Intensified Media: When Could It Be Effective in Manipulating Crowd Behaviour?

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Abstract

This research examines the impact of intensified media on crowd formation and maintenance during sociopolitical movements. Using an artificial agent-based simulation model, it investigates two different media strategies and their effects on crowd dynamics. The findings highlight several important observations. First, highly intensified media alone is insufficient to generate crowd momentum when general satisfaction levels are low. Secondly if intensified media successfully triggers crowd movements, acquaintances are unable to sustain the crowd once media coverage diminishes. Lastly, small activist groups demonstrate resilience and sustainability even in unfavourable conditions of intensified media or limited public support. This study addresses a gap in the literature regarding the manipulation of crowds through media and provides insights into the recent success of stimulating public engagement on a global scale.

Keywords: Revolutionary Crowd, Mass Media, Intensified Media, Sociopolitical Transformation, Satisfaction Levels, Agent-Based Modelling

1. Introduction

Since the dawn of civilization, media has played a critical role in shaping public opinion and influencing societal dynamics. From ancient Egyptian hieroglyphics to modern digital platforms, media has served not only as a tool for enlightenment and transparency but also, increasingly, as a mechanism of social control. In the contemporary context, mass and social media have become deeply embedded in the architecture of sociopolitical governance, capable of mobilizing populations, swaying public discourse, and amplifying dissent or compliance. Given their strategic use in recent revolutions, protests, and uprisings, understanding how media intensity affects crowd formation and behaviour is essential to both scholars and practitioners.

Crowd phenomena, especially in the form of mass demonstrations and political protests, can fundamentally alter the course of governance. From the French Revolution to the Arab Spring, crowds have proven to be powerful agents of regime change, policy transformation, and social disruption. The dynamics that drive these movements are complex, nonlinear, and deeply embedded in socio-psychological processes. As such, they demand interdisciplinary frameworks that integrate complexity theory, network dynamics, and governance studies. Protests, riots, and demonstrations are not isolated events but emergent properties of social systems with underlying feedback loops, thresholds, and contagion effects (Granovetter, 1978; Helbing et al., 2000) .

Early crowd theorists, such as Gustave Le Bon, characterized crowds as irrational and emotionally charged, an idea which has since evolved. Contemporary research in sociology and social psychology recognizes that while crowds can be unpredictable, they are not devoid of rationality. Concepts like risk perception, groupthink, social identity, and emotional contagion provide a more nuanced view of collective behaviour (Abrams & Hogg, 2020; (Reicher, 1984). Media influences, in particular, have been shown to affect individuals' perceived risk, sense of efficacy, and willingness to engage in collective action (Klandermans & van Stekelenburg, 2013; Krumm, 2013).

From a network perspective, the diffusion of protest behaviour can be modelled through individual decision-making nodes influenced by peers, acquaintances, and information sources (Watts, 2002). A number of recent studies have confirmed the suspicions around the negative influence of media with respect to manipulating public agendas, political beliefs, and individuals' attitudes. Damele (2022) for example, argues that crowds are not inherently irrational, but that they can be manipulated by elites to act in irrational ways. He warned that such a conventional interpretation of the crowd "irrationality" has been exploited to justify the view that masses are incapable of self-government which is evident in the emergence of populism and other anti-democratic movements (see also (Green-Pedersen & Stubager, 2010; Grossman, 2022; Shibanai et al., 2001; Yan, 2021). Other studies have stressed on the rule of mass media in revolutionizing societies and causing significant political and social changes (Bailly, 2012). Gong et al., (2020) demonstrated that social media data can effectively characterize crowds in city-scale events, opening new avenues for real-time applications in **crowd monitoring** and **management**. **Crowd management** refers to the systematic planning and implementation of strategies to ensure the safe, efficient, and orderly movement of crowds during large-scale events. It involves analysing crowd behaviour, demographics, and spatiotemporal dynamics to mitigate risks (e.g., overcrowding, incidents) and to enhance attendee experience. **Crowd monitoring**, on the other hand, entails the real-time or near-real-time observation and analysis of crowd dynamics (e.g., density, movement, behaviour), using data sources such as social media, sensors, or cameras to support evidence-based decision-making.

Crowd behaviour has been investigated in different disciplines including engineering, sociology, psychology, and political science. Computer simulation models have been recently used to explain crowd complexity. For example, simulation models have been employed to address the escape dynamics and evacuation (Almeida et al., 2011); panics (Helbing et al., 2000; Lemos et al., 2013) ; safety measures (Still, 2000); and traffic jams and flow (Hidas, 2002; Jiang & Wu, 2006; Tajima & Nagatani, 2001). Most of these models present visual animation to simulate crowd movements or behaviours under different conditions including speed and flow, focusing on the avoidance of the inherent dangers associated with such large gatherings.

Social conflict, protest, and civil violence are special kinds of crowd that have been also studied using computer models. For example, simulations, including *agent-based models*, have been used to explain segregation (Hatna & Benenson, 2012; Schelling, 1979); civil and ethnic violence or rebellion against a central authority (Epstein, 2002; Goh et al., 2006); riots as in London 2011 (Davies et al., 2013); revolutions (Makowsky & Rubin, 2013) ; consensus and public opinion dynamic (González-Avella et al., 2007; Malarz et al., 2011; Suo & Chen, 2008) ; and strategic agents' influence over normal agents (Hegselmann et al., 2015).

Although computer simulation models have considerable potentials in understanding crowd behaviour, they still have serious shortcomings. First, the theoretical background of many of these models needs to be supported by theories from the related scientific fields including social sciences (Lemos et al., 2013). Second, simulation models are apparently too artificial to be linked with reality. For example, using visual grids to represent the agents' spatial environment is quite an oversimplification of the physical world. In addition, such models usually represent only two rival groups, such as, *police* and *crowd*, ignoring many other types of groups in the society including the counter-revolutionary groups that back the police and support the regime (see Davies et al., 2013; Epstein, 2002; Fonoberova et al., 2012; Goh et al., 2006). Moreover, tractability is a main concern in this kind of models, therefore, many essential factors, including risk aversion, media, acquaintances, and different stages of crowd formation like assembly and contagion phases, are intentionally ignored (Davies et al., 2013; Granovetter, 1978). These drawbacks might inhibit simulation models from realising their full potentials to explain crowd conditions, formation, or dynamics and raise some concerns about their validity or possible generalization of their results.

Despite advances, current models often fall short in representing the diverse motivations and interactions that define real-world crowds. They typically reduce agents to binary categories (e.g., protesters vs. police) and rely on overly stylized environments. Additionally, many models neglect media as an active driver of crowd behaviour and fail to account for stages such as assembly, contagion, and decay phases of collective action (Granovetter, 1978; Makowsky & Rubin, 2013).

To address these gaps, this research introduces a refined Revolutionary Crowd Model (RCM), grounded in prior work by (Ibrahim & Hassan, 2017), which integrates a broader array of agents, stimuli, and behavioural parameters. In particular, the focus is on understanding how intensified media— defined as state of heightened media activity characterized by frequent, emotionally charged, and repetitive messaging across multiple channels, aimed at amplifying public attention, framing events in a specific ideological direction, and influencing perception and behaviour at scale—affects the formation, maintenance, and decay of revolutionary crowds (Entman, 1993; Mccombs & Shaw, 1972). Through simulation experiments, this study explores conditions under which media can ignite or suppress collective action, and the extent to which small activist groups can sustain momentum in the absence of broad public support.

This work contributes to the governance and complexity literature by linking media dynamics to regime stability and crowd resilience. It offers theoretical and practical insights for policymakers, activists, and scholars alike, especially in a time when digital media ecosystems can rapidly amplify both social cohesion and unrest.

The paper is organized as follows. In Section 2, a summary of the related research is presented. In Section 3, the *Revolutionary Crowd Model* (*RCM*) is summarised. Section 4 presents the experimental design and results. Section 5 offers a discussion and Section 6 concludes the findings. Finally, Appendix A provides model validation and sensitivity analysis.

2. Related Research

Understanding the dynamics of crowds—particularly in the context of protest and revolution—has been the focus of multiple disciplinary traditions. Early conceptualizations of crowd behaviour emerged from **classical sociology and social psychology**, with theorists such as **Gustave Le Bon (1895)**, **Sigmund Freud (1921),** portraying crowds as irrational entities governed by anonymity, contagion, and suggestibility (Bon, 2005). While influential, these views have been critiqued for their deterministic and pathologizing stance.

Later models introduced more **rational and identity-based approaches**. Scholars like **Turner and Killian (1987)** and **Reicher (1984)** argued that crowd behaviour is often guided by shared social identities and group norms, rather than mindless emotionality. These frameworks laid the groundwork for **collective action theory**, which highlights how factors like perceived injustice, social efficacy, and risk tolerance influence an individual's decision to participate in protest movements (Klandermans & van Stekelenburg, 2013) .

In parallel, **complex systems theory** and **network science** have contributed significantly to our understanding of emergent protest dynamics. Granovetter's (1978) threshold models demonstrated how small shifts in individual willingness can cascade into mass mobilizations. **Watts (2002)** extended this logic using network-based contagion models, revealing how protest behaviour propagates through social ties and information flows. However, most of these models emphasize structure over agency and often assume homogeneity among actors.

The rise of **agent-based modelling (ABM)** has further advanced the field by enabling simulation of heterogeneous agents with rule-based interactions. Notably, **Epstein's (2002)** civil violence model incorporated grievance, legitimacy, and policing into a computational framework. His work inspired a series of ABMs exploring topics such as insurgency (Epstein, 2002), political polarization (Axelrod, 1997), and crowd panic (Helbing et al., 2000). However, many of these models are either overly stylized or focus narrowly on binary roles (e.g., rebels vs. authorities), with limited attention to nuanced media effects or evolving crowd psychology.

In recent years, scholars have increasingly emphasized the **role of media—particularly social media—in shaping crowd dynamics**. Studies have shown that media can reduce perceived risk, increase emotional arousal, and alter beliefs about the probability of success, thus encouraging participation (Steinert-Threlkeld, 2017; Tufekci, 2017). Media also serves as a critical amplifier, turning local grievances into global spectacles and mobilizing solidarity across geographies. Yet, few models explicitly simulate **media as a dynamic and interactive force**, capable of both escalating and defusing unrest. Moreover, most simulations treat media as a static background variable rather than an agentive actor influencing decision pathways.

Another limitation in the literature lies in the **lack of attention to the multi-stage lifecycle of protests**. While many models focus on the outbreak of mobilization, fewer consider the processes of crowd maintenance, decay, and transformation. As **Makowsky and Rubin (2013)** argue, crowd behaviour is temporally dynamic and often non-linear, with tipping points, feedback loops, and chaotic bifurcations. Capturing these temporal dynamics requires more sophisticated modelling approaches that combine behavioural psychology, governance structures, and information theory.

