities of each faction is calculated by Eqs. 9, 10 and 11 (Moldovan and Goldenberg 2004):

$$PA_A(t) = 1 - (1 - q_A)^{k(t)_A}(1 - q_{ZA})^{k(t)_{ZA}} \tag{9}$$

$$PA_B(t) = 1 - (1 - q_B)^{k(t)_B} \tag{10}$$

$$PA_{AB}(t) = 1 - (1 - p_{AB})(1 - q_{AB})^{k(t)_{AB}} \tag{11}$$

where $q_A =$ internal influence of extremists (A)
$q_B =$ internal influence of extremists (B)
$q_{ZA} =$ internal influence of zealots A
$q_{AB} =$ internal influence of moderates (AB)
$p_{AB} =$ external influence of moderates (AB)
$k(t)_A =$ population of extremists (A) at iteration t
$k(t)_B =$ population of extremists (B) at iteration t

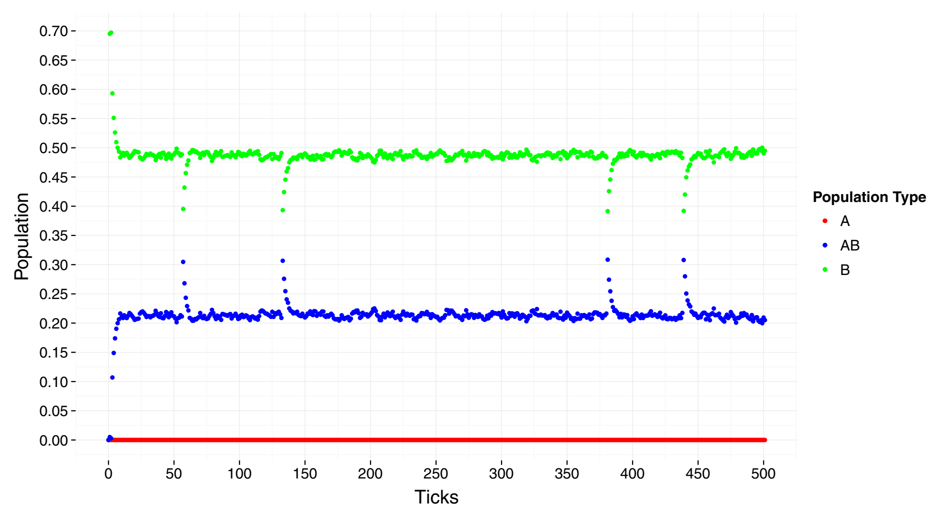

Fig. 8 Variation of fractional population of ideologies with respect to ticks, $ZA = 3000 > A_c$ and $p = 0.03$

$k(t)_{ZA}$ = population of zealots (A) at iteration t
$k(t)_{AB}$ = population of moderates (AB) at iteration t

Aforementioned parameter settings maintained a stable moderate population (Table 3). An increase in external and internal influence of AB ensures moderation. Figure 9 shows adoption probabilties for $ZA = 3000$. As depicted PA_A and PA_B remains low (PA_A remains lower than PA_B) to allow the conversion of only a fewer moderates into other two ideologies.

Entropy

Another objective of this exposition is to analyse the macroscopic state of the system in terms of the distribution of microstates as the system evolves. Entropy is the measure of the disorder in a system. The disorder can be defined as the number of microscopic states that can be achieved for a given system configuration. The entropy of the model is evaluated using adoption probabilities (Eqs. 4, 5, 6, 9, 10, 11) of the ideologies as defined by Eq. 12

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{12}$$

where H = Shanon entropy of the system and p_i = Adoption probability of i opinion state.

Figure 10 illustrate the entropy measurement derived from the model. It is evident from Fig. 10c that the fluctuation in the magnitude of entropy is less aberrant where external influence is used. The system remains relatively steady for this scenario because of the presence of stable, moderate population. For systems, where external influence was not used (Fig. 10a, b), fluctuations are high due to the continuous inter-conversions of opinions between the two opposite ideologies and moderates.

