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A Study of Norm Formation Dynamics in Online Crowds

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Abstract

In extreme events such as the Egyptian 2011 uprising, online social media technology enables many people from heterogeneous backgrounds to interact in response to the crisis. This form of collectivity (an online crowd) is usually formed spontaneously with minimum constraints concerning the relationships among the members. Theories of collective behavior suggest that the patterns of behavior in a crowd are not just a set of random acts. Instead they evolve toward a normative stage. Because of the uncertainty of the situations people are more likely to search for norms.

Understanding the process of norm formation in online social media is beneficial for any organization that seeks to establish a norm or understand how existing norms emerged. In this study, I propose a longitudinal data-driven approach to investigate the dynamics of norm formation in online crowds. In the research model, the formation of recurrent behaviors (behavior regularities) is recognized as the first step toward norm formation; and the focus of this study is on the first step. The dataset is the tweets posted during the Egyptian 2011 movement. The results show that the social structure has impact on the formation of behavioral regularities, which is the first step of norm formation. Also, the results suggest that accounting for different roles in the crowd will

uncover a more detailed view of norm and help to define emergent norm from a new perspective. The outcome indicates that there are significant differences in behavioral regularities between different roles formed over time. For instance, the users of the same role tend to practice more reciprocity inside their role group rather than outside of their role.

I contribute to theory first by extending the implications of current relevant theories to the context of online social media, and second by investigating theoretical implications through an analysis of empirical real-life data. In this dissertation, I review prior studies and provide the theoretical foundation for my research. Then I discuss the research method and the preliminary results from the pilot studies. I present the results from the analysis and provide a discussion and conclusion.

"*Found nothing more joyful than the sound of words of love*

In this turning Merry-Go-Round that you rewind."

--*Hafez Shirazi*--

This dissertation is dedicated to my beloved parents.

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1. Introduction

In January 2011, the Egyptian revolution started, when 29 year-old Egyptian-born Wael Ghonim started a Facebook page in solidarity with a fellow Egyptian (Khaled Said) who was beaten to death by the Egyptian police force (Vargas, 2012). Soon after, many people from heterogeneous backgrounds joined the campaign. The movement went through several phases in its lifetime and eventually ended on February 11, 2011 after resignation of Hosni Mubarak, the president of Egypt at the time. The role of online social media such as Facebook and Twitter in facilitating the Egyptian 2011 movement is undeniable (Howard et al., 2011; Khondker, 2011; Oh, Eom, & Rao, 2015; Oh, Tahmasbi, Rao, & Vreede, 2012; Stepanova, 2011; Tufekci & Wilson, 2012; Van Niekerk, Pillay, & Maharaj, 2011; Wolfsfeld, Segev, & Sheafer, 2013). The online social media technology enabled people from heterogeneous backgrounds to spontaneously form an online collectivity in support of the movement. This form of collectivity is called "*crowd*". Turner and Killian (1964) define *collective behavior* as a spontaneous social process or action of crowds. In Turner and Killian's perspective, collective behavior takes place in unusual situations with the aim of redefining the situation and making sense of confusion.

The uncertainty of a situation is the triggering factor, which drives people to search for norms. For example, during extreme events such as natural disasters or terrorist attacks, the crowd feels the urge to share information by connecting to each other and spreading the firsthand information. However, there are situations in which people are unsure about what to share and what not to share. In some cases, such as posting violent or graphic images in online social media, the appropriateness of the content to be posted is made clear by the social media policy and regulations. But in some cases, there are no pre-established norms and regulations. In such cases, uncertainty about the appropriateness of the content being posted may lead to situations in which misinformation is spread (Oh, Agrawal, & Rao, 2013). The original poster then needs to compensate for his/her action or at least apologize the crowd to maintain their credibility. For example, during the Boston Marathon Bombing in 2013, the social media site Reddit played a role in posting false information about the suspect of the bombing and had to apologize for its action[1]. Reddit attributed the bombing to a missing Brown University student who was misidentified on social media[2]. The emergency nature of the crisis makes users reluctant to share images that are unrelated to the situation or posting stories of their everyday life. Users doubt whether to use the social media in the same way as they used before the crisis. At the beginning of the crisis there is uncertainty about which source to rely on and what kind of contents to share. People gradually learn and practice the appropriate behaviors and contribute to norm establishment through the interaction and social influence. Even though people's behavior may appear arbitrary in this situation, it is not in fact completely random. This is in line with Giddens' (1991) Structuration theory that suggests that a social system is not merely a mass of individual random acts. Instead, human agency and social structure are in constant relationship with each other, which gives such systems a dual structure. Giddens (1991) believes that structure is not the shape itself but the *process*, which gives form and shape to social life (Giddens, 1991; Giddens, 2013). During the use of social media technology, crowds gradually gain perception of the technology and define and redefine the normative