Finally, **governance and public administration scholars** have increasingly looked to computational models to understand the resilience of political regimes under stress. Crowds can act as both a stressor and a signal within governance systems, triggering repression, reform, or collapse. However, most existing models fail to simulate how governments adapt, respond, or learn over time in the face of crowd pressure.

Since the Arab uprisings, crowd behaviour has been often contributed to media activities (Waldherr & Wijermans, 2017). Breuer (2012) claimed that such collective behaviour would not be possible without modern communication technologies, although it is still unclear how the media could influence the crowd. Krumm (2013) argued that social media is a key player in igniting and sustaining modern crowds. More recently, Clarke and Kocak (2020) confirmed that Facebook and Twitter helped to launch the 2011 Egyptian uprising by mobilising the first protesters who took to the streets. The researchers were affirmative that social media facilitated the protest through three aspects: recruiting protesters, planning, and coordinating the protest, and updating the protesters about the situation on the ground.

The influence of media over crowds is a relatively complex, interdisciplinary topic. The main aim is to study the impact of media on the crowd formation and dynamics. Waldherr and Wijermans (2017), for example, combined different models of social media and crowd behaviour to investigate modern street protests. Similarly, Pulick et al., (2016) merged various models including Axelrod's (1997) culture model and Deffuant et. al. (2000) models to examine the influence of media and town meetings on public opinion (Deffuant et al., 2004). (Übler and Hartmann (2016) presented trends, descriptive norms, social networks, group structures, and four types of models to study the spreading of trends in social influence networks . Krumm (2013) recommended, should understanding the influence of social media on crowd behaviour is required, to fully comprehend the operational environment, including the multidimensional aspects of the phenomenon, e.g., tactical techniques and operational procedures.

Studying crowd phenomena has till now proven complex to fully understand. Even highly abstracted models show emergences that require insight to explain. For example, the simple model of Granovetter (1978), with only two groups to join, showed emergence behaviour, e.g., different results from groups with similar preferences (Übler and Hartmann (2016) excluded the possibility of predicting the spreading of trends in social networks, confirming the uniqueness of the outcomes under each single situation. Kuran's (1987b, 1987a) models of public choices and unanticipated revolutions confirmed the conclusion of Übler and Hartmann, showing, for example, that a policy advocated by few might receive strong public support.

Epstein (2002) presented two elaborated models of civil violence. The first model presented a central authority against a decentralised rebellion while the second model presented a central authority attempting to stop mutual violence between two rival ethnic groups. Both models showed unintuative behaviour. For example, in the first model, the active agents deceived the cops by changing their status to nonactive when cops were near, and active themselves back when cops moved away. In the second model, a peaceful coexistence between the two ethnic groups is sustained as long as they both have a high legitimacy. Neverthless, if the legitimacy of any group is reduced by barely 20%, ethnic cleansing and ultimate eradication of a group were reported (Epstein, 2002).

Epstein's work has been refined by different researchers. Goh et al., (2006), for example, included greed and grievance as additional motives in their model. They showed that grievance is more significant than greed for civil voilance. They also confirmed the significance of the number of cops and arresting time on sustaining order. Fonoberova et al., (2012) attempted to determine the number of cops required for order. A nonlinear relationship between the number of cops and the population size is confirmed. In addition, they showed a significant difference in crowd patterns between large and small cities. Davies et al., (2013) then investigated the spatial development of disorder and the influence of police arrangements as happened in London riots in 2011. The results confirmed the significance of cops numbers, time of reaction, and spatial characteristics.

Ibrahim and Hassan (2017) introduced a refined crowd model that is based on Kuran's (1989) and Epstein's (2002) work along with some common social and psychological theories. The model represents a different 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. It is used as a framework to study the pattern and dynamics of the crowd in response to different types of stimuli including media (Ibrahim & Hassan, 2017).

This study contributes to this evolving body of work by presenting an enriched Revolutionary Crowd Model (RCM) that incorporates agent heterogeneity, dynamic media intensity, and multi-group interactions. Building on prior work by Ibrahim and Hassan (2017), this model integrates sociopolitical, psychological, and informational variables within a complexity-theoretic framework. The RCM allows the exploration of the dynamics of protests emerge, evolve, and dissolve under varying conditions.

Table 1 synthesizes key crowd simulation models from the literature, highlighting their contributions, limitations, and how RCM addresses these gaps. Prior models have advanced the understanding of collective behaviour, from threshold-based participation (Granovetter, 1978) to civil violence dynamics (Epstein, 2002), but often oversimplify media influence, agent diversity, or crowd lifecycle phases. The RCM integrates these dimensions by incorporating a dynamic media intensity as a variable, heterogeneous agent groups with ideological and network diversity, and multi-stage crowd formation of assembly-contagion-decay. This comparison underscores RCM's novel capacity to simulate how intensified media interacts with sociopolitical contexts to drive or suppress collective action.

Table 1. Comparison of prior crowd models and RCM's advancements.

Model	Key Outputs/ Contribution	Limitations	How RCM Address these Gaps
Threshold Model (Granovetter, 1978)	Demonstrated threshold-based participation in collective action	No social networks Ignores emotional contagion Static thresholds	Acquaintance networks Media-modulated thresholds Emotional priming effects

Civil Violence Model (Epstein, 2002)	Simulated rebel-cop dynamics Showed tactical deception (agents hiding activity)	Binary agent types (rebels/cops) No media dynamics Oversimplified spatial interactions	7+ agent groups (activists, bystanders, etc.) Dynamic media intensity parameter Networked spatial interactions
Goh et al. Model (2006)	Grievance vs. greed motives Cop-population ratios	No information diffusion Binary violence outcomes Elite manipulation ignored	Information cascades Gradual radicalization Elite media strategies
Schelling-Style Segregation (Hatna & Benenson, 2012)	Neighbourhood segregation patterns	No collective action component Static agent preferences	Dynamic preference shifts via media Cross-group mobilization
London Riots Model (Davies et al., 2013)	Police-crowd spatial dynamics Repression strategies	Focused only on repression No media influence Limited to riot contexts	Media-driven mobilization Applies to protests / revolutions Incorporates legitimacy dynamics
Axelrod/Deffuant Culture Models (Pulick et al., 2016)	Opinion diffusion in networks	No link to physical crowds No behavioural outcomes	Opinion-to-action pipeline Media-induced behavioural triggers
Ibrahim & Hassan Model (2017)	Multi-group ideologies Basic media stimuli	Passive media role No crowd lifecycle phases Limited agent diversity	Active media manipulation Assembly-contagion-decay phases Enhanced agent typology

3. The Experimental Model

This section includes a brief presentation of the *Revolutionary Crowd Model* (*RCM*). The RCM model is a conceptual framework that is based on the work of (Ibrahim & Hassan, 2017) . It seeks to comprehend the *pattern* and *dynamics* of a crowd based on the micro-level interactions of individuals in a non-spatial society. The society has an implicit passive government. Individuals can be classified into three general categories: those who are in opposition to the government and thus *with* revolution, those who are in support of the government and thus *against* revolution, or those who are indecisive, i.e., neutral.

The model is based on a theoretical framework from social and psychological theories to avoid the main concerns about crowd models presented in previous research (Klandermans & van Stekelenburg, 2013; Locher, 2002). The model incorporates a hardship level for each agent to represent the social, economic, and political satisfaction toward the government. The theoretical basis for this is attributed to Ibn Khaldun (1967), who contributed social change to fanatical, moral, social, economic, political, and historical factors. A general Satisfaction Level (SL) is assumed to represent the overall contentment of the public, i.e., the relative deprivation or social injustice experienced in the whole society (Anderson, 1998). The SL is generally the average hardship of all the agents in the system. Three fuzzy sets of SLs are assumed: Bad, Moderate, and Good.

The model assumes that agents belong to one of seven distinct group ideologies. Each agent has a certain degree of *tolerance* or *preference* for the other six groups. The model assumes that the lower the tolerance, the higher the fanaticism in the society. Three factors determine the groups: (1) attitude towards the revolution (*with*, *against*, or *neutral*), (2) activity level of the agent in promoting its group (*active* or *inactive*), and (3) willingness to join the crowd (*participate* or *not-participate*) (see Table 2).

Table 2. Valid alternative groups of agents.

Group no.	Group name	With or aGainst revolution	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

The model is based on the convergence theory, which states that communication can change people's beliefs and values (Chen, 2012). The model then divides the society into interrelated sub-populations that are connected to each other and have their own structure, preferences, and beliefs. The agent's group and their *tolerance level* for the others in the society define their *preferences* for all the groups. The agent's *overall emotion* for the seven groups depends on their *preferences*, their *hardship* level, and the general SL. The model captures the human attitude toward uncertainty by using a level of *intolerance to risk* for each person. The risk intolerance depends on the agent's *risk aversion*, *general risk likelihood* of joining each group, and the current dominant crowd. The agent's *emotion* and *risk intolerance* for the seven groups are the *internal factors* that influence its behaviour.

Relevant research (Ahmed, 2011; Green-Pedersen & Stubager, 2010), suggests that people's beliefs are mainly influenced by two *external factors*: *acquaintances* and *media*. The model assumes that each agent has four logical acquaintances who represent their close circle of influence and can affect its decision. These acquaintances are not spatially bound but can be anywhere in the logical space. The model also considers two types of media: *With-revolution-Media* (*WM*) that supports the revolution and *aGainst-revolution-Media* (*GM*) that opposes it. Each type of media has a certain *intensity* that reflects its overall effectiveness. Each agent also has a different level of *sensitivity* to each type of media. The media intensity and the agent sensitivity determine the media influence on each agent. The influence of the acquaintances and the media form the *external factors* that affect the agent's decision about the group to join.

The RCM uses a utility function that combines an agent's personal preferences and external influences to determine group choice. It follows the social value model approach by McClintock (1972) in which values are defined as a simple linear combination of outcomes to self and the others (Liebrand & McClintock, 1988) . The final decision uses a Cobb-Douglas function:

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

Where, c represents conformity to external influences, h reflects intrinsic factors, and β weights their importance, $\beta \in [0,1]$. Agents calculate utilities for all groups and join the one maximizing their utility, with the process repeating each simulation step. Figure 1 provides an overview of the model, while Appendix A details its validation procedures and sensitivity analysis.