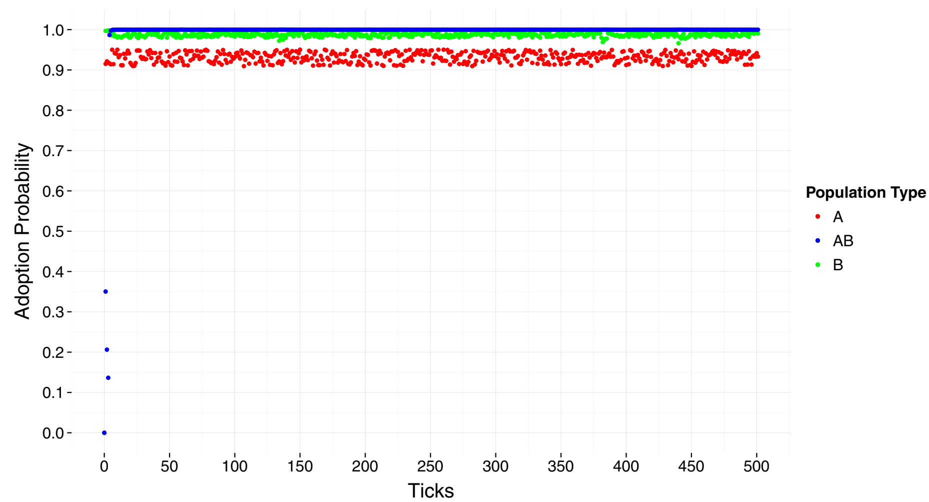

Fig. 9 Variation of adoption probabilities of ideologies with respect to ticks, $ZA = 3000 > A_c$ and $p = 0.03$

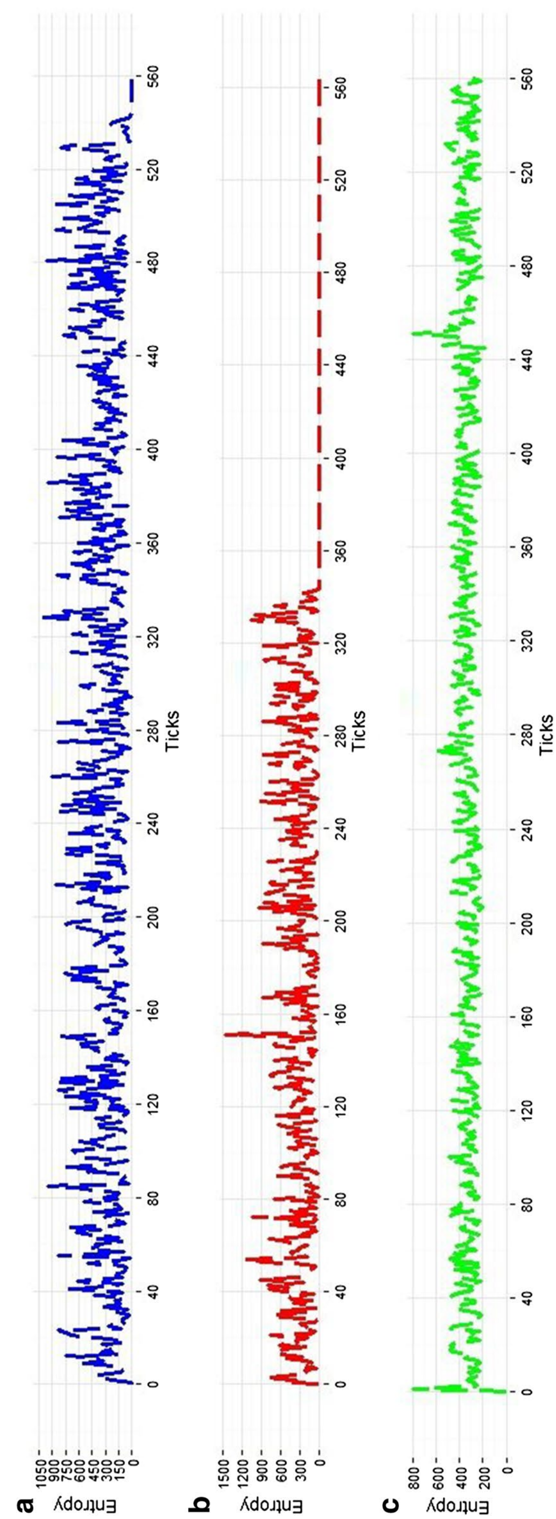

Fig. 10 Variation of System entropy as ticks progress for **a** $ZA = 2100 > A_c$, **b** $ZA = 2250 > A_c$, **c** $ZA = 3000 > A_c$ *and* $p = 0.03$

The statistical analysis of a particular simulation exhibits that there is no correlation between entropy and the different opinion states due to of the dynamic nature of interactions within the system (Table 4). Similar non-correlation was observed in other simulations as well. Furthermore, relationships are not mere aggregations of the individual static entities; this adheres to a basic yet essential property of a typical complex adaptive system.