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[1] http://www.bbc.com/news/technology-22263020
[2] http://www.bbc.com/news/technology-22214511

behavior of technology use. Understanding the nature of human behavior and norms formation in online social media gives us an insight on how people use the technology and employ it to meet their social needs. This has the potential to get us closer to an understanding of user needs and behavior in the sociotechnical age. However, little is known yet regarding patterns of technology use. In particular, the process of norm formation and rule establishment in online crowds is a phenomenon of interest, which has not been given extensive attention in the field of Information Systems. Therefore, the following research question is proposed: *What are the dynamics of norm formation in online crowds?*

In this study, it is proposed that despite the spontaneous nature of the crowd and the lack of constraints in the relationships among the online crowd members formed around a social movement, the pattern of collective behavior in the crowd is not just a set of random acts. Instead the collective behavior evolves toward a normative stage. This claim will be investigated through the analysis of the real-life data. Through this analysis, I demonstrate that even the fluctuations in the strength of a loose social tie such the ones defined by retweet or mention actions have the power to enhance the formation of behavioral regularities. Also I will show that in spite of the absence of an explicit role assignment, actors recognize their role and collectively behave in accordance to the unwritten norms of their role.

The remainder of this dissertation is structured as follows. In section 2 the main concepts of my research will be explained. First I discuss *crowds* and different types of crowds according to their behavioral patterns. Then I define *norm* and types of norms based on what has been discussed in the literature from a traditional perspective. After defining the main terms, I extend the scope to online social systems and articulate the definition of crowd and norm from the perspective of the online social context. I ground the discussion by providing the relevant theoretical foundations of my study. I close the section 2 by introducing my proposed research model. The data collection and my proposed research method will be explained in detail in section 3. In section 4, I provide the preliminary results of the pilot studies of the research. I provide the results of the study with the discussions in section 5. Then I conclude the dissertation with summary and future steps.

2. Theoretical Foundations

The aim of this section is to provide the foundations of my research and introduce the theoretical lens through which I am looking at my phenomenon of interest, i.e. norm emergence in online crowds. First, I provide the definition of the key terms, which comprise the essential parts of my research. I will define the terms ‘crowd’ and ‘norms’ from a traditional perspective. Then I extend the scope of these phenomena beyond their conventional scope and introduce the context of sociotechnical systems. Within this context, I discuss some relevant theoretical lenses, which have been used to study sociotechnical systems. At the end of this section, I articulate the research problem by bringing the new definitions of ‘online crowd’ and ‘online norms’; and provide my research model based on the theoretical foundations of the study.

2.1. Crowds

2.1.1. Crowd definitions

In general, the term *crowd* has been defined from multiple perspectives. A general definition for crowd is “*a large number of people gathered together, typically in a* *disorganized or unruly way.*"[3] From the sociology perspective, a crowd is defined as "*a temporary gathering of people responding to common stimuli and engaged in any of various forms of collective behavior.*"[3] From each of these views some key characteristics of crowd are implied. First, the spatial dimension of the crowd seems to be an essential characteristic, which determines the essence of the crowd. From the first definition it is implied that in order to call a collection of people 'crowd', the number should be large. However, there is no indicator of the criteria for crowd size to be able to call it 'large' in this context; in other words, how many people are considered large enough to be called a crowd. The second characteristic of a crowd, which is highlighted in the first definition, is the disorganized nature of the crowd. These characteristics give us a hint about the process of forming a crowd, which seems not to follow any pre-established regulations or guidelines. Particularly, the unorganized characteristic of the crowd highlights the fact that the crowd is shaped in the absence of any leader or director. The second definition (from a sociology perspective) points out the temporal characteristic of a crowd. It states the fact that a crowd is not a long-term stable number of people. It is rather a temporary gathering of people, which may depart away in the near future. This temporal characteristic returns back to the other characteristic mentioned in the same definition: responding to a common stimuli. This highlights the motivation as a precedence of forming a crowd. A common stimuli is what brings people together and may keep them together as long as it exists; thus a crowd may fade away after the common stimuli is not relevant anymore.