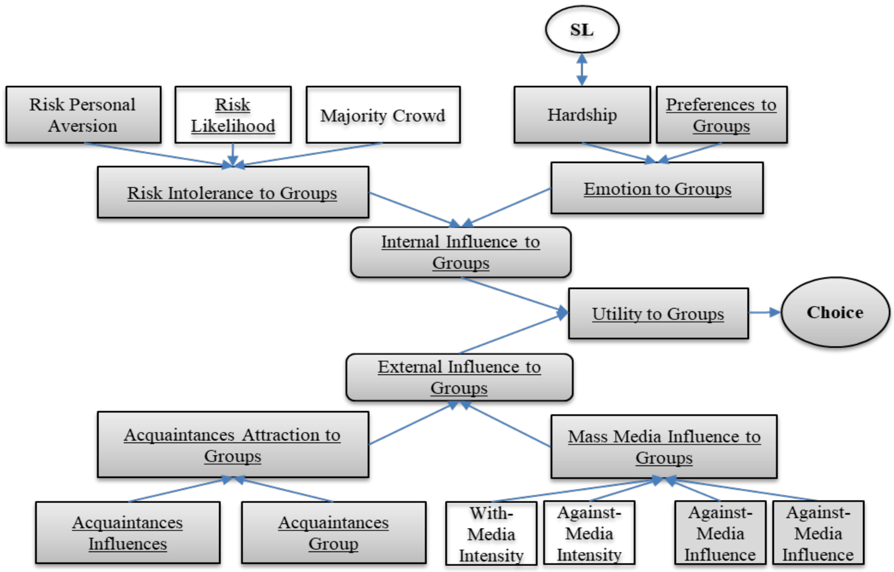

Figure 1 . Model structure.

Note. Shaded = agent parameters; unshaded = population parameters; underlined = vectors

As depicted, the model describes how internal and external factors shape revolutionary decisions. An agent internal factor is influenced by both personal emotions, determined by the satisfaction level, perceived hardship, and tolerance of others, as well as risk tolerance, influenced by individual risk aversion, group risk likelihood, and majority crowd behaviour. External factors include the competing influences and intensity of the with- and against-revolution media, as well as social networks of the acquaintances.

4. Experiments and Results

This research examines the prospective of an intensified media strategy over an uninterrupted period of time on the crowd pattern and dynamics. The experiments examine the assumption that an intensified *With-revolution-Media* (*WM*) over a particular period of time could lead to revolutionary crowd behaviour through gathering momentum that would not only lead to the crowd formation but would also keep it last even when the media intensity lessens. In other words, revolution that is supposed to be ignited due to a high media spending should be capable of maintaining itself when the media intensity diminishes or even completely vanishes. Whether contagion, de-individuation, or convergence mechanisms might work through the acquaintances to sustain the crowd gathered is then mechanically examined.

In this model, media intensity reflects the relative effectiveness of pro- and anti-revolution messaging, quantified as a budget allocated to each media type (*WM* and *GM*). While the term budget abstracts financial or logistical resources, the experiments focus on *strategic allocation over time* rather than platform-specific mechanisms (e.g., social media vs. traditional media). This simplification allows us to isolate the impact of temporal intensity variations on crowd dynamics, though we acknowledge that distinct media types may operate differently in practice.

The two experiments assume that the WM is intensified over a particular period of time in contrast to a uniform consistent intensity of the *aGainst-revolution-Media* (*GM*) for the whole simulation time. The experiments are run under the assumption of equal budgets; that is, the total sum of the budget, and hence intensity, of the WM and GM all over the simulation period are assumed equivalent. The first experiment, E1, assumes that the entire budget of the WM is uniformly spent over the first half of the simulation. This implies double intensity of the WM at that period of time but no intensity at all at the rest of the simulation. Considering a 100-step simulation, this case is represented as ((50 steps, double intensity), (50 steps, zero intensity)) or in short ((50,2), (50,0)). The second experiment, E2, in contrast, investigates a uniform spending of 75% of the WM budget at the first 50-cycles, and the remaining 25% of the budget is spent at the rest of the simulation. This is represented as ((50,1.5), (50,0.5)).

The experiments are run under three Satisfaction Levels (SLs): *good*, *moderate*, and *bad*. Each experiment is run *7* times and the average result is finally recorded. Each run goes for 100 iterations and includes 2000 agents. The society is divided as 50% neutral agents; 10% in each of WIN, WIP, GIN, and GIP groups; and 5% in each of WAP and GAP groups. Each agent has four acquaintances that are randomly selected.

The results are contrasted with a neutral scenario in which consistent with- and against-media broadcast is applied. Under this scenario, the SL is the main factor influencing the results. Under a good SL, the GGs monotonically increase in numbers reaching up to double their initial numbers mainly at the expense of the neutral group and marginally at the expense of the WGs. Similarly, under a bad SL, the WGs almost doubled in size at the expense of the neutral agents mainly and the GGs marginally. At a moderate SL, the neutral group increases by almost 50% at the expense of the WGs and GGs.

Two metrics are used to address the changes in the structure of the seven groups over time. First, the *Standardised Euclidian Distance* (*SED*) addresses the immediate changes in the structure of group *g* at time *t*, calculated as follows:

$$SED(g,t) = \frac{\sqrt{in_t^2 + out_t^2}}{num_{t-1}} \qquad where\ t > 1$$

Where *in* and *out* are the numbers of the agents joined and left group *g* at time *t*, respectively. The divisor *num* is the number of the agents in the group *g* at time *t*-1, applied for standardisation purpose. Typically, *SED*(*g*,*1*)=*0*. Second, *Initial Stability* (*IS*) metric is used to measure the current stability of the group with respect to its initial state. That is, it measures the percentage of the native agents, i.e., existed in the group at the beginning of the simulation, that still currently exist in the group. Normally, *IS* of a group *g* at the beginning of a run is 100%: *IS*(*g*,*1*)=*100*, as all native agents still exist in the group at step 1.

4.1 E1: Double Intensified Media

Figure 2, Figure 3, and Figure 4 respectively show the dynamics of the seven groups at the good, moderate, and bad SL. The uninterrupted intensified *With-Media* (*WM*) at the first half of the simulation implies an expected general upward trend in the number of agents in the three *With-Groups* (*WGs*). It is worth mentioning that under good and moderate SLs, supporters acquired to the WGs are mainly from the neutral group. This is typically due to the consistent *aGainst-Media* (*GM*) and the good/moderate SLs that support the *aGainst-Groups* (*GGs*) to sustain their numbers. Nevertheless, the rising trend is reversed once the WM runs out of budget and inevitably stops at step 51. The number of agents in the three GGs then normally increases at all SLs. The continuation of the GM enables the GGs to gain supporters from the WGs even under bad and moderate SLs.

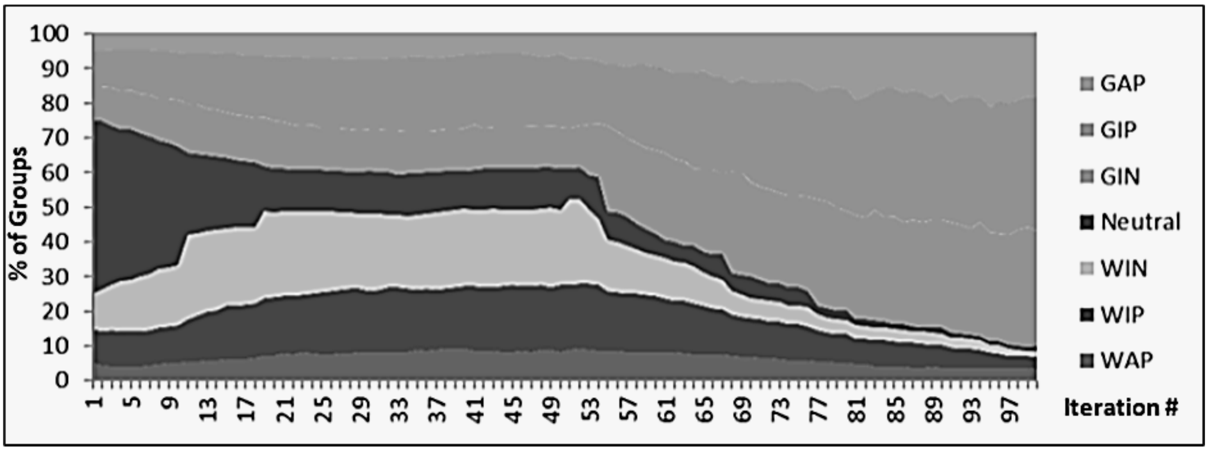

Figure 2. Groups dynamics under Intensified with-Media ((50,2),(50,0)) and Good SL.

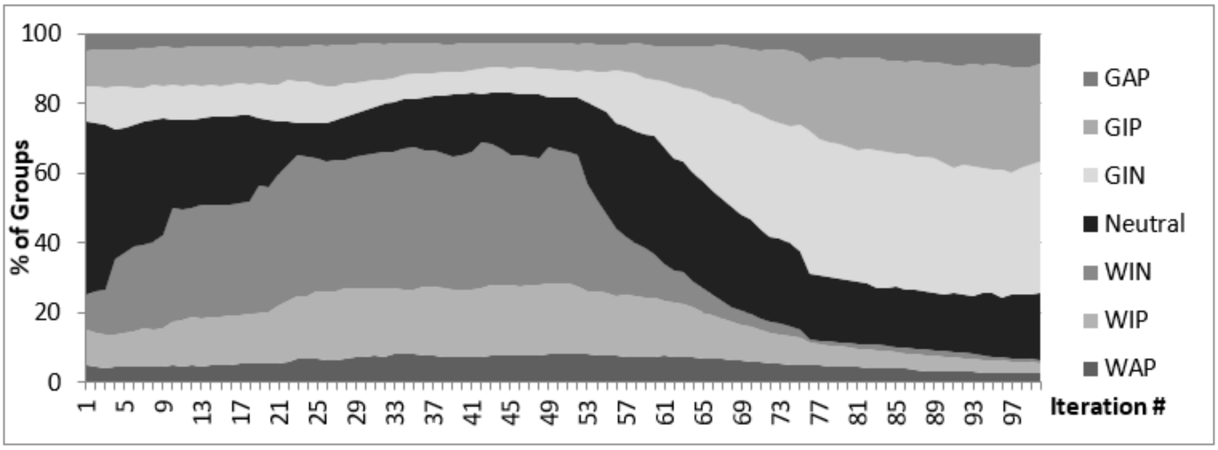

Figure 3. Groups dynamics under Intensified With-Media ((50,2),(50,0)) and Moderate SL.