Evenness

Evenness is defined as the relative abundance of species, i.e., how equally the species are distributed in an environment (Hill 1973).

Ecologists and biologists frequently use this term to measure the distribution of species in the observed environment.

The abundance of a species can be described by diversity indices. Pielou's evenness based on Shannon's index is formulated as in the equation below (Heip 1974).

$$E = \frac{H}{H_{max}} \tag{13}$$

where $E =$ Evenness of species of a system, $H =$ Shanon-Wienar Index, and $H_{max} =$ Maximum diversity possible.

Evenness $E = 0$ reflect a highly unequal spread of species, whereas $E = 1$ infers to the equal spread of all species. Therefore, evenness approaches to one, when the subpopulation sizes becomes comparable with one another.

Shanon-Wienar index is an indicator in ecology. This index measures species diversity similar to the measurement of information present in a message.

Shanon-Wienar index is measured as defined by the equation below (Grice et al. 2009).

$$H = -\sum p_i \log(p_i) \tag{14}$$

where $H =$ Shanon-Wienar index and $p_i =$ Proportion of individuals in species i. Shanon-Wienar index has been extensively used to analyze the richness of groups in the several domains analogous to the theme of this study. Other studies utilize evenness to examine the network community structure (Rendell et al. 2011; Aldecoa and Marín 2011; Min et al. 2014).

In our study evenness measures the ideological diversity of opinions as the system evolves. We consider each ideological group (A, B and AB) as a species.

For simulations where $ZA < A_c$, an ideological shift occurs when evenness crosses a minimum permissible value during the transition phase (Fig. 11). This can be associated with the rapid conversion of AB to B. As the system attains an stable state, evenness decays to its minimum value. Therefore, the minimum permissible evenness in this type of system can be viewed as a population threshold beyond which the old ideology (B) prevails.

Table 4 Correlation between entropy and system parameters

	A	B	AB	PA_A	PA_B	PA_{AB}
Entropy	0.013285325	−0.2420373	0.31351204	0.07141409	0.042696631	0.15678736

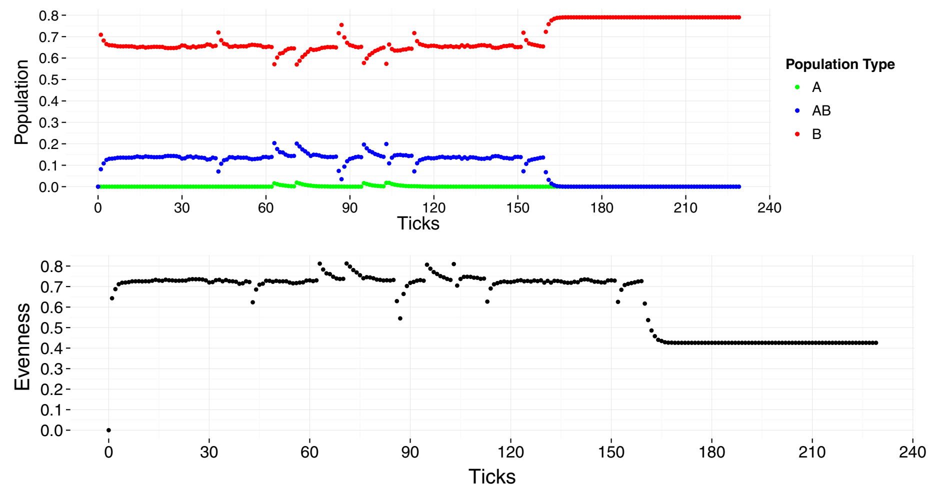

Fig. 11 Opinion evolution for $ZA = 2100$

For simulations where $ZA > A_c$, evenness reaches a maximum during the transition phase, as all three subpopulation sizes (A, B and AB) becomes comparable with one another (Fig. 12). In the transition phase, inequality between subpopulation becomes minimum as effect of interactions between A and B. Therefore, attainment of maximum diversity may mark the beginning of an ideological shift.