[3] http://dictionary.reference.com/browse/crowd

Based on the aforementioned characteristics of a crowd, some essential differences between *crowd* and *group* can be highlighted: There are no pre-determined rules or expectations on how to behave to address the crowd's concern. Because of this characteristic, people in crowds usually go along with what other members do, which also are not necessarily the things they would normally do. Crowds often feel the urge to act right away, and their actions and attitudes and thoughts also spread quickly among members.

2.1.2. Types of crowds

Blumer (1969) defined four types of crowds based on crowd behavior and purpose: *casual crowd, conventional crowd, expressive crowd,* and *acting crowd* (Blumer, 1969). *Casual crowds* start gathering spontaneously around a common place and they are loosely organized with minimum interaction with each other; they do have a common goal, but the goal is relatively small and temporary and does not usually keep the crowd together for a long time. People, who happen to be at the same place and at the same time, like people shopping at a mall or people who cross the street at an intersection are the examples of causal crowds. The most common thing that casual crowd members share is their physical location (Goode, 1992). A *Conventional crowd* gathers around a usually specific purpose and it is more planned and organized compared to a causal crowd. Attending a graduation ceremony, a concert, or a funeral are examples of casual crowds. The purpose of an *expressive crowd,* as its name implies, is more of letting out the emotions regarding a specific concern, such as protesting against the approval/rejection of an unpleasant bill by the city council, or a celebrity ceremony. *Acting crowds* are more directly acting toward their specific goal and the behavior is usually pre-planned. The behavior in acting crowds may tend to be violent or destructive and sometimes may be out of control. A collectivity of people reacting suddenly to an unexpected condition is an example of an acting crowd. In such situations (e.g. when a fire breaks a building), crowds may act out self-destructive behavior.

As an addition to the typology of crowds identified by Blumer, McPhail and Wohlstein (1983) identified a fifth type of crowd as the *protest crowd*. They define the protest crowd as a collection of people who gather to protest a political, social, cultural, or economic issue in a demonstration of different types (McPhail & Wohlstein, 1983).

There seems not be always a clear-cut line between the different types of crowds. Indeed, over time, one crowd type may convert into another type; for example, a conventional crowd at a football game may become an expressive crowd while they shout and cheer for a team.

2.1.3. Crowd Behaviors

Collective Behaviors. Turner and Killian (1957) define *collective behavior* as a spontaneous social process or action of crowds. In Turner and Killian’s perspective, collective behavior takes place in unusual situations with the aim of redefining the situation and making sense of confusion (Turner & Killian, 1957).

A common characteristic of all crowds is the uncertainty about appropriate actions, which seems to be the triggering factor, which derive people to search for norms. During this process the crowd gradually forms a conception of appropriate actions, which are communicated in the crowd, and more people come to think and feel the same way at which point the normative behavior emerges from the crowd. This process is called milling (Turner & Killian, 1957). In the milling process, because of the lack of formal information sources, and the need of the crowd to gain information about the crisis, the chance of rumors to be spread around the crowd is high. The milling process is gradually replaced by the keynoting process, in which the crowd gets the better understanding of the situation (Turner & Killian, 1957). A crowd starts to develop some norms and symbolization of crowd objects. Symbolization of objects means development of a shared image of an object. Crowd symbols serve as a basis for unified actions of a crowd. Also the changing in the mood of crowd occurs gradually in the transition from the milling process to the keynoting process. In other words, the chaos, which was present in the communication pattern of crowd in the milling process, will gradually fade.

Norms and social structures in crowds. Traditionally, collective behavior was considered to be abnormal, non-social, and emotional. This perspective was eventually changed by Turner and Killian (1957). Earlier studies identify collective behavior as a set of random acts lacking social structure (e.g. Broom and Selznick, 1968). However, by relating institutionalized behavior and theories of collective behavior, Weller and Quarantelli (1973) identified the social properties of collective behavior and recognized that social organizational dimensions (i.e., social norms and social relationships) are embedded components of collective behavior. From these dimensions, Weller and Quarantelli (1973) categorize collective behavior into four types, where institutionalized behavior is considered to be enduring in both the social norms and social relationships dimensions.

Indeed, based on the level of the emergence of the norms and relationships, Weller and Quarantelli (1973) categorize collective behavior into four types. Figure 1 shows the topology of collective behavior introduced by Weller and Quarantelli (1973).