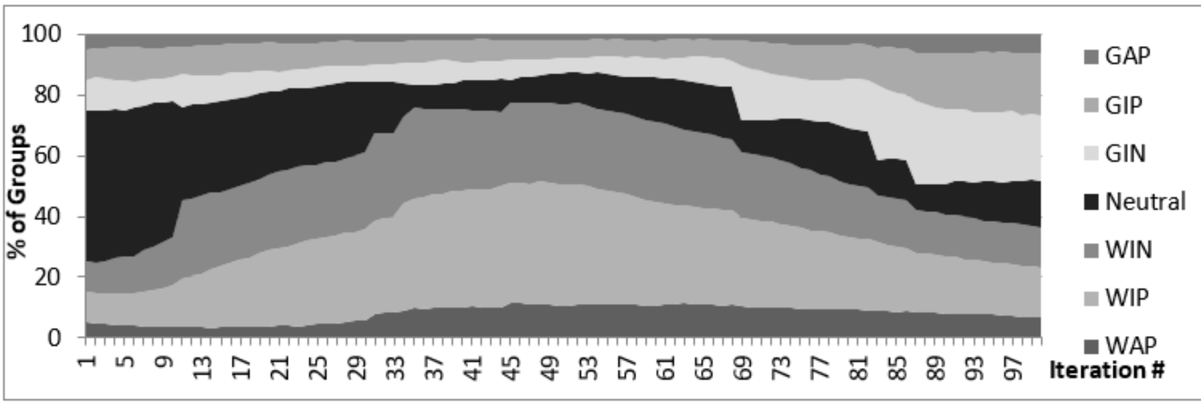

Figure 4. Groups dynamics under Intensified With-Media ((50,2),(50,0)) and Bad SL.

In addition to the intuitive results, a number of emergent behaviours are revealed. First, the rising trend of the WGs could not be sustained as expected through contagion and acquaintances during the second half of the simulation. The upward trend is unexpectedly reversed in a short period of time after the complete halt of the WM. Moreover, at the first 50 cycles, the number of agents in the three GGs does not decline much as intuition might suggest. On the contrary, at the good SL, the total number of agents in the GGs remarkably increases. Under moderate and bad SLs, the GGs hardly decrease in numbers. The double intensity of the WM could not achieve a one-directional attraction of followers from the GGs to the WGs. In other words, with only half media intensity and under unfavourable moderate and bad SLs, the GGs could manage to retain almost the same number of agents during the first half of the simulation. The *Standardised Euclidian Distance* (*SED*) metric, that addresses the changes in the structure of the groups, shows significant dynamics of the GGs similar to that of the WGs (see, for example, Figure 5 depicting the SED under the moderate SL). This indeed refutes the idea that the GGs retention is due to any model steadiness. Obviously, agents move freely back and forth the GGs, however, with almost an equivalent in- and out-flow. At the micro level, the model thus exhibits a lot of dynamism among the agents, in contrast to the macro level that shows more stability among the groups.

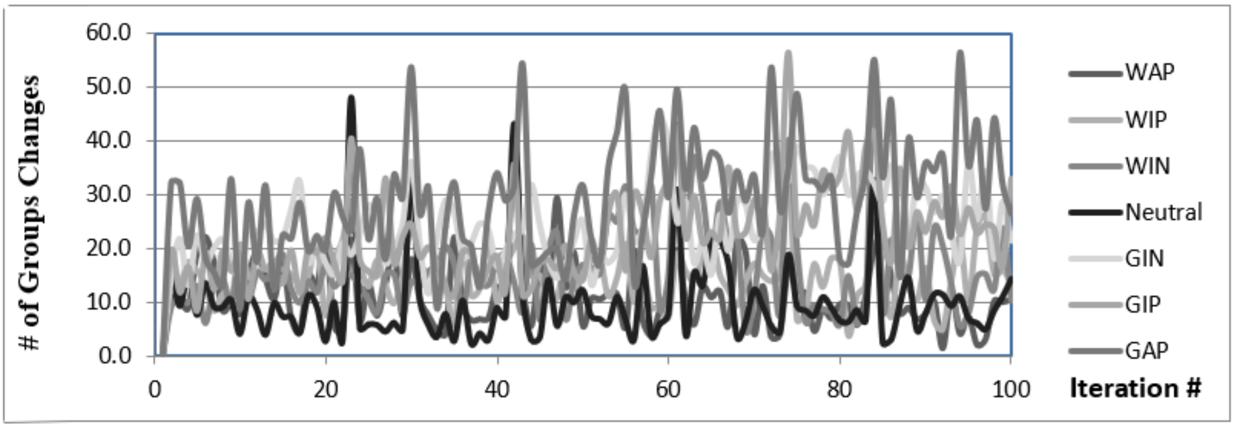

Figure 5. Standardised Euclidian Distance-Groups changes magnitude under Intensified With-Media.

((50,2),(50,0)) and Moderate SL.

The results show a more interesting behaviour for the most radical active, participating groups: WAP and GAP. Neither of these two extreme groups declines or disappears for good under any satisfaction level. In the first half of the simulation, the GAP group could maintain itself under the double WM intensity, even under a bad SL. More interestingly, in the second half of the simulation and without WM broadcast, the WAP group could manage to sustain almost the same number of agents even under a good SL. In addition, the less radical groups, GIP and WIP, have also their emergent behaviour. Under a good SL and during the first half of the simulation, the agents' number in the GIP group slightly increases, especially between steps 26 and 33. Similarly, under a bad SL and during the second half of the simulation, the number of the agents in the WIP group slightly increases between steps 61 and 65.

Neutral agents prove to play a key role in determining the crowd pattern and dynamics at the three SLs. The results show that a large percentage of the agents joining the WGs or GGs come from the neutral group. At the good SL, the number of the neutral agents monotonically decreases first in favour of the WGs and then in favour of the GGs, declining from 50% to only 2% of the population. At the moderate and bad SLs, neutral group, though oscillating during the simulation, tend to shrink and end up with almost 19% and 15% of the population, respectively.

Regarding the magnitude of the preference-switching, the results indicate that agents do not usually change their group preference in a systematic, gradual manner. For example, under a good SL, some of the with-agents just jump to any of the GGs without passing through the neutral state. Starting from cycle 51, without any influence from the WM, the good level of satisfaction along with the broadcast of the GM, implies continuous attraction of followers to the GGs from the with- and neutral-agents, simultaneously.

With respect to majority, results reveal another unpredictable behaviour. Under a good SL, the double intensity of the WM at the first half of the simulation leads to only two cycles of 52% with-majority: at steps 51 and 52. Out of the 52% with-majority, only 53% of the agents are participant agents (see Figure 6). During the same period, in contrast, the GGs comprise 39% of the whole population, however, with 70% participant agents. By any means, the two-step of a with-majority, with 47% out of them are not ready to participate in any revolutionary activities, could not be considered a formation of a with-crowd. Starting from step 55, the majority inverts in favour of the GGs. The GGs continue to have the majority up to the end of the simulation with 90% of the population become against-supporters, 70% out of which are participant agents. By all means, this is a landmark, unintended victory for the against-supporters.

In contrast, at the bad SL (Figure 8), a with-majority is achieved between steps 18 and 81, with the highest hit at step 52 with 78% supporters and 67% out of which are participants. Taking into consideration that the against-majority is not achieved at any stage under the bad SL, this result implies a high probability of a with-revolution.

Under the moderate, impartial SL (Figure 7), a with-majority is achieved between steps 15 and 54, with 69% supporters, half of which are participants. Starting from step 69, the situation gradually changes in favour of the GGs, ending up with a 75% against-majority, almost half of which are participants. A with-revolution subsequently followed by a counterrevolution is an intuitive description of this situation.

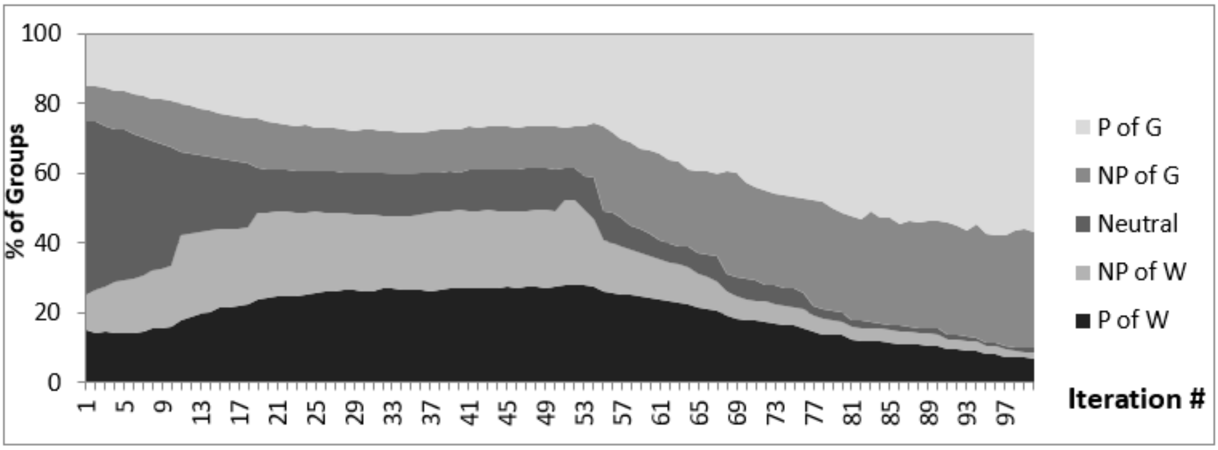

Figure 6. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50,2),(50,0)) and Good SL.

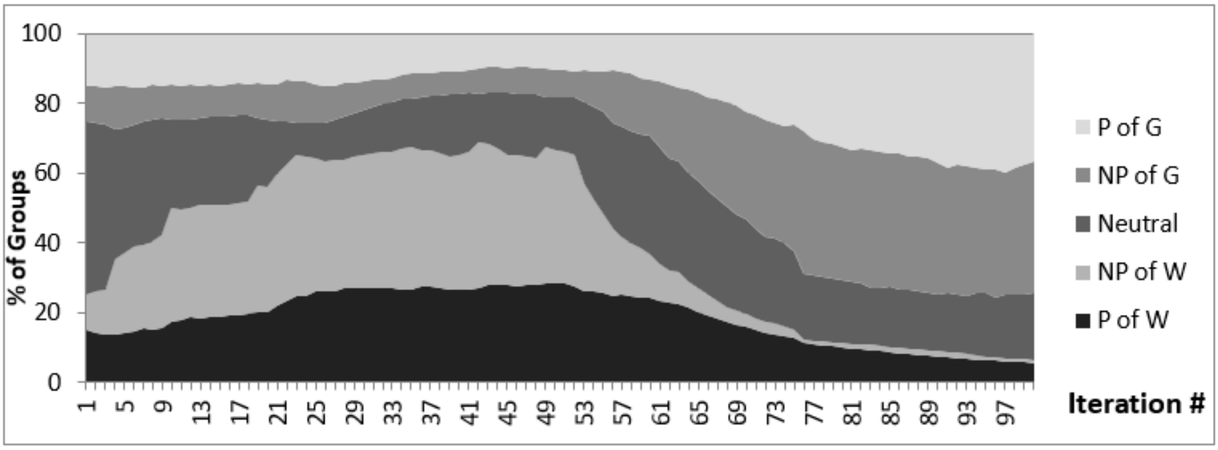

Figure 7. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50,2),(50,0)) and Moderate SL.

