

An adaptive media strategy for influencing crowd behaviour

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Abstract

Purpose – Media has always been used as a key manipulator of public agendas, political beliefs and individuals' attitudes. The purpose of this study is to investigate the impact of three adaptive media strategies on the pattern and dynamics of potential crowds.

Design/methodology/approach – An agent-based approach is used to simulate the three adaptive media strategies on the pattern and dynamics of potential crowds. During the experiments, the media broadcast is intensified to gather momentum for crowd movements or is lessened to maintain the budget.

Findings – The results show that a slight change in the media management strategy could lead to a radical different impact on the crowd dynamics. The results also show that a quite smart media strategy could outperform a strategy with an unlimited budget. Finally, the structure of the society shows a significant influence on the crowd dynamics than it could be inferred.

Originality/value – The model presents an explanatory toolkit for the crowd complexity. The results provide deep insights into the crowd formation and a basis for understanding the influence of media and the impact of its strategies on the crowd dynamics.

Keywords Agent-based modelling, Mass media, Revolutionary crowd

Paper type Research paper

1. Introduction

Media has been always a powerful means to communicate with public. In addition to their long list of use, media have recently emerged as a main motive of several crowd waves around the globe. Contrary to what people might believe, Arab protests, ignited at 2010, have not been the first to be triggered and maintained by the media. Coordinated protests against the Iraq war held worldwide in 2003 and Iran Twitter revolution in 2009 are counter examples.

Gustave Le Bon, at the end of the nineteenth century, was a pioneer in presenting an initial crowd theory (Bon, 2005). According to the theory, crowd behaviour is a complex phenomenon that can lead to radical socio-political transformations. The mystery of the crowd is inherent in its diverse composition that includes individuals of different ages, professions, attitudes, values and beliefs. Regardless of the chances that have brought them together, these individuals naturally interact and usually behave in an unplanned, unpredictable manner. The crowd, as a whole, then emerges with different traits from those constitute it. This new formulated entity, i.e. the crowd, starts to feedback the system and inform the interaction of its individuals who in turn think and behave accordingly to reformulate the crowd.



Quite recently, computer simulation has been used in an attempt to crack the crowd complexity and understand its dynamics. For example, simulation models, including *agent-based modelling*, have been used to explain civil and ethnic violence (Epstein, 2002); rebellion against a central authority (Goh *et al.*, 2006); riots as in London 2011 (Davies *et al.*, 2013); revolutions (Makowsky and Rubin, 2013); segregation (Schelling, 1979; Hatna and Benenson, 2012); consensus and public opinion dynamic (Suo and Chen, 2008; Malarz *et al.*, 2011; González-Avella *et al.*, 2007); and the influence of strategic agents on normal agents (Hegselmann *et al.*, 2015). In addition to social conflict models, computer simulation has been also used to investigate other crowd behaviours including the escape, evacuation and panics dynamics (Almeida *et al.*, 2011; Lemos *et al.*, 2013; Helbing *et al.*, 2000); safety measurements (Still, 2000); and traffic jams and flow (Hidas, 2002; Jiang and Wu, 2006; Tajima and Nagatani, 2001). The typical computer models present visual animation to simulate crowd movements and activities in different situations and under different conditions including speed and flow and focusing on the avoidance of the inherent dangers associated with large gatherings.

Despite the potentials of the simulation models in understanding revolutionary crowd behaviour, they still have some significant drawbacks to overcome. One of the main critiques of these models is about their theoretical background that often requires to be underpinned and synchronized with the research in the related fields (Lemos *et al.*, 2013). In addition, these models are still considered artificial. For example, they are regularly represented in a form of a visual grid that is quite often considered an oversimplification of reality. Moreover, they usually focus on only two rival groups: *protesters* and *police*, thus ignoring the different types of protesters or the vastly influential counter-revolutionary groups that back the police and support the regime. Similarly, these models, for the sake of tractability, usually ignore a number of essential factors, including emotion, risk aversion, media and acquaintances, or avoid presenting vital processes such as the assembling stage or the contagion process, which are indispensable for understanding the complexity of the crowd (Davies *et al.*, 2013; Makowsky and Rubin, 2013; Granovetter, 1978). These problems have hindered the capabilities of these models to explain revolutions' conditions, formation or dynamics and raised serious concerns about the validity of any possible generalization of their results.

This research adopts a new agent-based experimental model, called *Revolutionary Crowd Model (RCM)*, which avoids a number of the concerns about crowd simulation. The model is used to assess the impact of different *adaptive media* strategies on initiating and maintaining crowds. In reality, media that aims at revolutionising societies typically oscillates between intensification mode to shake the societies and ignite revolutions, and decline mode to maintain the crowd and control the eruption. In this research, the experiments investigate the pattern and dynamics of the crowd under controlled broadcast strategies that adaptively change the media intensity according to the crowd status and the budget allocated.

The rest of this paper is structured as follows. In Section II, a summary of the related research is presented. In Section III, the *RCM* is summarised. Section IV introduces the experiments and discusses the results. The results are then concluded in Section V.

2. Related work

Since the uprisings of the Arab world, crowd behaviour has been substantially linked to concurrent media activities (Waldherr and Wijermans, 2017). Breuer (2012) claimed that there is a widely shared assumption that such collective behaviour would not have been possible without modern communication technologies and social media, though it is still unclear how the media along with the other influential factors, could have led to such protest

movements. [Krumm \(2013\)](#) argued that social media has to be recognised as the leading mechanism for inciting, organizing, sustaining and broadening the scope of modern crowds.

Media influence over crowd behaviour is a relatively *complex*, highly *interdisciplinary* research field. It simultaneously addresses the contexts of the impact of the different types of media, the complexity of the crowd dynamics and social behaviour and a set of interrelated aspects including social networks and physical movements. For example, with respect to *multidisciplinarity*, [Waldherr and Wijermans \(2017\)](#) had to integrate a set of existing models of social media, protests and crowd behaviour to study recent street protests. Similarly, [Pulick et al. \(2016\)](#) had to merge different models including [Axelrod's \(1997\)](#) culture model, with modifications from [Deffuant et al. \(2000, 2002, 2004\)](#) to address the contexts of the influence of media and town meetings on shaping public opinion. [Übler and Hartmann \(2016\)](#), in their agent-based model about the spreading of trends in social influence networks, had to discuss the trends, descriptive norms, social networks, group structures and four different types of models to present their conceptual framework. [Krumm \(2013\)](#), in his monograph about the influence of social media on crowd behaviour, recommended to the US Army to expand their understanding of “the operational environment, incorporating the multidimensional aspects of social media and crowd behaviour across its lexicon, tactical techniques, and operational procedures” should they want to understand the phenomenon.

With respect to *complexity*, [Bon \(2005\)](#) has addressed the unexpected manner in which crowds behave. According to [Kuran \(1989\)](#), the main feature shared by the major revolutions is their unpredictability. [Breuer \(2012\)](#) stated that the Arab protests were such a “surprise” to many middle east experts and even against what is believed about the role of middle classes as a bedrock of regimes’ stability.