Further, we decrease internal influence of ideology A, B and increase internal influence of AB to realise third scenario. Additionally we use external influence for moderates to determine the corresponding evenness of the system. Evenness in this scenario fluctuates closer to 1 (Fig. 13).

Although minor perturbations are observed in evenness but are not sufficient to initiate an ideological shift, which in turn preserves diversity. This supports our previous conclusion that increasing evangelical forces of moderates leads to moderation in society.

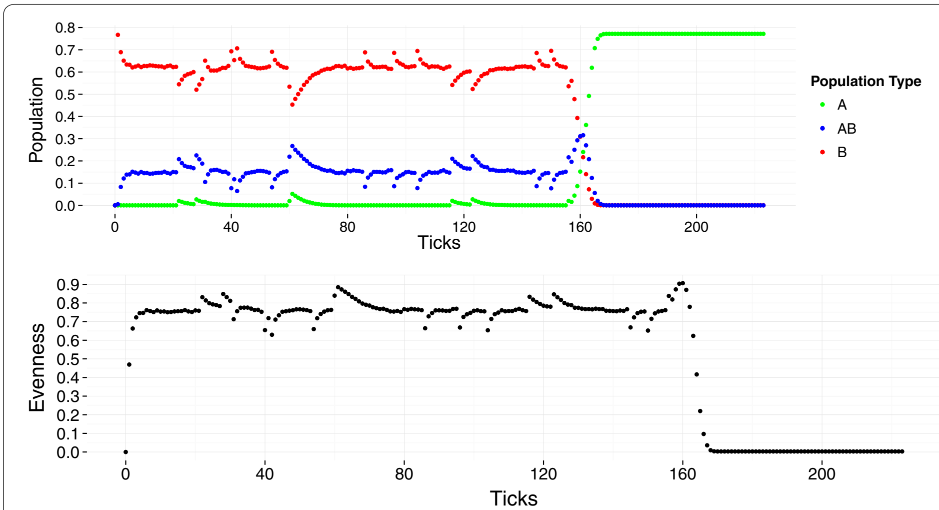

Fig. 12 Opinion evolution for $ZA = 2280$

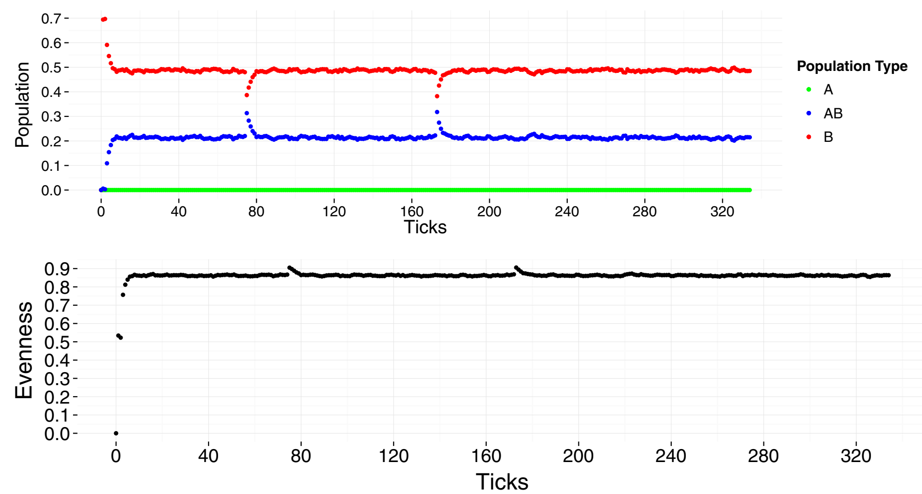

Fig. 13 Opinion evolution for $ZA = 3000$ and $p = 0.03$

Without external influence and zealots of old ideology

Fanatics or zealots of a particular group plays a key role in disseminating their own opinions and resisting the opposite faction. To analyse the impact of zealots of old ideology (ZB), we conducted 170 simulations using the parameters listed in Table 5.

We observed that an increment in the ZB leads to opinion shift towards majority opinion (B) even with the ZA that are well beyond critical population except in a few runs due to perturbations. Such an increase in supporters of majority opinion acts as a resistance (Gündüç 2015) for the opinion shift towards the ideology A (Fig. 14).