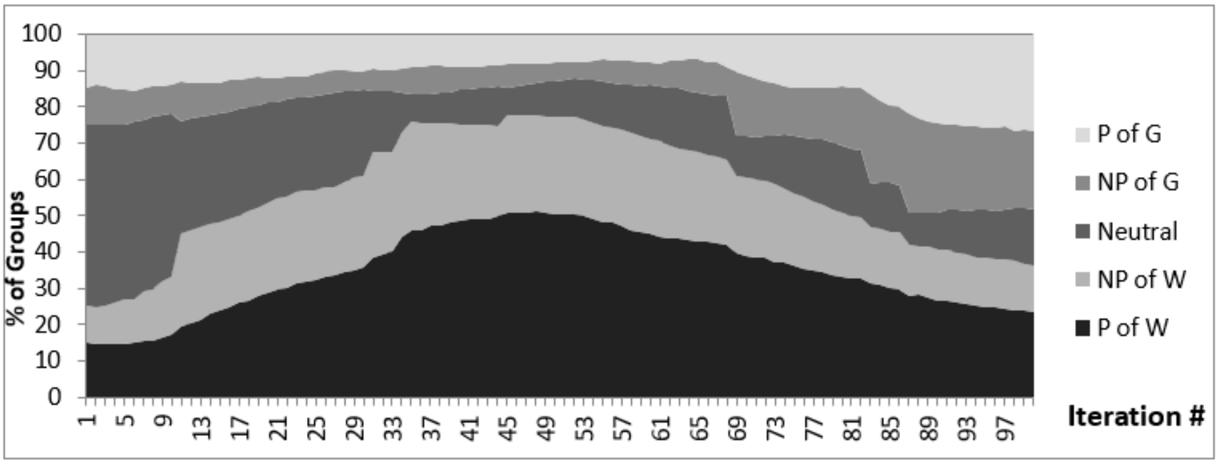

Figure 8. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50,2),(50,0)) and Bad SL.

Finally, with respect to the changes in the initial state of the groups, the *Initial Stability* (*IS*) metric, that shows the percentage of the native agents that remains in each group, reveals symmetric behaviour at the three SLs. At a good SL (Figure 9), GIP group comes first in keeping most of its native agents during the whole simulation, while at a bad SL (Figure 11) the corresponding WIP group is the highest in reserving its natives. At the moderate SL (Figure 10), symmetrically, the WIN group keeps most of its native agents at the first half of the simulation, while the GIN group gets back its original agents at the second half of the simulation. It has to be stressed that there is no whatsoever mechanism or rule in the model that guides or directs the agents for such a behaviour.

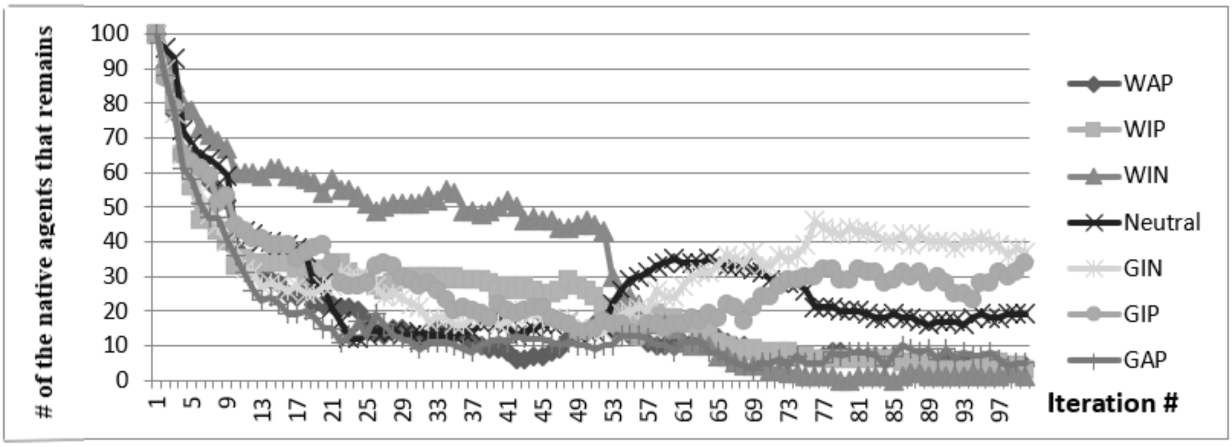

Figure 9. Progress in percentages of native agents in each group under Intensified With-Media Intensity ((50,2),(50,0)) and Good SL.

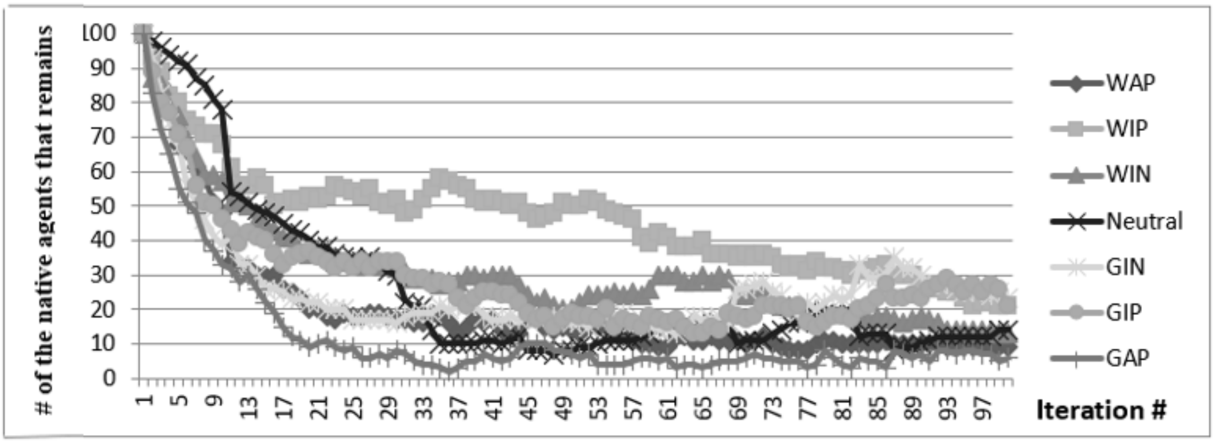

Figure 10. Progress in percentages of native agents in each group under Intensified With-Media Intensity ((50,2),(50,0)) and Moderate SL.

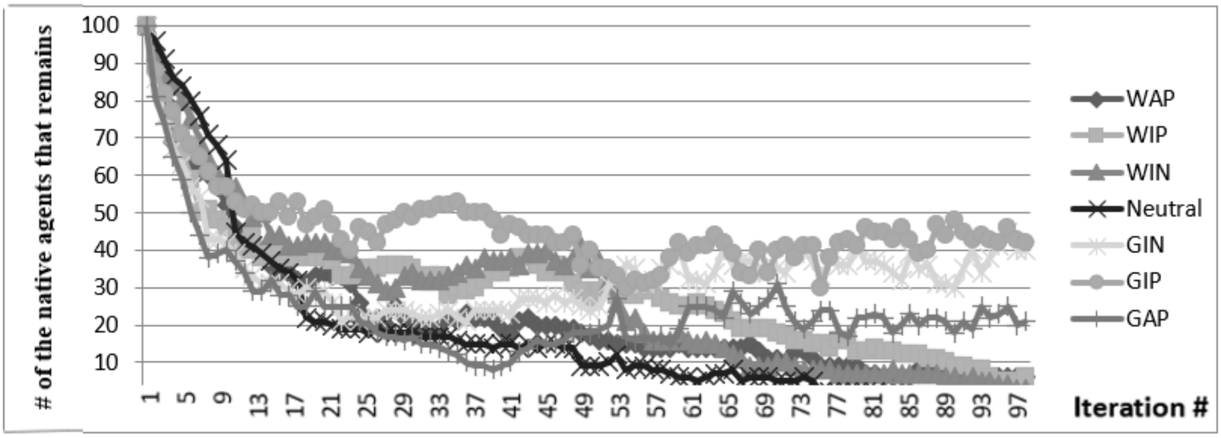

Figure 11. Progress in percentages of native agents in each group under Intensified With-Media Intensity ((50,2),(50,0)) and Bad SL.

4.2 E2: Semi Intensified Media

The unexpected failure of the previous budget management strategy in maintaining the with-crowd is apparently due to the total absence of the WM at the second half of the simulation. This experiment, E2, thus examines another strategy that preserves 25% of the budget for the second half of the simulation in an attempt to sustain the crowd after the first 50 cycles of 1.5 intensified media.With respect to the dynamics of the groups, Figure 12 to Figure 14 depict the results at the good, moderate, and bad SLs, respectively. Similar to the previous experiment E1, the 1.5 intensified media enables the WGs to acquire supporters at first, then, with the intensity declines to 0.5 at the second half of the simulation, the GGs restore the situation. However, in contrast to E1, the general trend under the three SLs shows that the WGs normally acquire lower number of supporters at the first half of the simulation and higher number at the second half than in E1. On the contrary, GGs maintain higher supports first and get lower number of agents at the end than in E1. This is intuitively happening because of the (75%, 25%) strategy in comparison to the (100%,0%) strategy applied in the previous scenario.

Similar to E1, at the good and moderate SLs, the supporters acquired are mainly from the neutral group typically because of the consistent GM that support the GGs to sustain their numbers and even allow them to attract new members. In contrast to E1, in the second half of the simulation, the GM could not enable the GGs to gain many supporters under the bad or moderate SL, due to the low but consistent WM that enables the WGs to sustain their numbers.

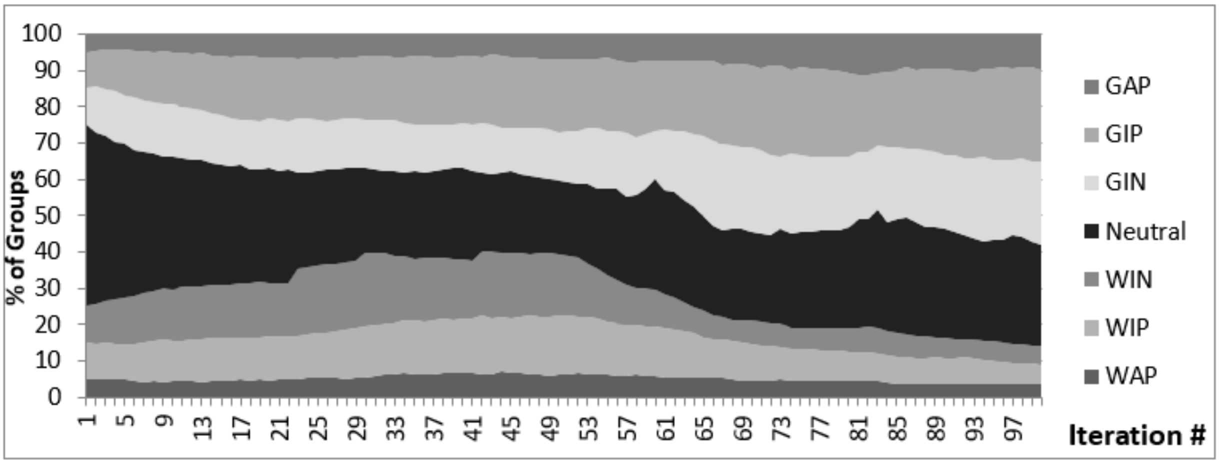

Figure 12. Groups dynamics under Intensified With-Media Intensity ((50,1.5),(50,0.5)) and Good SL.