Accordingly, studying such complex multidisciplinary collective behaviour has been requiring a delicate selection of the level of abstraction to use. Even highly abstracted models have been showing some kind of emergences that require insight to understand, explain, and more importantly, be linked to reality. For example, the early simple mathematical model of [Granovetter \(1978\)](#) about a set of actors with only two groups to join showed “paradoxes” including the very different results that may be generated even from groups with similar average preferences. [Übler and Hartmann \(2016\)](#) confirmed the prediction complications of the trends spreading in social networks as a single aspect of the phenomenon, stating the uniqueness of the situations of the emergence of trends. [Kuran's \(1987b, 1987a\)](#) research about public choices and unanticipated political revolutions showed similar unintuitive behaviours including the possibility of strong public support of policies that were privately advocated by few people.

Since Kuran’s work, researchers have built more elaborated models. The two well-known agent-based models of civil violence of [Epstein \(2002\)](#) are an example. In the first model, simulating a central authority seeking to suppress a decentralized rebellion, the active agents showed “unexpected deceptive” behavior because they changed their status to nonactive when cops were near, and turned back active when cops moved away. The second model, simulating a central authority seeking to suppress mutual violence between two rival ethnic groups, showed that a peaceful coexistence occurs when both of the two groups have a high legitimacy; however, when the legitimacy was reduced by only 20 per cent, local episodes of ethnic cleansing and ultimate eradication of one group were reported.

Based on Epstein’s work, another set of refined models have been developed. [Goh et al. \(2006\)](#) considered greed as an additional motive, confirming the significance of the grievance over the greed with respect to civil violence and the importance of the number of cops and the arresting period of time on maintaining order. [Fonoberova et al. \(2012\)](#) extended this model in an

attempt to identify the number of cops required to keep order. The results showed a nonlinear relationship between the number of cops required to sustain order and the population size, and a significant difference in eruption patterns between large and small cities. Similarly, [Davies et al. \(2013\)](#) examined the spatial development of disorder against the effect of varying policing arrangements as occurred in London riots in 2011. The results highlighted the importance of the police numbers, reaction time and spatial features when planning for such events.

3. The experimental model

This section briefly presents the *RCM* (Appendix A for a detailed formalism). The *RCM* is a *conceptual microscopic model* that is developed for *understanding* the crowd *pattern* and *dynamics* based on the interaction of the individuals in an *artificial non-spatial socio-political system*. The model assumes that an implicit passive government is in power and the agents could be in opposition to it (*with* revolutionary crowd), in support of it (*against* revolutionary crowd) or remain indecisive (*neutral*). The model is based on the work of [Kuran’s \(1989\)](#), [Epstein’s \(2002\)](#) and [Ibrahim and Hassan’s \(2017\)](#) work. The model is also based on common social and psychological theories to underpin its theoretical framework and thus avoid the main concern about crowd simulations presented above ([Locher \(2002\)](#) and [Klandermans and van Stekelenburg \(2013\)](#)).

First, according to [Khalidun \(1967\)](#), social change is fundamentally based on fanatical, moral, social, economic, political and historical factors. Accordingly, the *RCM* assumes that each agent has a *hardship* level representing its social, economic and political satisfaction toward the regime. A *general satisfaction level (SL)* that reflects the overall contentment of the public is also implemented to represent the relative deprivation or social injustice experienced in the society ([Anderson, 1998](#)). In particular, the general SL is the average hardship of all the agents in the system. Three fuzzy sets of general SLs are considered in the model: *Bad*, *Moderate* and *Good*.

To enable the representation of the fanaticism, the model assumes *seven mutually exclusive groups* of agents, each of which reflects a specific “ideology.” Each agent is assumed to belong to only one of these groups. The agents of each specific group have some level of *tolerance* or *preference* to the agents in the other groups. The less that tolerance is assumed, the more the fanaticism in the society should be. The seven groups are divided based on three dimensions:

- (1) belief in the revolutionary crowd (*with*, *against* or *neutral*);
- (2) activity the agent might perform to support its group (*active* or *inactive*); and
- (3) participation in the crowd (*participate* or *not-participate*).

[Table I](#) summarizes the *valid* possible groups. The first three groups are called the *With-Groups (WGs)* and the last three groups are called the *aGainst-Groups (GGs)*.

Group No.	Group Name	With or aGainst	Active or Inactive	Participate or Not
G ₁	WAP	With	Active	Participate
G ₂	WIP	With	Inactive	Participate
G ₃	WIN	With	Inactive	Not participate
G ₄	Neutral	Neither with nor against (indecisive)		
G ₅	GIN	aGainst	Inactive	Not participate
G ₆	GIP	aGainst	Inactive	Participate
G ₇	GAP	aGainst	Active	Participate

Table I.
The seven valid alternative groups of agents

The model also considers the *convergence theory* main assumption that the communication process results in a change in the beliefs, values and behaviours of a culture (Chen, 2012). Therefore, the model assumes that the whole population of the agents could be divided into a number of interrelated sub-populations, each of which might have its own structure, preferences and parameters. Not only does this grouping and population structure approach admit the representation of different opposing crowds, which is not usually assumed in the literature, but it also enriches the analysis as presented in the experimentation section below.

The group the agent belongs to, along with the *level of tolerance* to others, identifies the agent's *preferences* for all the other groups. The preferences, in addition to the agent hardship level and the general *SL* in the society, are assumed to determine the agent *overall emotion* toward the seven groups.

To simulate the differences in human attitude toward uncertainty, each agent is assumed to have a particular level of *intolerance to risk*. This risk intolerance is affected by the agent own *risk aversion* parameter, *general risk likelihood* of joining each group in the society and the current *majority crowd*. Both of the agent's *emotion* and *risk intolerance* to the seven groups shape its *internal factors* that stimulate its behaviour.

In addition, according to the recent research (Ahmed, 2011; Green-Pedersen and Stubager, 2010), the *acquaintances* and the *media* are identified as the most significant *external* manipulators over the individuals' beliefs. The RCM incorporates both of these two influencers. With respect to the acquaintances, each agent is assumed to have a typical structure of four logical neighbours, representing its close network that has influence over its decision. With respect to the second external influencer, the model considers two types of competing media: *With-Media (WM)* that tries to convince the agents to join the anti-regime crowd and *aGainst-Media (GM)* that broadcasts to persuade them with the opposite. The *intensity* of each of these two types of media is assumed to reflect the media overall effectiveness over the public. Typically, each agent has different *sensitivity* to both media, which along with the media intensity, identifies the *media influence* over the agent. Both of the acquaintances and media influence shape the external factors that direct the agent behaviour toward the seven groups.

Based on a specific utility function, internal factors and external stimuli, each agent repeatedly takes a decision with respect to the group to join. Figure 1 summarises the model.

It has to be stated that the complexity and the multidisciplinary nature of the phenomenon have led to a relatively low level of abstraction of the model. However, this level of detail has been carefully decided and systematically handled in all the experimentations. A fundamental evidence of the model stability, as presented amongst others below, is the low number of runs (seven, in particular) required for the average convergence of results.

4. Experiments and results

This research investigates the effectiveness of an adaptive media strategy in which the intensity of the broadcast is adjusted, as necessary, to control the crowd formation. More specifically, the experiments examine the assumption that the *With-crowd Media (WM)* could adaptively be either intensified to gather momentum for attaining with-crowd majority or reduced to maintain the budget betting on the contagion to sustain the crowd. This process is repeated as necessary and contrasted with a uniform intensity of the *aGainst-crowd Media (GM)* that broadcasts consistently throughout the entire simulation time.