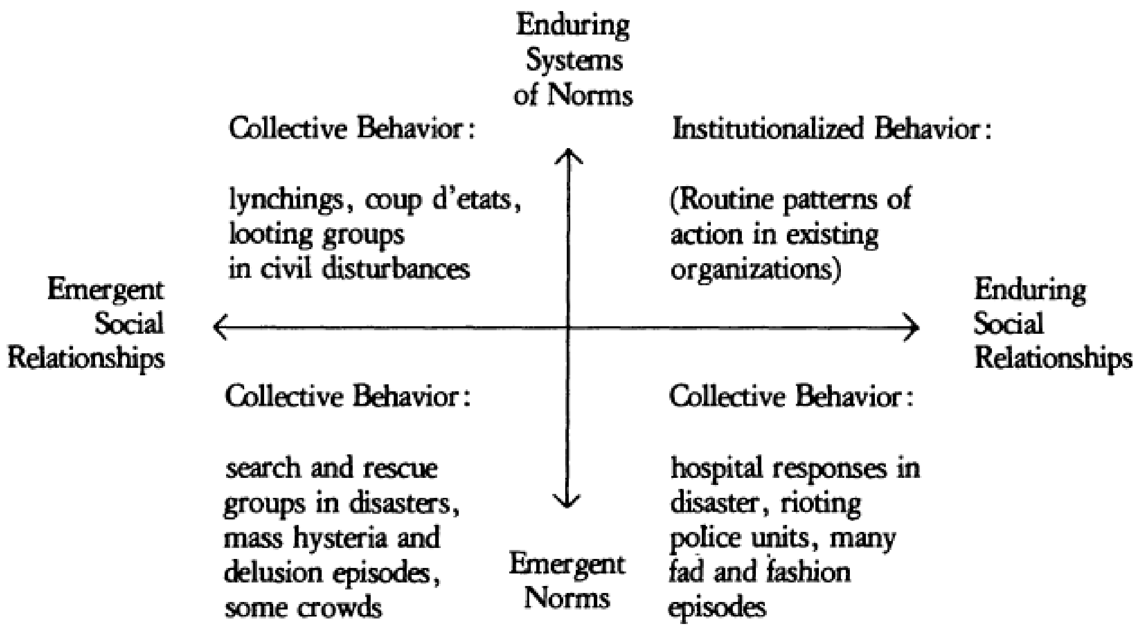

Figure 1: Institutional and collective behavior collectivities (Weller and Quarantelli, 1973)

In Weller and Quarantelli's typology, some types of crowds defined in the previous section are identifiable. It is argued in the literature that not all crowd types act out collective behavior. For example, Goode (1992) believes that the conventional crowd does not actually engage in collective behavior as the social relationships are relatively structured (Goode, 1992). Similarly he states that the behavior in casual crowds is relatively structured and is following conventional norms to some extent, thus they may not act out collective behavior. Having this said, a crowd may not necessarily engage in collective behavior. In collective behavior, either norms or relationships or both could be emergent. An emergence in any of these means the crowd is reflecting a collective behavior. This is represented in the collective behavior typology. The top-left end of the spectrum in Weller and Quarantelli's typology seems to mostly represent the acting crowd defined in the previous section. According to the typology, the social structure in this type of crowd is emergent (no specific structure). However, the norms are relatively enduring in this category of crowds.

As discussed in this section, collective behavior is a result of either emergent norms or emergent social structures or both. However, if the temporal dimension of the collective behavior is long enough to allow for behavioral recurrences and behavioral regularities, social norms may emerge even in unstructured crowds, where the restrictions on the relationships among individuals are minimal and thus the crowd structure is not intact. Emerged social norms may affect the behavior in return. This will create a feedback loop, which includes the effect of crowds' behavior on social norms and the reciprocal effect of social norms on crowd behavior. This loop will occur as long as the collective goal is valid.

In the following sections, the process of emergent norm formation and types of norms will be explained in more detail.

2.2. Norms

As discussed in the previous section, a crowd's collective behavior may lead to the formation of norms in the crowd. There are several steps through which norms are formed and not all repetitive behaviors necessarily lead to norm formation. In this section I provide definitions of norms and types of norms. Then I discuss the process of norm formation in general and specifically in crowds.

2.2.1. Norm definition

Norm, also known as *convention,* is defined as "*something that is usual, typical, or standard.*"[4] It is also defined as "*an established standard of behavior shared by members of a social group to which each member is expected to conform*"[4]. Examples of social norms include shaking hands when meeting someone, or facing the front on the elevator, or not using the cellphone in the classroom. These definitions of norms from a social perspective emphasize the repetitive pattern that exist and are accepted by members of a group. Hence, a norm is considered to be a result of reciprocal expectations of people in a reference group (Mackie, et al., 2012).