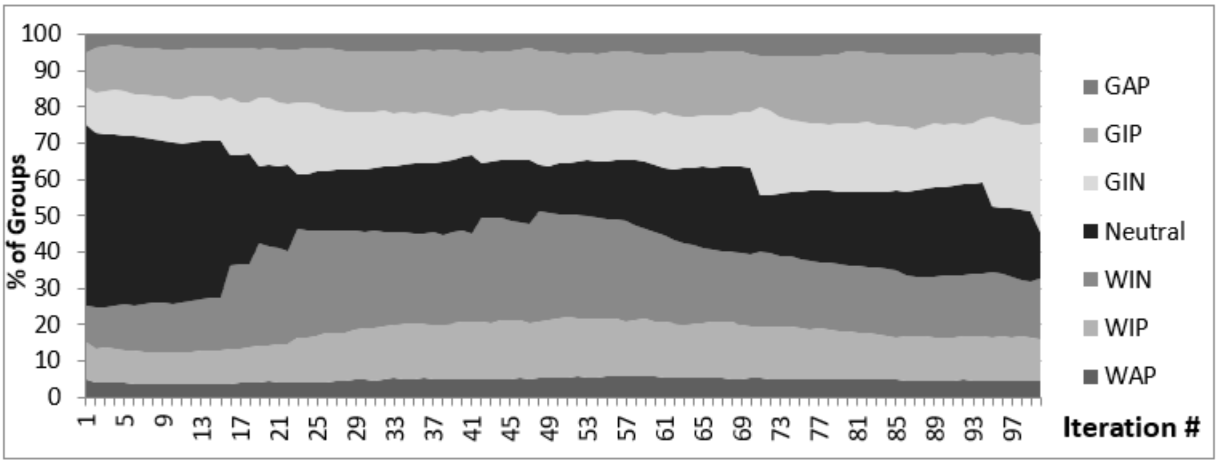

Figure 13. Groups dynamics under Intensified With-Media Intensity ((50,1.5),(50,0.5)) and Moderate SL.

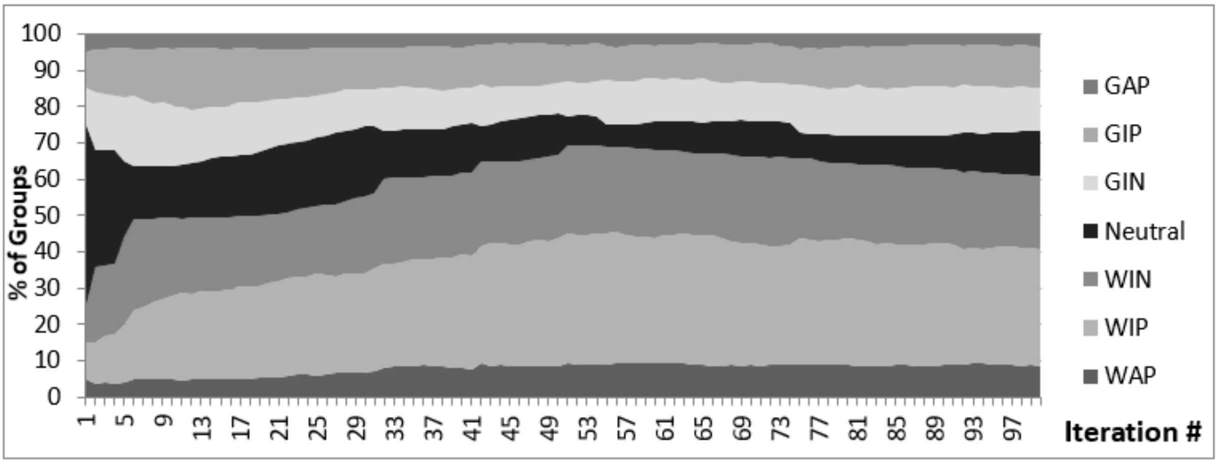

Figure 14. Groups dynamics under Intensified With-Media Intensity ((50,1.5),(50,0.5)) and Bad SL.

Apart from the intuitive results, some more promising outcomes from the perspective of the revolution supporters are revealed. With respect to the majority, under the good SL, during the first half of the simulation, the 1.5-WM intensity cannot lead to any with-majority (Figure 15). Starting from step 65, an against-majority arises and lasts up to the end of the simulation, however, with only 58% supporters, 60% out of which are participants. In contrast to E1, in which (90% supporters, 70% participants) is achieved, the results of this case are much promising for the regime-opponents. This relatively-low against-majority would open at least a window for negotiation which might yield a better payoff for the with-supporters than the two cycles of majority achieved in E1 which is followed by a dominant against-majority.

At the moderate SL (Figure 16), a with-majority is attained between steps 47 and 53, with 51% supporters, and 43% out of which are participants. The time span of the with-majority and the percentage of the with-supporters are lower than in experiment E1 where an outcome of 69% supporters with 50% participants is attained between steps 15 and 54. In experiment E2, however, the 25% reserved budget maintained the crowd momentum and prevent any counter-revolution as in E1. This could be also considered a better situation for revolutionary crowd that might enable reaching a compromise than in E1 in which a tough counter-revolution of 75% supporters might revert back any possible gains from the with-revolution.

At the bad SL (Figure 17), a with-majority is achieved from step 18, similar to E1, but lasts up to the end of the simulation. In contrast to (78% supporters, 67% participant) situation in E1, the with-majority is attained at step 52, comprising (70% supporters, 65% participants). As the with-majority lasts in this case up till the end, the (75%, 25%) budget strategy could manage to achieve the sustainability missing in the previous strategy, though with a bit lower number of followers, which might not count much in this case.

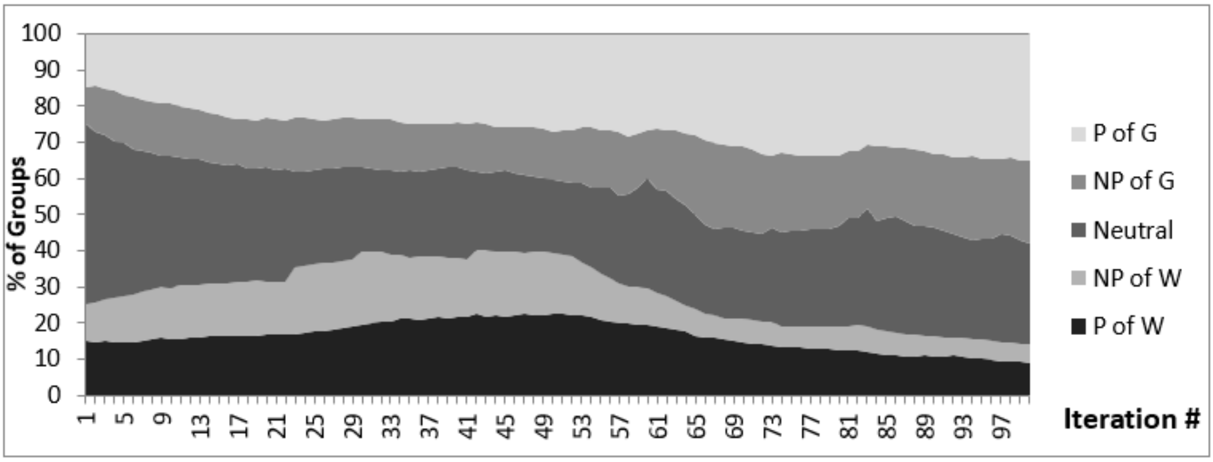

Figure 15. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50,1.5),(50,0.5)) and Good SL.

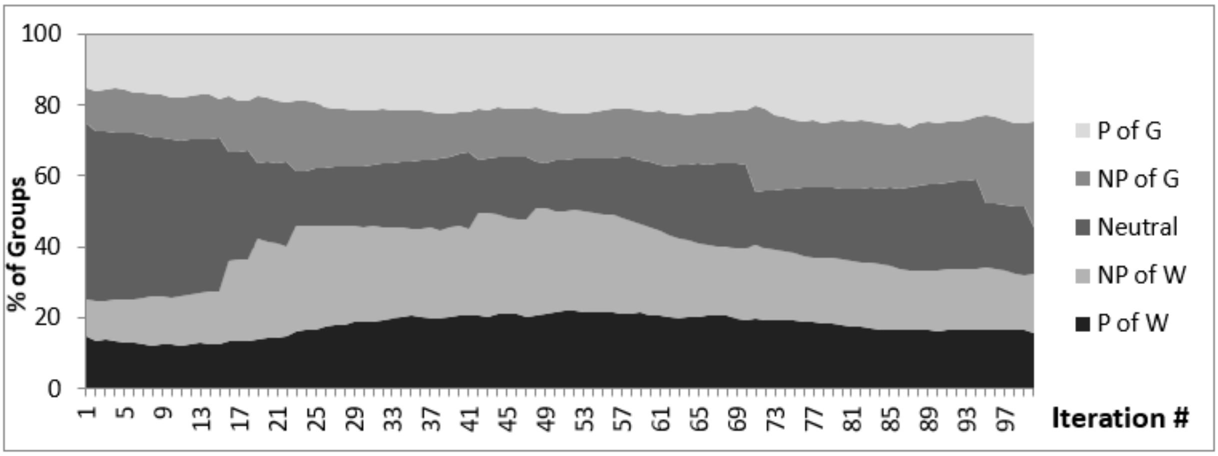

Figure 16. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50,1.5),(50,0.5)) and Moderate SL.