For convenience, *media intensity*, which is used to reflect the overall power of the media, can be represented in terms of the budget dedicated for the broadcast. Therefore, the experiments can be seen as an investigation of the influence of different budget management strategies over the crowd. Three adaptive media strategies/experiments are investigated.

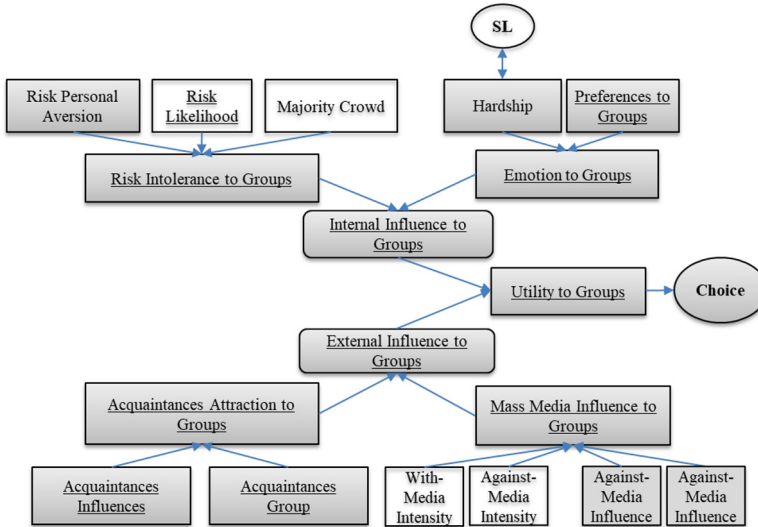


Figure 1. The revolutionary crowd model structure (agents' parameters are shaded, population parameters are unshaded, and vector parameters are underlined)

The first experiment, E1, assumes that the WM intensity is increased or decreased by 10 per cent according to the with-majority status; it is thus referred to as a *symmetric adaptive strategy*. In the second experiment, E2, every time the majority is required to be attained, the intensity is consistently increased by 10 per cent. Similar to E1, until reaching the majority, then the remaining budget is equally divided overall the remaining period of time to sustain the crowd gathered. The third experiment, E3, follows the symmetric adaptive strategy of E1; however, it assumes that the budget of the WM is unlimited. This is in contrast with the first two experiments in which equal budgets of both media are assumed. The intention of E3 is to estimate the budget required to maintain the majority for the longest period of time in face of the fixed budget of the GM.

All the experiments are conducted under three general *SLs*: *good*, *moderate* and *bad*. Each experiment is run *seven* times and the average result is reported. Each run starts with a population of 2000 agents and goes for 100 cycles/iterations. Out of the whole population, 50 per cent of the agents are assumed neutral; 10 per cent are in each of WIN, WIP, GIN and GIP groups; and 5 per cent are in each of WAP and GAP groups. Each agent has four randomly assigned acquaintances.

All of these predefined conditions are systematically examined and/or rationally decided. A set of preliminary investigations has shown that seven runs with 2000 agents in each experiment are adequate for achieving stability in the average results. Time granularity of the model is supposed to be measured in few days; thus, 100 iterations, which almost count up to a year, are sufficient for studying the possible formation of crowd and its dynamics. The equal division of the entire population over neutral (50 per cent), and with- and against-supporters (50 per cent) is estimated based on the reported election participation out of the voting-age population in different countries. The acquaintances number is based on previous studies (Pulick *et al.*, 2016; Ahmed, 2011; Suo and Chen, 2008).

Because of the decomposition of the population into seven groups, intuitive outcomes are paid little attention to preserve more space for the insights into noteworthy behaviour of the model. The results are mainly represented with respect to key dimensions including the dynamics of the groups, emerging majority group, period of time the majority lasts and

participant/non-participant ratio in the majority group. Stacked area charts are used to represent the dynamics of the seven groups of agents. Stacked area charts are convenient as the total number of agents in all the groups is fixed throughout the simulations. In addition, they are more comprehensible as there will not be any overlapping among the groups as, for example, in line charts.

4.1 E1: Symmetric adaptive media

In this experiment, the WM intensity is consecutively increased by 10 per cent of its initial value until the majority is achieved, then consecutively decreased by the same percentage (10 per cent) as long as the majority is retained. Once the majority is lost, the same process is repeated. The 10 per cent value is decided based on a preliminary experiment that indicates its appropriateness for balancing the budget spending and the intensity effectiveness.

Figure 2 shows the pattern of the WM spending at the three SLs. At the good SL, the WM is constantly intensified by 10 per cent, reaching up to 300 per cent of its initial value at step 29 when the with-majority is attained, as shown in Figure 3. The intensity is then declined as planned to maintain the budget; however, the budget runs out at step 36 and the WM broadcast has to stop until the end of the simulation. This strategy enables the with-majority to be maintained for 12 steps, reaching up to 56 per cent of with-supporters, 54 per cent out of which are participant agents. However, the situation is critically reversed in favour of the against-revolution crowd at step 45. With the total absence of the WM, the consistent GM continues to attract followers. At the end of the simulation, the against-majority dominates the population with about 95 per cent of against-supporters, 62 per cent out of which are participant agents. In other words, out of the entire population, almost 59 per cent become against-revolution supporters who are ready to participate in any action against revolutionary agents.

Figure 2. With-media spending under symmetric adaptive strategy at good, moderate, and bad SLs

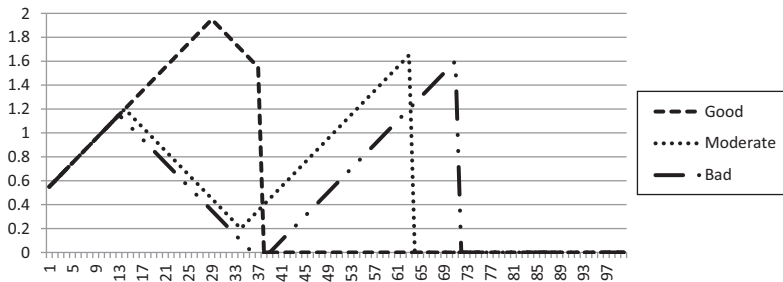
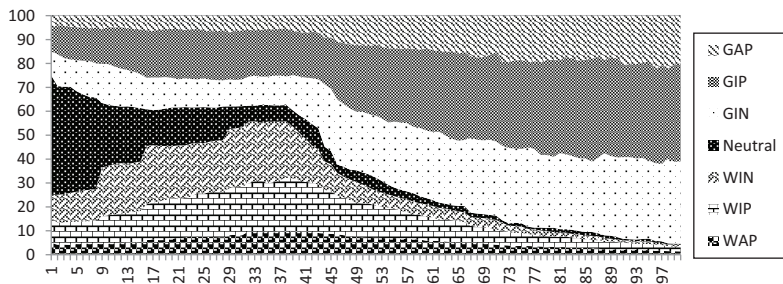


Figure 3. Groups dynamics under symmetric adaptive with-media and good SL



At the moderate SL, [Figure 2](#) shows that the spending has to be increased up to 140 per cent of its initial value for the majority to be attained at step 14, as shown by [Figure 4](#). Afterwards, the spending is decreased to maintain the budget. Under the pressure of the continuous cut of the spending, the with-majority is lost at step 33 where the spending has to be re-increased. However, the budget runs out at step 64 before acquiring enough supporters to regain the majority. The best hit for the *WGs* is 57 per cent supporters, 44 per cent out of which are participant agents. The against-majority is gained at step 72 and typically lasts until the end of the simulation reaching up to 78 per cent supporters, 60 per cent of them are ready to participate in any potential against-revolution crowds.