2.2.2. Types of norms

Various studies categorize norm from different perspectives. Opp (1982) categorizes norms based on their process of formation. He recognizes three types of norm formations: institutional norm formation where certain individuals or institutions enforce norms, voluntary norm formation where only the participants in the decision are affected by the norms, and evolutionary norm formation where the enforcement is not explicitly planned but the norm emerges spontaneously over time Opp (1982). The evolutionary norm formation is the process, which defines the type of norm relevant to the context of my study.

From another perspective, Cialdini and Goldstein (2004) argue that there are two general types of norms: Descriptive norms and injunctive norms. In the former type of norm, people rely on what others do and go along with their actions. The goal of this action is to

[4] http://dictionary.reference.com/browse/norms

seek social proofs in novel, ambiguous, or uncertain situations (Griskevicius et al., 2006; Cialdini and Goldstein, 2004). The latter is constructed based on one's perception of what others' expectations of the correct behaviors are, or what others approve or disapprove. The two types of norms are formed through the process of social influence that responds to social forces. In this process, one's opinion or behavior is changed in response to others' opinions. Social influence can occur in one of the two forms of compliance and conformity. While the former refers to the particular kind of response to a particular kind of request, the latter refers to the change of behavior to match the responses of others (Cialdini and Goldstein, 2004). As suggested by Deutsch & Gerard (1955), conformity itself can be in the form of either normative or informative conformity. The former is the type of conformity in the desire to be liked by others and gain social approval. The latter refers to the conformity in the desire to be correct and right. According to the two types of norms and the two forms of conformity, it is implied that the descriptive norms are more likely formed through normative conformity, while the injunctive norms are more likely established through the informative conformity process.

2.2.3. Norm development

Emergent Norm Formation Process. Going back to the definition of norms above, the context in which norms form is usually defined as groups. As discussed before, groups are fundamentally different from crowds as groups have a more enduring social structure and the systems of norms are also more stable. Based on these characteristic, it can be implied that the norms in groups may be enforced differently that in crowds. Because of the existence of an institutionalized structure in groups, norms in groups are enforced by the institution. In crowds, there is barely an evidence of any form of institution, at least at the initial stages of crowd formation. When a norm is neither pre-defined nor regulated by an institution, it will emerge from the crowd and thus is called emergent norm. Turner and Killian (1964) propose Emergent Norm Theory (ENT) in the context of crowd (a collectivity of people with heterogeneous background and perceptions). According to ENT, emergent collective behavior evolves or changes when existing social norms and regulations cease to function within the new situation. Since there are no specific guidelines and rules on how to behave and interact with other members, a crowd starts to learn and practice the norms gradually through experience, interactions, and looking at what others do. In extreme events such as a crisis, the emergency situation forces people to give up established and legitimized actions and take the appropriate action in response to the crisis. ENT proposes that crowds shape normative structures through the processes of milling and keynoting. Crowds start to make sense out of the situation by interacting with each other and going through a milling stage. Searching for appropriate behavior in a particular unexpected situation is the main concern in the milling stage. At this stage, particular individuals play the role of keynoters in the crowd. The keynoter is an individual who can help to explain the situation and reduce the ambiguity. The keynoting process occurs when the crowd starts to build a shared image of what is happening and separate facts from rumors (Turner & Killian, 1964). According to the Emergent Norm Theory, during the milling and keynoting processes norms emerge and shared understandings of appropriate behaviors form.

From this perspective, Locher, (2002) explains the process of emergent norm formation in four stages. These stages include confusing situation, milling (rumor), emergence of new group norms, and crowd behavior (Figure 2).

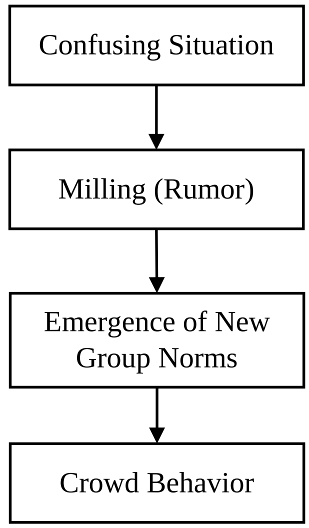

Figure 2: Development of collective behavior from emergent norm perspective (Locher, D.A., 2002).