The inclusion of zealots (ZB) resulted in more coupling or inter-agent communication within the old ideological group (B+ZB), thereby, converting more number of moderates into their opinion types. Figure 14a elucidates the impact of adding the lesser population of ZB and yields results similar to Fig. 5. However, an increased ZB population tends to aggregate an opinion resistance effect and change more and more moderates to their type (Fig. 14b, c). Therefore, an opinion shift towards the new ideology does not occur even in the presence of fluctuating inter-agent opinion influence.

Table 5 Initialisation parameters after introduction of zealots of B

Variables	Range
Population A	0
Population B	3900–8900
Population AB	100
Population ZA	1000–5000
Population ZB	0–1000
Random-threshold	0–1
Internal influence parameter for ideology A	0.0008–0.004
Internal influence parameter for ideology B	0.0008–0.004
Internal influence parameter for ideology AB	0.0008–0.004

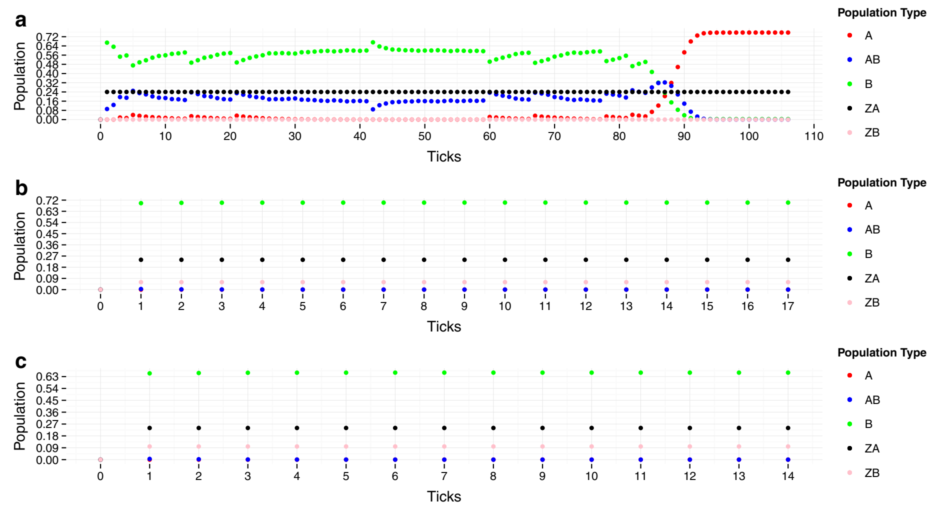

Fig. 14 Opinion evolution for $ZA = 2400 > A_c$ with increasing ZB. **a** $ZB = 100$, **b** $ZB = 600$, **c** $ZB = 1000$

With external influence and zealots of old ideology

Simulations were administered (total 504 simulations) to analyse the impact of external influence of moderates in the presence of zealots of old (ZB) and new ideology (ZA). We observed survival of moderates in the presence of increased ZB and $ZA > A_c$ with parameter settings as defined in Table 6.

Due to the limitations imposed on evangelical capabilities of the two opposing groups (Table 3), adding ZB increases interactions between the two opposite ideologies (A and B), and results in more moderates (AB). This, however, contradicts the outcome of the effect of ZB without external influence, wherein a shift towards ideology B occurred. Justification made above regarding stable population of moderates can be explored further by observing the changes in the adoption probabilities. PA_B remains comparable PA_{AB}, however, greater than PA_A . The constantly high values of PA_{AB} facilitate more conversions towards the moderate ideology (Fig. 15). Further, if any AB converts to B ideology ($ZB + B$) during the interaction, it reverts its opinion to AB due to variation in the adoption probabilities of corresponding populations (Fig. 16).

Table 6 Initialisation parameters after introduction of zealots B and external influence

Variables	Range
Population A	0
Population AB	100
Population ZA	2100–3000
Population ZB	300–2500
Population B	4400–7500
Random-threshold	0–1
External influence parameter (p)	0.001–0.5
Internal influence of ideology A	0.0008–0.001
Internal influence of ideology B	0.0008–0.001
Internal influence of AB	0.001–0.004