At the bad SL, [Figure 2](#) shows that the WM spending pattern is quite similar to the moderate case until step 33. However, with the aid of the favourable bad SL, the with-majority is gained at step 13 and maintained for a longer period of time until step 38. [Figure 5](#) shows that the with-supporters reach up to 54 per cent of the whole population, 54 per cent out of which are participant agents. The spending has to be re-increased at step 39 to reclaim the majority but as usual the budget runs out at step 72 before regaining it. The against-majority is soon attained at step 80 and surely maintained until the end of the simulation reaching up to 68 per cent supporters, half of which are participant agents. [Table II](#) summarises the results under the three SLs.

Under the three SLs, although the generous spending of the WM enables the with-agents to attain the majority, the entire budget always runs out quite fast and consequently the *GGs* could always flip the situation to their advantage. At the best case, under the bad SL in specific, the WM strategy could sustain the majority for 26 steps reaching up to 54 per cent with-majority. This is in contrast to the GM consistent budget strategy that could always reverse the situation in favour of the *GGs*. For example, even under the bad SL, it could manage to sustain a 21-step of against-majority, with 68 per cent supporters.

The results reveal a number of unpredictable outcomes, i.e. emergent behaviours. First, at the good SL ([Figure 3](#)), the increasing WM spending takes 29 steps to influence enough

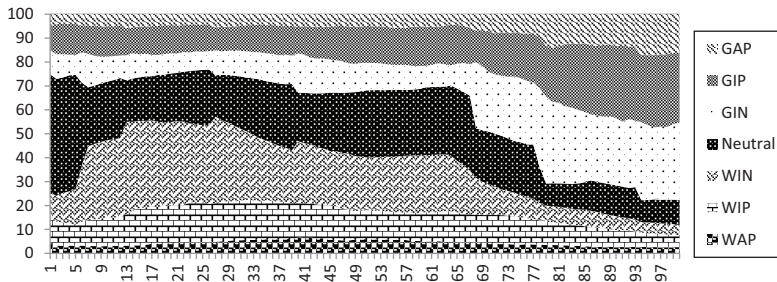


Figure 4. Groups dynamics under symmetric adaptive with-media and moderate SL

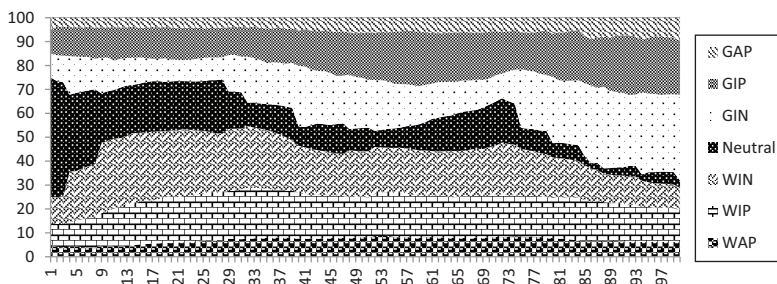


Figure 5. Groups dynamics under symmetric adaptive with-media and bad SL

supporters to join the WGs and attain the majority. This result reveals a significant influence of the unfavourable good SL along with the low but consistent GM broadcast. Second, although the WM spending, starting from step 53 at the moderate SL and step 64 at the bad SL, exceeds the initial spending that enables reaching the with-majority at step 14 and step 16 under the two SLs, respectively, the majority could not be regained. Moreover, despite the spending exceeding the level required to attain the majority at the beginning of the simulation with about 30 per cent, the majority still could not be attained. This crucial result indicates the significance of the conditions and structure of the society, in addition to the general SL and the media influence, on the crowd pattern and dynamics. For example, at the moderate SL, the increasing WM intensity has first to face the decrease in the numbers of the with-revolution supporters at step 50 before it slowly starts to manage acquiring few supporters. At the bad SL, in contrast, the radical shrinking of the neutral group in favour of the with- and against-groups is the main reason that hinders the high WM intensity gaining the majority as quickly as it does at the beginning of the simulation.

As the WM has run out of budget under the three SLs, the domination of the against-supporters has been always the case at the end of the simulation. Accordingly, the following experiment examines a different strategy that tries to maintain the WM broadcast for a longer period of time and thus disallow the counter revolutions to happen.

4.2 E2: Asymmetric adaptive media

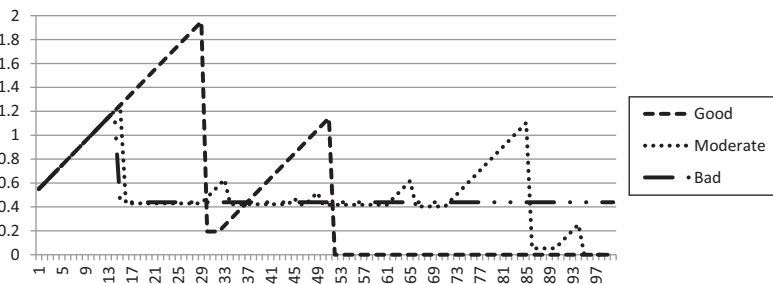
In this experiment, the WM intensity is consecutively increased by 10 per cent of its initial value until the majority is achieved, then the remaining budget is divided equally and distributed overall the remaining period of time until the end of the simulation. This process is repeated each time the majority needs to be re-attained. Figure 6 shows the pattern of the WM spending at the three SLs. The pattern is normally similar to the previous experiment up to reaching the majority for the first time.

At the good SL, Figure 7 shows that the with-majority is achieved at step 29. Therefore, the remaining budget is divided equally among the remaining 71 steps. Under the sudden

Table II.
Majority under
symmetric adaptive
with-Media at the
three SLs

Satisfaction level	Duration	With-majority				Against-majority			
		Supporters (%)	Participants (%)	Budget duration	Maximum spending	Supporters (%)	Participants (%)	Duration	
Good	12	56	54	36	300	56	95	62	
Moderate	20	57	44	64	140	29	78	60	
Bad	26	54	54	72	130	21	68	50	

Figure 6.
With-media spending
under asymmetric
adaptive strategy at
good, moderate, and
bad SLs



huge reduction in the WM spending, the majority could be sustained for only three steps with no sign of contagion. At step 32, the spending has to be re-increased to re-attain the majority; however, the budget runs out at step 52 before reclaiming it. Starting from step 65, the majority is reversed in favour of the GGs and lasts to the end of the simulation, reaching up to 93 per cent supporters, 62 per cent out of which are participant agents. These results are quite similar to the experiment E1 with two exceptions. On the one hand, the time span of the with-majority is only three steps in this case unlike the 12 steps in E1. This is of course because of the sudden reduction in the spending unlike the gradual reduction in E1. On the other hand, after achieving the majority, the WGs are maintained better in this case than in E1. In particular, reversing the situation in favour of the GGs is delayed here until step 65, unlike step 45 in E1.