The first stage of the emergent norm formation in Locher's perspective is facing an uncertain situation. This implies that uncertainty is a pre-requisite for new norms to emerge, consistent with Turner and Killian's perspective of emergent norm theory in which the uncertainty of the situation is a triggering factor for a crowd to abandon already established norms of behavior. As a result of uncertainty, the milling stage occurs in a quest to determine what is going on and which behavior is right and appropriate at that moment. In the next step, the crowd members gradually converge on the appropriate actions. This is when new group norms emerge. Emergence of new group norms then leads to acting upon them. Crowd members tend to act out collective behavior in respect to the emerged norms.

The main concern of my study is the mechanism of emergence of new group norms. Opp (1982) explains this mechanism and influential factors affecting this process by focusing on the emergence of new group norms in Locher's model. He investigates the steps of the process of norm formation and the conditions, which lead to evolutionary emergence of norms. He defines the norm as "*expectations that something should or must be the case*", and refers to *evolutionary norm formation* as an unplanned, spontaneously, or by *trial and error* emergence of norms (Opp, 1982). He recognizes the emergence of recurrent behavior as the first step in evolutionary norm formation and identifies two situations, which lead to regular behavior: direct rewards and imitation. He argues that the situation is reinforcing particular behavior because of its direct perceived rewards, thus there is no need to communicate and bargain to reinforce the norm (Opp, 1982). Moreover, as he states, behavioral regularities can emerge through "imitation of successful models" in which "the behavior of high status individuals becomes diffused" (Opp, 1982). In addition to situations leading to regular behavior, Opp identifies two characteristics of social structures, which may reinforce regular behavior: the communication structure and the cohesion of a group. He argues that certain communication structure is necessary for imitation to occur. Also, he states that higher group cohesion facilitates the diffusion of a recurrent behavior (Opp, 1982). The model of evolutionary norm formation suggested by Opp (1982) and the conditions which facilitate this process are represented Figure 3.