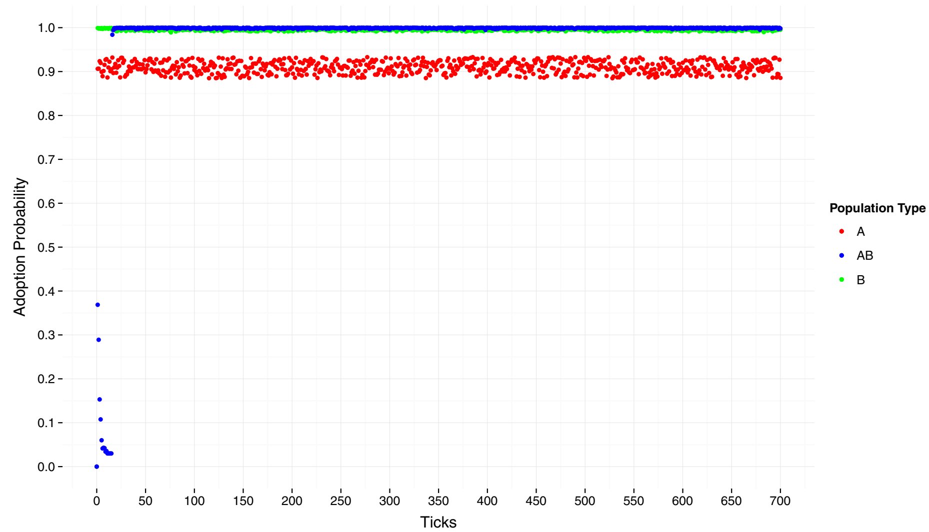

Fig. 15 Adoption probabilities for $ZA = 2700$, $ZB = 1700$ and $p = 0.03$.

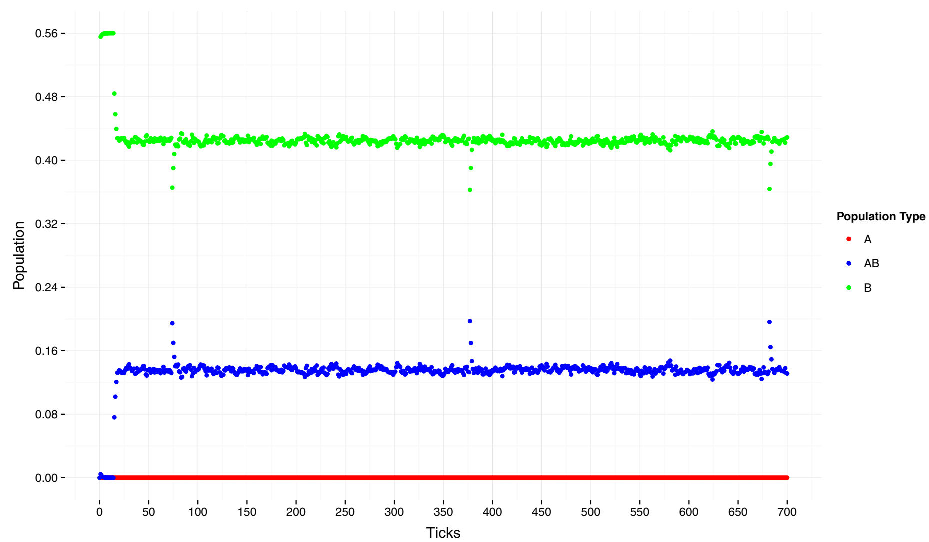

Fig. 16 Variation in fractional population with respect to ticks for $ZA = 2700$, $ZB = 1700$ and $p = 0.03$.

Conclusion

In this study, we analysed opinion formation in a population of five sub populations, i.e., extremists of old and new ideology, zealots of old and new ideology, and moderates with the neutral opinion. We use a two-phase opinion model that includes Bass model as an opinion diffusion mechanism followed by cellular automata to carry out further interactions. Through the results of simulations, we find a threshold value of zealots population beyond which the ideological shift occurs. A critical proportion of committed minority ensures the conversion of a certain fraction of moderates to their extremist counterpart, thereby leading to a consensus towards the minority ideology. Moreover, non-social influence plays a significant role in maintaining moderates population. These results have been reported in earlier studies of opinion formation. However, we validate these results through different simulation procedures in different experimental settings. Future scope of this work lies in analysing other aggregating descriptors along with entropy measurements to get a deeper insight into the underlying adoption of views in the system with time.

Authors' contributions
All authors contributed equally to the paper. All authors read and approved the final manuscript.

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Competing interests
The authors declare that they have no competing interests.

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