At the moderate SL, the with majority could be attained once and regained five times during steps 15-28, 33-43, 45-46, 49-60, 65-70 and 85-89 (Figure 6 and Figure 8). The average percentage of the with-supporters during these intervals is 51 per cent, 43 per cent out of which, in average, are participant agents. The total number of the with-majority steps is 50 in contrast to only 20 steps of majority in the experiment E1. Moreover, the new spending strategy enables the WM broadcast to last until step 95, denying the GGs to ever reach the majority. This is unlike the domination of the GGs in E1 in which a 78 per cent against-majority is achieved and maintained since step 72.

At the bad SL, Figure 9 shows that the with-majority is achieved at step 14 and remarkably lasts to the end of the simulation, with a highest hit at step 79 of 61 per cent supporters with 56 per cent participant agents. The WM budget lasts until the end and denies any majority for the against-supporters unlike the 21 steps of domination in E1. The results of the moderate and bad SLs clearly reflect the superiority of the asymmetric adaptive media control over the symmetric budget spending presented in E1 (Table III).

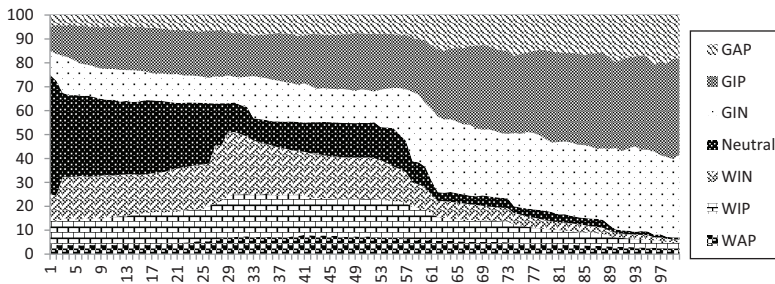


Figure 7.
Groups dynamics under asymmetric adaptive with-media and good SL

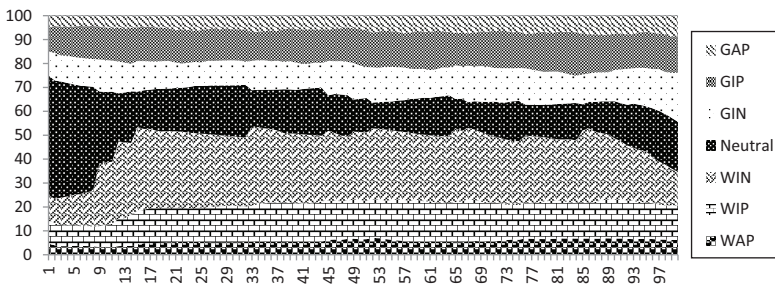


Figure 8.
Groups dynamics under asymmetric adaptive with-media and moderate SL

The promising performance of the asymmetric strategy over the symmetric strategy reveals an essential unexpected result that a basic adjustment in the media spending could lead to a considerable change in the outcome. However, once again, the with-majority under a good SL is still not easily attainable or sustainable using both media strategies. Hence, the following experiment tries to estimate the budget required to handle the majority for the longest period of time. The experiment is applied to the symmetric case as the unlimited budget assumption is unapplicable to the asymmetric strategy.

4.3 E3: Symmetric adaptive media under unlimited budget

Similar to the experiment E1, this experiment assumes that the WM broadcast is symmetrically intensified or reduced by 10 per cent of its initial value to achieve the majority or maintain the budget. However, this experiment considers an unlimited budget for the WM to estimate the total sum required to maintain the majority for the longest period of time. Figure 10 shows the pattern of the spending at the three SLs. The pattern is normally similar to the case E1 up to the point of the total budget exhaustion.

At the good SL, Figure 11 shows that the with-majority is achieved after 27 steps of media intensification. Figure 10 shows that the budget has to be increased by 270 per cent to achieve the majority. Media intensity is then reduced to minimise the spending and the majority is lost at step 62. Media intensification process is repeated; however, a 300 per cent increment was not enough to re-attain the majority. This is essentially because of the period between steps 53 and 70 during which the WM broadcast is maintained at a lower level than the GM. Majority once again seems to require more time to reach than the 27 steps required at the beginning of the simulation. The best hit for the WGs in this experiment is reached at step 42, where about 60 per cent of the population become with-supporters, 56 per cent out of which are participant agents. However, the main virtue of the generous spending of the WM, which is in total 114 per cent more than the total GM spending (107 units of spending for the WM versus 50 units for the GM), is that it enables a 35-step with-majority during the simulation while denies any majority

Figure 9. Groups dynamics under asymmetric adaptive with-media and bad SL

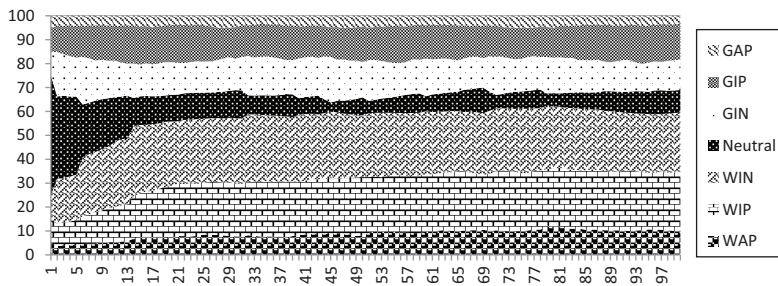


Table III. Majority under asymmetric adaptive with-Media at the three SLs. (*average of five periods of majority)

Satisfaction level	Duration	With-majority				Against-majority			
		Supporters (%)	Participants (%)	Budget duration	Maximum spending	Supporters (%)	Participants (%)	Duration	
Good	3	52	48	52	300	93	62	36	
Moderate	50	51*	43*	95	142	None			
Bad	87	61	56	Till End	138	None			

Note: *average of five periods of majority

of the GGs. This is in contrast to only a 12-step-with-majority/56-step-against-majority in E1 and 3-step-with-majority/36-step-against-majority in E2.

At the moderate SL, the majority is attained at step 18 and lasts for 27 consecutive steps (Figure 10 and Figure 12). At step 45, the spending has to be re-increased for 39 successive steps, until step 84 in specific, to regain the majority. The total spending in this case is almost double (104 per cent) than the GM spending. This budget enables a 45-step with-majority, over two periods of time, while denies the GGs to ever reach the majority. The best achievement of the WM is at step 30 with 69 per cent supporters but only 39 per cent participant agents. These results are unlike those of a 20-step majority in E1 and the remarkable 50-step majority at E2. Recall that, in E2, an average of 51 per cent supporters with 43 per cent participants are achieved under the assumption of equal budgets.