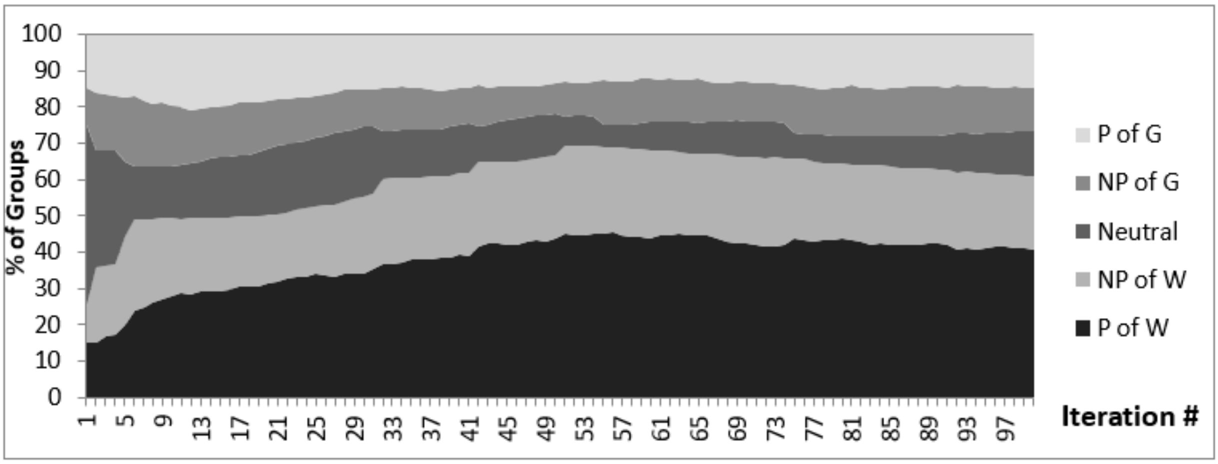

Figure 17. Progress in participants, non-participants, and neutral agents under Intensified With-Media ((50, 1.5),(50,0.5)) and Bad SL.

Finally, regarding the changes from the initial state, the following three figures depict the results. At a good SL (Figure 18), in contrast to E1 in which GIP kept about 40% to 50% of its native agents, all the groups in this experiment struggle to keep more than 30% of their natives. This is due to the tougher conditions occurred at the first half of the simulation of E2, which heavily shuffle the population. In particular, the double WM intensity in E1 balances the good satisfaction level at the first 50 cycles more than the 1.5 intensity does in E2. At a moderate SL (Figure 19), all the groups, except the radical WAP and GAP groups, behave proximally with respect to keeping their natives. This is again because of the relative consistency, throughout the whole simulation, that is achieved by the (75%, 25%) WM intensity strategy. At a bad SL (Figure 20), similar to E1, the WIP group is still the highest in reserving its natives. However, the changes in the second half of E2 are a bit higher than in E1 as the 0.5 media intensity unbalanced the situation more than the zero spending which is balanced by the bad SL.

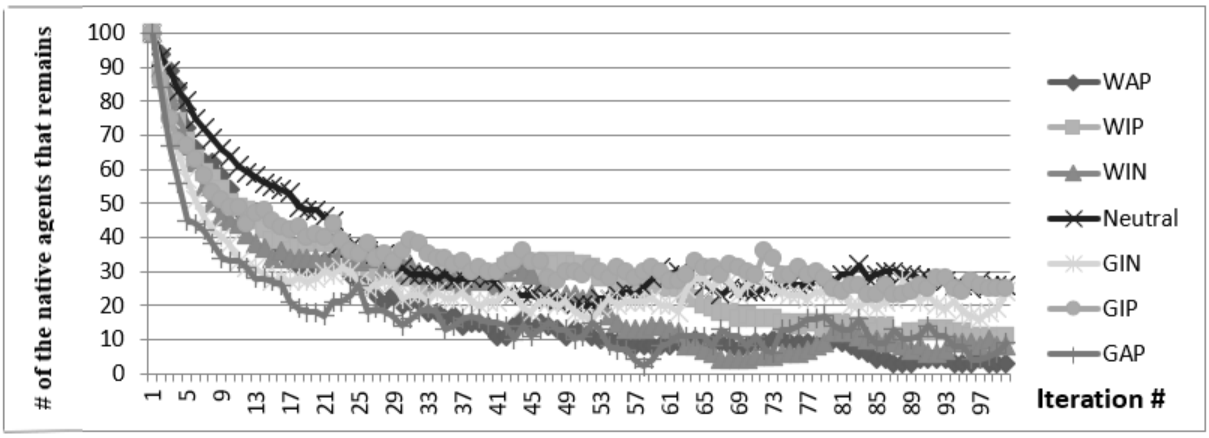

Figure 18. Progress in Percentages of native agents in each group under Intensified With-Media ((50,1.5),(50,0.5)) and Good SL.

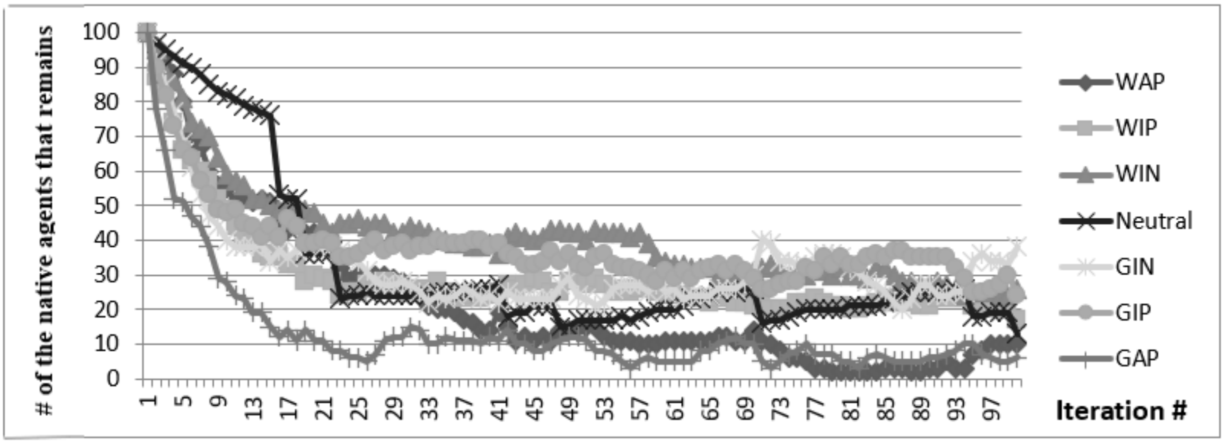

Figure 19. Progress in percentages of native agents in each group under Intensified With-Media ((50,1.5),(50,0.5)) and Moderate SL.

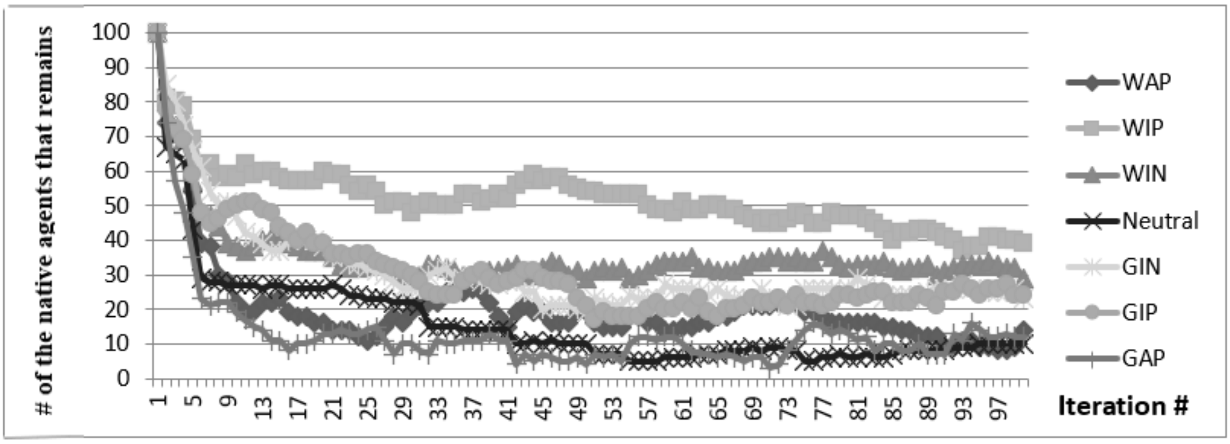

Figure 20. Progress in percentages of native agents in each group under Intensified With-Media ((50,1.5),(50,0.5)) and Bad SL.

Despite the results of this media management strategy are more promising from the perspective of the with-supporters than the previous case E1, this strategy is still incapable of gathering a revolutionary crowd under the good SL or guarantee its effectiveness under the moderate SL. The results of the two experiments refute the current belief of the inevitable influence of the intensified media as concluded in the following section.

5. Discussion

The results revealed unique and sometimes counterintuitive dynamics in the way media intensity influences crowd formation under different satisfaction levels (SLs). As expected, the intensified With-Media (WM) in the first experiment (E1), in which all the budget is allocated to the first half of simulation, produced a clear upward trend in the numbers of With-Groups (WGs) during the first half, particularly under good and moderate SLs. However, this strategy left WGs vulnerable to Against-Media (GM) after cycle 50. For example, under good SL, E1 achieved a brief with-majority (two cycles at 52% support only 53% of them ready to participate) before a decisive against-majority: 90% supporters with 70% participants.

The second experiment (E2) investigated a revised media strategy which allocated 75% of the budget to the first half while reserved the remaining 25% for the second half to sustain the with-crowd formation. Under good, moderate, and bad SLs, this strategy caused an increase in the WGs, followed by a recovery of the GGs as the WM intensity decreased. However, compared to E1, E2 yielded lower gains during cycles 1 to 50 and higher retention in cycles 51 to 100 for the WGs, while GGs displayed an inverse trend.

Majority-formation patterns further demonstrated the delicate balance media strategies must strike in the light of the level of satisfaction. For example, under good SL, the intensive WM in E1 achieved only a short two-cycle majority with low participation commitment, whereas under bad SL, the same campaign secured a stable majority with high participation, indicating the importance of the satisfaction levels on shaping the crowd formation and durability. Moderate SL resulted in a mixed pattern of a temporary with-majority gives way to a sustained against-majority, indicating a counter-revolution scenario. Table 3 summarises the results of the two experiments under the three satisfaction levels.

Table 3. Summary of With- and Against-Revolution Majorities in the two experiments under three satisfaction levels.

SL	**Good**		**Moderate**		**Bad**	
Experiment	With-Majority	Against-Majority	With-Majority	Against-Majority	With-Majority	Against-Majority
E1	[51-52] (52%-53%)	[55-End] (90%-70%)	[15-54] (69%, 50%)	[69-End] (75%-50%)	[18-81] (78%, 67%)	No
E2	No	[65-End] (58%, 60%)	[47-53] (51%, 43%)	No	[18-End] (70%-65%)	No

Note. Square brackets [ ] indicate the majority interval; parentheses ( ) denote the percentage of majority and participant share.