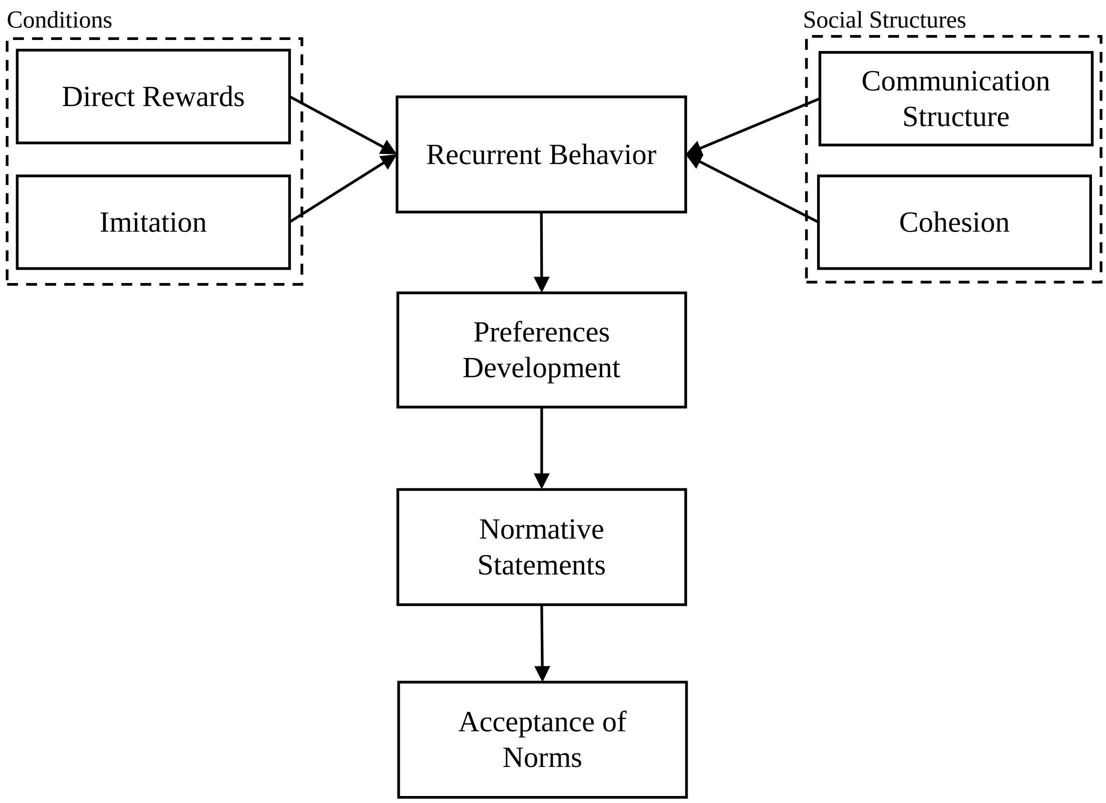

Figure 3: Evolutionary Norm Formation Model

In this model, norm is an outcome of the four-step process. The recurrent behavior (which I also refer to as behavioral regularities throughout this dissertation) is the first step in this process. Behavioral regularities have the potential to evolve into norms if they are developed as a preferred action and are accepted by the group. In this dissertation, the focus is on the analysis of the formation for behavioral regularities over time, which may end up being accepted as group norms. The norm formation model discussed in this section was originally defined for group settings. As stated before, crowds are fundamentally different from groups in terms of structure and their norms system. While the traditional views on norms formation help us understand the mechanisms of norm formation in groups, they may not cover all the sufficient components required to explain the norm formation process in crowds. The emergent norm formation model does explain the process of norm formation in crowd and can serve as a basis for the study of norm formation in our research. However, when it comes to crowds in online settings, the constructs of the model would gain a different meaning, which fits more, to the settings. In the next section, I introduce the concept of online crowds and discuss the literature on norm formation in online settings.

In studying crowds from the perspective of psychology and sociology, the most prominent theory is the collective mind. To explain this phenomenon, sociologist use Emergent Norm Theory which suggests that the collective behavior form as a result of social interaction under the governance of emergent norms formation (Radianti et al., 2013).

Cheshin, Kim, Nathan, Ning, & Olson (2013) studied the effect of different communication media in the emergence of different norms in partially distributed teams. The papers groups the team member based on their communication media and suggests that different in-group norms are developed because of different communication media that they are using. The paper suggests an interesting result, which focuses on the formation of different norms in different groups. In this dissertation, I suggest a similar concept but from a different perspective: different norm are formed according to different social roles.

Meeussen, Delvaux, & Phalet (2014) also suggests that emergent norms differ in groups. In his study suggests that norms and values may change over time and also may vary between different groups. As individuals interact in work groups they gradually form their identity through value convergence and social influence. In my study, the group identities are already established in advance. Each user is either a professional (e.g. journalists, mainstream media) or an individual. But I propose that the emergent norms are different between different role groups. While one might not see any evidence of norm formation in a crowd, they might find it evident in a role group.

2.3. Sociotechnical Perspectives on Online Crowds

2.3.1. Online Crowds

Turner and Killian (1957) define the crowd in a more precise way as a large number of people who are in close proximity and act at once in response to a common concern. In their definition, the spatial dimension is defined more strictly and is limited to a close proximity. This form of crowd is also referred to as a localized collectivity (also called a compact crowd) which includes individuals who are close to the location in which the triggering event (stimuli) has been observed; and they are usually eye witnesses of the incidents and report their observations and interpretations of the incident. On the other hand, the mass is a collectivity of people who are not in close proximity but are reacting to a common concern. The mass is thus called a dispersed collectivity (Turner & Killan, 1957) or diffuse crowd, where the people are more geographically dispersed and have not necessarily met each other. They are considered as an extension to the compact crowd contributing by spreading the word usually coming out from the compact crowd.

With the invention of online social media technologies, new forms of crowds have also appeared. Online crowds are a recent phenomenon that is increasingly getting attention as new online social media technologies are continuously introduced. The collective behavior in online crowds is potentially different from physical crowds. With the advent of handheld devices and online social media technology, diffuse crowds are able to easily participate in the discussion and contribute to the crowd's discourse. The online social media technology breaks the walls of physical barriers and enables more citizens to join the crowd albeit being from far geographical distances. While people in the core crowd who are in close physical proximity to the location of an event share their observations, the diffuse crowd connects to the core crowd and contributes to dissemination of the information created by the core crowd if not communicating original information. Thus, online social media technologies facilitate the connection between compact crowds and diffused crowds. I refer to both as crowd. By phrase 'online crowd' I refer to the combination of the compact and diffused crowd participating in information dissemination using online social media regarding a particular social event. An example of mass behavior or diffuse crowd is the participation of online citizens in dissemination of information on Twitter during the Egyptian uprising in 2011.