At the bad SL (Figure 13), the with-majority is achieved at step 14 and lasts up to step 51. Although during steps 35-51 the WM does not have to spend a penny, the with-majority could still be maintained. This is mainly because of the supportive bad SL. The spending has to be re-increased during steps 52-64 and 67-85 because the majority is attained for only

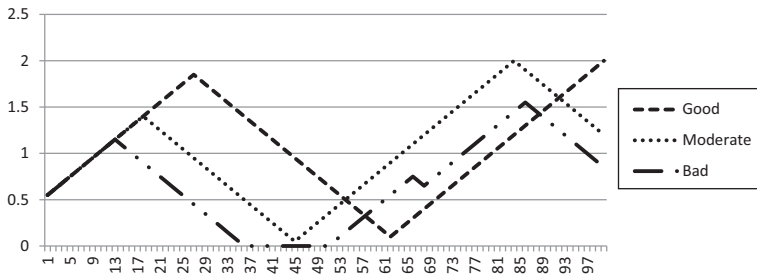


Figure 10. With-media spending under symmetric adaptive strategy-unlimited budget at good, moderate and bad SLs

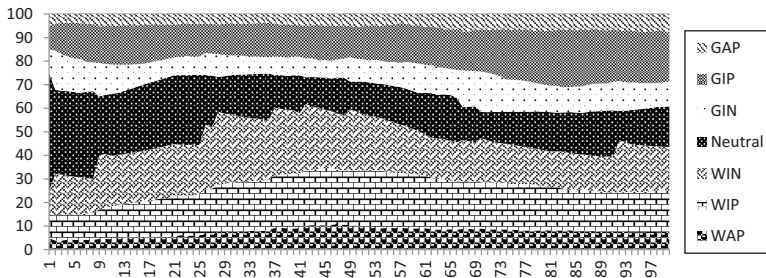


Figure 11. Groups dynamics under symmetric adaptive with-media, unlimited budget and good SL

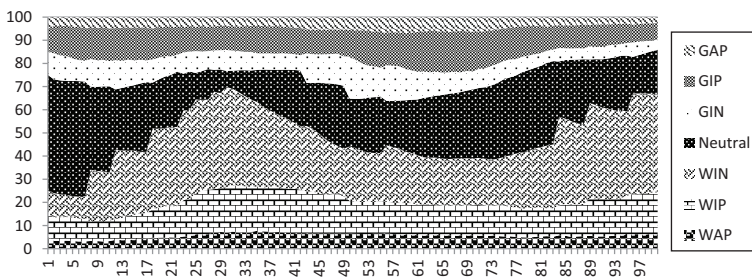


Figure 12. Groups dynamics under symmetric adaptive with-media, unlimited budget and moderate SL

three consecutive steps, from step 64-step 66, and from step 85 till the end of the simulation. Apart from these three steps, the majority takes 30 steps to recapture. This is about double of the time required to gain it at the beginning of the simulation. The best hit in this case occurs at step 33 with 61 per cent supporters with 53 per cent participants. The total spending in this case is only 34 per cent more than the GM spending. This budget enables a 53-step with-majority, while denies the GGs to reach majority. However, the asymmetric strategy has remarkably achieved an 87-step of 61 per cent majority with 56 per cent participant agents. [Table IV](#) summarises the results of the three experiments.

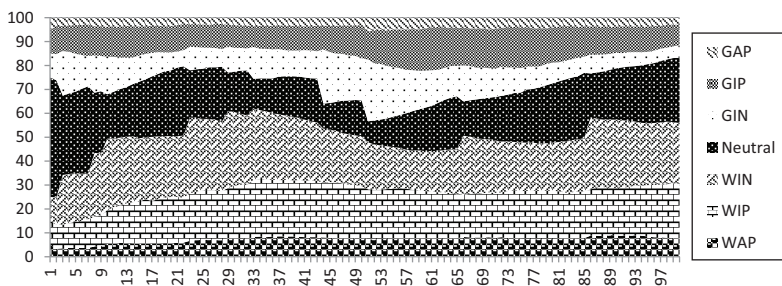
Contrasting the results of this experiment with the experiment E2, it is revealed that the influence of the budget management strategy could be superior to the influence of the budget itself. For example, under the bad SL, the asymmetric strategy in E2 has shown better influence on the with-groups than the symmetric strategy with an unlimited budget in E3. Moreover, under the moderate SL, the asymmetric strategy has shown a quite similar outcome compared with the symmetric strategy with a double budget.

5. Conclusion

This research investigated the impact of three adaptive media strategies on the potential crowd pattern and dynamics. A model, called the *RCM*, was used. The model represents a new perspective with an elaborate set of groups, parameters and stimuli. For example, it includes seven groups of agents to represent a wide range of ideologies and two types of media to represent the opposing viewpoints about the revolution. The model is non-spatial to avoid the restriction of physical lattices, enable a more realistic representation of social neighbourhood and allow the representation of the novel types of communication, including social media. It was implemented as an agent-based testbed to allow more descriptive outcomes and provide more insights into the pattern and dynamics of the crowd in response to different types of stimuli including the media. The model was validated through four main stages and tested. The runs showed that the model is elaborate, stable and has the potential to work as an explanatory framework.

With respect to the experiments, three adaptive media strategies were investigated. The results have revealed a number of emergent behaviours. First, it has been demonstrated that a basic adjustment in the media spending strategy could lead to a considerable change in the outcome. More specifically, a quite trivial change in the symmetric media strategy, which led to the asymmetric media strategy, has considerably enhanced the with-media influence over the crowd. In other words, it was shown that any limitations of the media budget could be overcome with a smarter media strategy because the asymmetric strategy has outperformed the symmetric *unlimited-budget* strategy in the case of bad satisfaction level, while it has had a quite similar performance to it under the moderate satisfaction level.

Figure 13.
Groups dynamics
under symmetric
adaptive with-media,
unlimited budget and
bad SL



Majority Sat. Level	E1		E2		E3		Extra with-budget (%)
	With	Against	With	Against	With	Against	
Good	12 (56, 54)	56 (95, 62)	3 (52, 48)	36 (93, 62)	35 (95, 62)	-(39, 74)	114
Moderate	20 (57, 44)	29 (78, 60)	50 (6 periods) (54, 42)	-(44, 50)	45 (2) (69, 39)	-(35, 72)	104
Bad	26 (54, 54)	21 (68, 50)	87 (61, 56)	-(31, 58)	53 (3 periods) (61, 53)	-(42, 48)	34

Table IV. Summary of majority duration and best hit of (supporters %, participant %) of the with- and against-Groups in the three experiments under the three SLs. “.”sign indicates no majority and shaded cells show the best result at each SL

Second, under an unfavourable good satisfaction level, extra budget is typically required to enable igniting and maintaining crowd as well as to suppress any counter revolutions. Accordingly, an accurate measurement and serious consideration of the general satisfaction level in a society has proven to be quite essential for any accurate prediction of the pattern and dynamics of any potential crowd and hence for assessing its potentiality in turning into massive protests. This result is supported by the large number of Egyptian protests that have been ignited before the massive 2011 revolution such as the major textile workers strike in 2008; nevertheless, none of these protests have turned into a revolution or even exceeded their local areas. This is perhaps because of a moderate satisfaction level of the Egyptians until 2010 that could be claimed a turning year in the Egyptians' mood to bad that set up the optimal conditions for the 2011 revolution.