Counter to the contagion theory and the assumption of social influence, these results showed that the interpersonal ties could not sustain the WGs numbers after the drop or disappearance of the WM broadcast. In other words, without ongoing external reinforcement, contagion alone proves insufficient to maintain the gains of the initial intensive media. The GGs have been shown to recover and expand once the WM ceased, suggesting that continuous, uniform lower-intensity GM broadcast were better in sustaining the GGs numbers even without clear dominance or majority. This result confirmed the effectiveness of steady media on maintaining group cohesion even when faced with an aggressive counter-media.

Analysis of native-agent retention showed that E2 balanced media produced more uniform retention of the native agents of each group, whereas E1 abrupt cutoff leads to divergent retention patterns and more noticeable shuffle in some groups. The results show that neutral agents were the key reservoir for both WG and GG expansions. Their steady reduction, e.g., from 50% down to as low as 2% under good SL in E1, revealed the critical influence of the neutral individuals on the crowd dynamics. Additionally, results showed that preference-switching is not always gradual as many agents jumped directly from one extreme group to another, suggesting that strong media can produces unexpected shifts.

The Standardised Euclidean Distance (SED) analysis showed a genuine micro-level dynamism with a surprisingly macro-level stability. Under moderate SL in E1, for instance, both WGs and GGs showed considerable internal changes, indicating high agent mobility between the subgroups. However, at the macro level, the GGs preserved their numbers through balanced inflows and outflows.

Radical, active participants (WAP and GAP) exhibit unintuitive robustness under all SL conditions. Neither subgroup ever fully disappears. While GAP individuals sustain themselves in the early intensive WM even under bad SL, the WAP group retains themselves under no WM and persistence GM in the second half of simulation. Less radical participants (GIP and WIP) also displayed emergent increases in their numbers at unexpected intervals, such as GIP under double WM intensity and WIP under no WM broadcast.

6. Conclusion and Further Research

This study showed that media intensity strategies must consider not only the intensity but also satisfaction level, timing, and opponent strategy. The two intensified media management strategies presented have been proven insufficient for initiating or maintaining substantial crowd formation unless under general dissatisfaction. A short high-intensity media can produce rapid gains, but these gains are fragile without sustained support and are vulnerable to rebound effects driven by a persistent counter-media. The results have even shown the effectiveness of low uninterrupted consistent media intensity, at least in the long run, over higher discontinuous intensified media. Under a double intensity of revolution-supporting With-Media (WM) and unfavourable bad SL, the aGainst revolution Groups (GGs), with only half but consistent aGainst-Media (GM) intensity, could manage to sustain their agents. Moreover, the GGs have been able to manage acquiring more agents after the WM has ultimately stopped. The results have unintentionally confirmed a common business rule that “customers” require a relatively long time of satisfaction to hardly get loyal, nevertheless, they can be much easily lost once they are dissatisfied (Kumar & Reinartz, 2012). The recent Arab protests might have proven this result as well. Through relatively low budget but consistent social media, with the aid of high level of dissatisfaction with the regimes, revolutions could have been ignited.

Intensified media has also proven to require more than the contagion theory or the epidemic principle, which have not worked in both experiments as expected, to maintain the crowd that might be gathered in response to it. Although the contagion has been occasionally noticed in experiments, e.g., the slight increase in the number of agents in the revolutionary inactive participants (WIP) group during the stoppage period of the WM, the general trend has shown different behaviour. That is, the large number of supportive acquaintances could not be able to maintain the spread of their ideas/signal or even sustain their numbers after their corresponding media is lessened or stopped. This result equally refutes the current claims of the insignificant role of leaders in igniting and maintaining modern crowds. Perhaps leaders are currently not as used to be, i.e., unique, charismatic, and identifiable; but they are unquestionably there in different contemporary shape. The cut-off of all communication networks, including mobile phones and Internet, during the 2011 Egyptian protests was perhaps a government spontaneous but cunning reaction that aimed to “assassinate” the invisible leader, resting assured that the revolutionary epidemic would then passively fade away.

Some other unintended emergent behaviours have been revealed as agents have shown an exceptional rare switching behaviour to their preferences for the groups to join. According to the results, a small portion of agents have been freely moving among the seven groups, shifting, for example, from the WGs to the GGs and vice versa without passing through the neutral state. Despite this behaviour might look artificial, it surprisingly complies with some documented global observations. For example, between Feb 2011 and June 2013, Egyptians have witnessed similar extraordinary behaviour. Groups of well-known figures of president Mubarak’s regime have publicly moved to the protesters side. Some of Mubarak’s National Party cadres have supported and cooperated with the Muslim Brotherhood government, then later after June 2013 protests, they have exculpated themselves from that “charge”. These are such examples of movements between the most radical GAP and WAP groups without passing through any medium status.

The results revealed that small activist groups could sustain themselves under highly unfavourable conditions. This result is supported, for example, by the sustainability of the socialist left parties in a number of Arab countries despite the enormous reduction in the numbers of their supporters and the unfavourable political conditions that usually classify them as “anti-religiosity” parities inside the Arab highly religious communities. Despite their limited numbers, this type of activist groups seems utilizable for shaking societies and initiating crowds when the right conditions are met. Future work could extend this model by investigating other variables such as risk intolerance, other social structures, and different media channels and strategies. Such extensions would further elucidate the complex interplay between media strategies and crowd behaviour dynamics.

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Appendix A: Model Validation and Sensitivity Analysis

While validation is crucial for any simulation model, no universal tests are agreed upon to ensure data and model accuracy (Sargent, 2011). The challenge increases with complex models like Agent-Based Models (ABMs) (Ibrahim, 2010). For example, due to the large parameter spaces and reliance on stochastic elements to simulate some types of behaviour, ABMs' validation is a daunting task, which is identified by Axtell (2000) as an ABMs' key disadvantage. Sargent (2011) highlights that unreliable data often further undermines validation efforts.

Regarding the model, while verification is responsible for checking whether the model is a correct implementation of the conceptual description of the target, validation is concerned with checking the degree of consistency between the model behaviour and the target. Social models often incorporate complex cognition, interactions, and nondeterministic elements, thus requiring extensive simulation runs for evaluation. Identifying whether errors caused by faulty models or inaccurate parameters is another challenge. Additionally, long simulation runs could be prone to numerical instability, which can amplify over time (Axtell, 2000). According to Broeke et al. (2016), existing methodologies of sensitivity analysis, which assess how input variations impact model outcomes, may not be adequate to capture the complexities of ABMs. In that respect, Gilbert & Doran (1994) consider a model valid if it shows rare spurious behaviours, while Zeigler (1976) views it valid only relative to the criterion of the modeler's satisfaction. Gilbert & Troitzsch (2005) emphasize that social simulation should be validated in the context of *understanding* human behaviour rather than *predicting* it.

Despite these complications, the RCM of this study has undergone several rigorous validation steps in the light of the purpose of the study: to *understand* the crowd pattern and dynamics. A set of preliminary experiments including sensitivity analysis, is applied to assess the impact of the changes in the main assumptions, variables, and parameters on the model behaviour and results. A paired t-test at 95% confidence is used to assess the significance of all the implemented changes. For example, Table A.1 shows the effect of number of agents (r) on the results, confirming 2000 agents for all experiments in this study.

Table A.1. The paired t-test of the significance of the differences due to changes in the number of agents r.

Number of Agents (r)	Means Equality t-test P(T≤t)	Decision
100 vs. 50000	0.03006	Rejection of equality
500 vs. 50000	0.04434	Rejection of equality
1000 vs. 50000	0.13372	Acceptance of equality
5000 vs. 50000	0.29312	Acceptance of equality
10000 vs. 50000	0.65411	Acceptance of equality

Similarly, the t-test outcomes indicated stability in the average results in various scenarios after 5 runs, hence, 7 runs were decided for the experiments. The sensitivity tests also showed that 100 iterations, which with one-week time-granularity almost count up to a year, is sufficient for studying the crowd formation and dynamics. The tests also showed few acquaintances are adequate to interconnect isolated subpopulations, however, some transformations in the acquaintances number and structure or population structure might lead to variation in the model behaviour. Therefore, based on relevant studies (Ahmed, 2011; Pulick et al., 2016; Suo & Chen, 2008), four acquaintances with a specific random influence have been decided. The population structure: 50% neutral; 10% inactive (WIN, WIP, GIN, and GIP groups); and 5% active (WAP and GAP) is estimated based on the reported election participation in different countries including presidential election of USA 2008 and 2012, and Egypt 2012 and 2014. To investigate the influence of the satisfaction levels, each experiment is run under *Good*, *Moderate*, and *Bad* SL. Agents' hardship and preferences are naturally aligned with their group affiliation. For instance, actively participating agents in crowd are intuitively assigned a high random hardship value (0.55 to 1) with stronger preference for pro-revolution groups and weaker preference for opposing ones.

To place greater emphasis on media influence, the risk intolerance is neutralised to moderate level while the internal and external factors are balanced by setting the model's elasticity level to 0.5. This approach of managing variables is commonly accepted in large-scale models (Doran, 2001). Future work could explore the roles of these variables.

Furthermore, the *extreme condition test*, the *model behaviour degeneracy*, and the *traces* are implemented to test the model validity. For example, the results under *extreme conditions* of bad/good SL with double intensity of with/against-revolution media were logical and intuitive. The *degeneracy of the behaviour* and the *traces* tracking all the agents' variables throughout the simulations are examined with the aid of *operational graphics* and *animation* of the NetLogo agent-based modelling environment. The results ensured logical accurate and valid behaviour of agents. For example, Figure A.1 and Figure A.2 show the tracing of the preferences and the choices of a specific agent during the whole simulation run.

Fig A.1. Preferences of an agent throughout simulation.

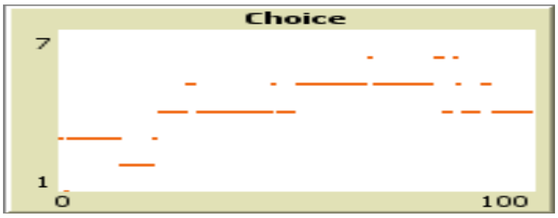

Fig A.2. Choices of an agent throughout simulation.

In addition, *face/independent validation* with experts is performed in two stages to evaluate the all the aspects of the model and behaviour. First, a seminar at Cairo University is held with 10 experts to describe the model and results, followed by a discussion and recommendations. After implementing the suggestions, the model is revised again thoroughly by four experts from the first panel. The comments are then presented in the final version of the model.

Finally, the *event validity* is used to contrast model behaviour with reality. For instance, consistent, low-intensity media has proven, in different real scenarios powerful, in sparking global protests, highlighting persistence over intensity. Similarly, the Egyptian government's blackout of communication networks during the revolution illustrates how maintaining momentum often relies on communication and symbolic or invisible leadership. Supporting this, Übler & Hartmann (2016) found that trends spread more effectively when influential individuals participate.