Third, the results have revealed a significant rule of the condition and structure of the population on the crowd dynamics. As shown in all the experiments, re-attaining the majority has always proven to be more difficult than gaining it for the first time. This is because of the normal distribution of the agents among the seven groups at the beginning of the simulation. However, after the manipulation of this normally distributed population, regaining the majority has proven to be much harder. In addition, an estimation of the total number of agents supporting the revolution is not adequate to measure their predictable influence without an accurate estimation of the participant to non-participant agents in each group. It could be argued here that the erosion of the middle class in Egypt has changed the conditions and structure of the Egyptian society that was perhaps a critical reason in igniting the 2011 protests, in contrast to any other protests prior to 2011.

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Appendix. The revolutionary crowd model

Model formalism

Let Z be a sociopolitical system of r interacting agents. The universe of the system is denoted by $Z = \{a_1, \dots, a_r\}$, where a_i is the i^{th} agent in the system. The model assumes an implicit passive regime is in power and the agents can be in opposition to it (with revolutionary crowd), in support of it (against revolutionary crowd), or indecisive (neutral).

Each agent has a particular level of opposition to the regime, represented by its *hardship* level. Let $hs_i \in [0, 1]$ be the hardship level of agent a_i ($hs_i = 0$, a_i is fully satisfied with the regime, $hs_i = 1$, a_i is fully unsatisfied with it). Three fuzzy regions are assumed for the hardship level: *Low*, *Medium* and *High*, with any appropriate membership function (Pelletier, 2000) for details related to fuzzy rules).

The hardship level of all the agents determines the general satisfaction level: $SL \in [0, 1]$. SL is typically the average satisfaction of all the agents: $1 - avg(hs_i)$. SL is a collective attribute of all the agents in the system that is in turn assumed to be perceived by all agents and influence their behaviour. Similar to agents' hardship, SL domain interval is divided into three fuzzy regions: *Bad*, *Moderate* and *Good* with an appropriate membership function.

Each agent in the system is assumed to belong to one of alternative, mutually exclusive, *groups*. Each group represents a specific "ideology." Three dimensions are assumed essential for categorizing the agents in the system:

- (1) belief in the revolutionary crowd (*with*, *against* or *neutral*);
- (2) level of activity the agent might perform (*active* or *inactive*); and
- (3) level of participation in the crowd (*participate* or *not-participate*).

Seven groups are resulted in: G_i , $i = 1, \dots, 7$, where $Z = \cup_{i=1}^7 G_i$. (See Table I above.)

WAP, WIP and WIN groups are referred to as the "with groups," while the GAP, GIP and GIN are called the "against groups." Some groups are not considered in the classification for their irrationality.

Each agent has different *preferences* for the seven groups. Let $P_i = (p_{i1}, \dots, p_{i7})$ be a 7-vector of preferences of agent a_i , where $p_{ij} \in [0,1]$ is the agent's preference for group G_j . Preferences of each agent are assumed to be based on the group it belongs to. A WAP agent, for example, is assumed to prefer WIP and WIN groups (perhaps neutral group as well) much more than any of the against-groups. However, this is not always true; each culture or society certainly has its own different preferences pattern, especially for the opposing ideas. Therefore, seven general rules are assumed to set the preferences of each agent, with some randomization to simulate individuals' differences. For each agent a_i , the general form of the seven rules ($\forall j$) is as follows:

$$\text{If } a_i \in G_j \text{ then } p_{ik} = RndDst(L_{jk}, U_{jk}) \forall k = 1, \dots, 7$$

Where *RndDst* refers to a specific random distribution with predefined parameters, and L_{jk} and U_{jk} are the lower and upper bounds, respectively, of the preference of an agent in group j to group k .

The hardship of a particular agent (hs_i), its preferences (P_i), and the general *SL* are assumed to control its overall *emotion* toward the seven groups. Let $E_i = (e_{i1}, \dots, e_{i7})$ be the emotion vector of agent a_i . The emotion vector, as a function of *SL*, hs_i and P_i , is proposed as a form of a set of nine fuzzy rules, summarized in Table AI.

Agent's hardship \ Satisfaction level	Satisfaction level		
	Good	Moderate	Bad
Low	$\uparrow p_{GAP}, p_{GIP}, p_{GIN}$	$\uparrow p_{GIN}$	$\downarrow p_{WAP}, p_{WIP}, p_{WIN}$
Medium	-	-	-
High	$\downarrow p_{GAP}, p_{GIP}, p_{GIN}$	$\uparrow p_{WIN}$	$\uparrow p_{WAP}, p_{WIP}, p_{WIN}$

Table AI.
Rules for setting the emotion vector of each agent (dash is for No-Change)

The first rule, for example, describes that if the hardship is *Low*, and the general SL is *Good*, then the agent emotion vector is the same as the preferences vector but with more preferences to the three *against* groups (GAP, GIP and GIN). The rule can be represented as follows:

If $hs_i = \text{Low AND } SL = \text{Good}$ Then

$$e_{ij} = p_{ij}^* (1 + \text{RndDst}(0, \theta)), \text{ where } j = 5, 6, 7 \text{ and } e_{ij} = p_{ij}, \text{ otherwise}$$

Where *RndDst* is a specific random distribution with predefined parameters and θ is the upper bound of the increment percentage.

The rationale of the rule is quite intuitive as the agent has no hard feelings toward the regime and the general atmosphere in the society is good; therefore, the implication is more emotional attraction to the against-groups. The rest of the rules adopt similar logic.

Each agent has a particular level of *intolerance to risk* that is affected by its own *risk aversion*, general *risk likelihood* of each group, and the *majority crowd*. First, let $ka_i \in [0,1]$ be the personal *risk aversion* of agent a_i ($ka_i = 0$, a_i is highly bold, $ka_i = 1$, a_i is most cautious). Risk aversion domain interval is divided into three fuzzy regions: *Low*, *Medium* and *High*, with any appropriate membership function.

Second, let $L = (l_1, \dots, l_7)$ be a 7-vector of the *general risk likelihood* assumed in the society on joining the seven groups. Typically, $l_j \in [0,1]$, ($l_j = 0$, no risk likelihood in joining G_j , $l_j = 1$, certain risk likelihood in joining the group).

Third, as people feel safer in larger groups, *Majority Crowd (MC)* is considered. Majority is determined by the number of the agents in the three with- or against-groups.

Based on the agent's risk aversion (ka_i), general risk likelihood (L) and majority crowd (MC), the *risk intolerance* of agent a_i of joining the seven groups is determined. Let $K_i = (k_1, \dots, k_7)$ be the vector of risk intolerance. The vector is calculated based on a set of fuzzy rules presented in [Table AII](#).

The first rule (A), for example, shows that if the agent is in one of the with-groups, its risk aversion is *Low*, and the majority is with-crowd, then the agent risk intolerance vector is as the same as the risk likelihood vector but with the risk of the with groups (WAP, WIP and WIN) decreased with a specific percentage. Assuming that the upper limit of the percentage is θ , the rule can be written as follows:

If $a_i \in \text{With} - \text{Groups AND } ka_i = \text{Low AND } MC = \text{With} - \text{Crowd}$, then

$$k_i = l_j^* (1 - \text{RndDst}(0, \theta)), \text{ where } i = 1, 2, 3 \text{ and } k_i = l_j; \text{ otherwise}$$

The rationale of the rule is intuitive as the agent is bold and it belongs to one of the majority groups (with-group), the typical implication is feeling lower risk likelihood in joining any of the with-groups. The rest of the rules adopt similar logic.

Agent group	Majority crowd	With		Against	
	With	Against	With	Against	
<i>Risk Aversion</i>					
Low (<i>Bold</i>)	$\downarrow l_{WAP}, l_{WIP}, l_{WIN}$	$\downarrow l_{Neu}$	$\downarrow l_{Neu}$	$\downarrow l_{GAP}, l_{GIP}, l_{GIN}$	
Medium	$\downarrow l_{WAP}, l_{WIP}, l_{WIN}, l_{Neu}$	$\downarrow l_{WIN}, l_{Neu}$	$\downarrow l_{GIN}, l_{Neu}$	$\downarrow l_{GAP}, l_{GIP}, l_{GIN}, l_{Neu}$	
High (<i>Cautious</i>)	$\downarrow l_{WAP}, l_{WIP}, l_{WIN} \uparrow l_{GAP}, l_{GIP}, l_{GIN}$	$\uparrow l_{GAP}, l_{GIP}, l_{GIN}$	$\uparrow l_{WAP}, l_{WIP}, l_{WIN}$	$\downarrow l_{GAP}, l_{GIP}, l_{GIN}, \uparrow l_{WAP}, l_{WIP}, l_{WIN}$	

Table AII.
Rules for setting the risk intolerance vector of agents

Both of the agent's *emotion* and *risk intolerance* to the seven groups shape its *internal factors* that stimulate its behaviour. Let $C_i = (c_{i1}, \dots, c_{i7})$ be the internal factors vector of agent a_i , where $c_{ij} \in [0,1]$ represents the general internal feeling of agent i toward group j . For each group j , $c_{ij} = 0$ indicates that a_i has no whatsoever positive feeling toward the group, while $c_{ij} = 1$ means that a_i is mostly attracted to it. Intuitively, the internal stimulus of each agent is positively influenced by its emotion toward each particular group, while negatively affected by its risk intolerance toward this group. The vector is calculated as follows, where λ_1 and ε_1 are weighting factors:

$$c_{ij} = \begin{cases} \lambda_1 e_{ij} - \varepsilon_1 k_{ij}, & \text{if } \lambda_1 e_{ij} \geq \varepsilon_1 k_{ij} \\ 0, & \text{Otherwise} \end{cases}$$

In addition, the model considers two main external factors: *acquaintances* and *media*. Each agent a_i has a predefined number (d) of acquaintances (AQ_i), which have some influence over its decision. Let $V_i = (v_{i1}, \dots, v_{id})$ be a d -vector representing the *influence strength* of the acquaintances on agent a_i , where $v_{ij} \in [0, 1]$. Typically, the more the acquaintances that belong to a particular group and the higher their influence strength, the more the attraction of the agent for this group is assumed.

Let $Q_i = (q_{i1}, \dots, q_{i7})$ be a 7-vector of the *attraction* of the acquaintances of agent a_i toward the seven groups, where $q_{ij} \in [0,1]$. For each group j :

$$q_{ij} = \frac{\sum_{\forall a_k \in AQ_i \& a_k \in G_j} v_{ik}}{\sum_{k=1}^d v_{ik}}$$

The model assumes two competitive media: *supporting revolution media* and *regime-supporting media*. Let MI_w and MI_g be the *intensity* of the supporting media (*with*) and opposing media (*against*), respectively. Media intensity can reflect the frequency, spread and/or effectiveness of the media. Intensity of both media $MI \in [0,1]$, where $MI = 0$ means no intensity of the media, while $MI = 1$ means full media intensity, where $MI_w + MI_g = 1$, at the beginning of the simulation.

While the intensity of each media is assumed constant for all the agents, the *media influence strength* on each particular agent is different. Let sw_i and $sg_i \in [0,1]$ be the influence strength of supporting and opposing media on agent a_i , respectively, where $sw_i + sg_i \leq 1$. The values of sw_i and sg_i are assumed to be functions of the general SL and the group of the agent. For example, if the general SL is bad and the agent is in any with-group, the agent acceptance to the with-media is naturally assumed greater than its acceptance to the against-media.

Both media intensity and influence strength determine the attraction of agents toward the different groups. Let $M_i = (m_{i1}, \dots, m_{i7})$ be a 7-vector of the *media influence* on agent a_i toward the 7-groups, where $m_{ij} \in [0,1]$. For each with-group (or against-group) j , media influence is the multiplication of the with media intensity MI_w (or against MI_g) by a randomly generated influence strength sw_i (or sg_i).

Both the acquaintances attraction and media influence shape the external factors that direct the agent behaviour toward the seven groups. Let $H_i = (h_{i1}, \dots, h_{i7})$ be the external-factors vector of agent a_i for each group, which is calculated as follows, where λ_2 and ε_2 are weighting factors:

$$h_{ij} = \lambda_2 q_{ij} + \varepsilon_2 m_{ij}$$

For each group, $h_{ij} \in [0,1]$ represents the general external stimuli of agent i toward group j ($h_{ij} = 0$, a_i has no external positive stimuli toward group j , $h_{ij} = 1$, a_i is mostly attracted to the group).

The agent final decision regarding the ideology and group to join is based on its internal factors and external stimuli. The utility vector of the agent toward the seven groups, $U_i = (u_{i1}, \dots, u_{i7})$, is calculated as follows, where $\beta \in [0,1]$ is the elasticity coefficient of the factors:

$$u_{ij} = c_{ij}^{1-\beta} \cdot h_{ij}^{\beta}$$

where the weighting coefficients of the internal and external factors are as follows: $\lambda_1 + \varepsilon_1 + \lambda_2 + \varepsilon_2 = 1$.

Each agent chooses the group with the maximum utility to join. After each agent has decided its new group, another iteration of interaction and decision making commences.

Validation process

The RCM has undergone a number of validation stages. The validation was applied to the conceptual model, data, model behaviour and results. The first stage of the validation process included a considerable set of *preliminary experiments*. First, a *sensitivity analysis* is applied to assess the impact of the changes in the main assumptions, variables and parameters including number of agents, number of runs and number of iterations. The other variables, including the number and structure of the acquaintances, have been logically decided based on some previous studies (Ahmed, 2011; Suo and Chen, 2008; Pulick *et al.*, 2016). Similarly, the population is structured based on the reported election participation out of the voting-age population in different countries including the USA and Egypt.

In the second validation stage, the model is run under *extreme conditions* and the results proved to be plausible and acceptable. Afterwards, the *degeneracy of the behaviour* and the *traces* are used to track all the variables of all the agents throughout the simulation runs to ensure that the agents behave correctly and hence the model is logically and behaviourally valid.

In addition, a number of metrics have been developed to get more insights into the aggregate model behaviour. This includes the structure of each group and the changes in each group with respect to its initial structure.

The third stage of the validation applied the *face/independent validation* technique where knowledgeable individuals were consulted to evaluate the model. This stage is composed of two rounds of revision. The reviewers' comments have been studied and considered in the version presented in this research.

At the last stage, the *event validity* is implemented to compare the simulation events with those of some target systems. In particular, all the conclusions of this research were correlated to real life experiences.

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