2.3.2. Norms in Online Environments

In the literature, the process of norm emergence is mostly studied from the perspectives of artificial intelligence and multi-agent systems (Mukherjee, et al., 2008; Savarimuthu, et al., 2009; Andrighetto, et al., 2010). Andrighetto et al. (2010) use simulations of agents in a social setting to understand the process of norm emergence. Studies show that restricted interactions lead to faster convergence to social norms (Mukherjee, et al., 2008). These restrictions can be caused by the technology that limits the interactions to immediate neighbors only. The social network topology can also introduce restrictions on the interaction between agents and thus affect the process of norm emergence. For example, individuals in a network choose their role models among their immediate neighbors. The network topology restricts the set of neighbors an individual may have

(Savarimuthu, et al., 2009). The current studies on norm emergence in agent-based systems introduce the potential factors, which affect the process of norm formation. However, the technological factor is missing in these studies.

The experimental based simulations of agent-based models dominate the body of works in the area of norm emergence in social environments. Few studies base their analysis on real-life data. Uski and Lampinen (2014) have studied social norms from the perspective of self-presentation on two social network sites. They used focus groups and one to one interviews to understand the sharing mechanisms on each social networking site. They found differences in terms of norms that guide the content sharing mechanism between the two sites, but the goal of self-presentation is common in both sites (Uski and Lampinen, 2014). This study does not try to investigate how these norms are formed. Instead, it identifies norms and finds the differences between the norms in the two social networking sites. This study is beneficial to my study as it demonstrate that norms guiding users' behavior in two different technology platforms are different. This emphasizes the important role of technology in the norm formation.

Besides the qualitative approaches to study the emergence of norms in online technology platforms, there are also a few quantitative studies, which are published in this area. Kooti et al., (2012a, 2012b) attempt to both identify norms and predict norm emergence in Twitter space. They identify the variations adopted during several phases of technology use, and also the factors that are influential on individuals' decisions on which variation to adopt in future. They identified the effect of network structure, such as density, on the adoption rate (Kooti et al., 2012a). The correlation between the network structure and individuals' behavior is confirmed by other studies as well (Centola, 2010; Delgado, 2002; Friedkin, 2001).

There have been few studies on ENT in groups in physical or digital environments. One study analyzed the formation of group norms through email communication among users of a computer-mediated course (Postmes et. al. 2000). Consistency of communication was defined as an indicator of the emergence of identity and norm. Postmes and colleagues identified various attributes of the communication and measured them through a longitudinal study to see the pattern of changes in the communication style within each group of users. Based on the result of their study, they concluded that the content of communication is normative and conformity to the emerged norms increases over time.

Kootie et al (2012a) found out that the well-connected early adopters in a dense and highly clustered network have an influential role in the diffusion of social practices in the network. Choi and Park (2014) confirm this finding by using the concept of "mention" in Twitter. They investigated how individual behavior is linked to network structure from micro to macro level and found that denser networks tend to increase norm establishment and collective actions (Choi and Park, 2014). Another study, which confirms the effect of network structure on behavior diffusion, is a study by Centola et al. (2010). They investigated the effect of network structure on behavior diffusion and found two competing theories. One states that networks with a highly clustered structure are hard to diffuse the information. The other states that local connections are good for fast adoption because reinforcement from multiple resources has a positive impact on adoption. This article uses the diffusion of disease as a metaphor to explain the process of information dissemination. While in the former a single contact would be enough for the contagion, in the latter, one needs multiple sources of "infection" to be influenced (Centola et. al, 2010).

Many studies in this area claim that the network structure and consequently the behavioral practices are self-organizing. This means that a stable normative stage will be reached over the course of a social event. González-Bailón, et al. (2013) studied how self-organizing a political movement is. They divided their data into two time frames: before and after the movement became visible in mainstream media. Then they analyzed the diffusion in social activism through network influence and changes in behavior. They claim that each actor needs to see a specific number of others who are participating before they decide to join the network. This threshold is different among individuals. They argue that sequential decisions allow actors to decide later once their threshold is reached (González-Bailón, et al., 2013). Starbird and Palen (2011) study the self-organizing process of Twitterers in the aftermath of the Haiti Earthquake in 2010. They analyzed how users tweak tweets to fit their information needs in the emergency situation and how their tweaking becomes self-organized.

Many studies in social media have shown that network influence in online social media follows a power law distribution. This means that a small fraction of the crowd is responsible for the majority of the information that is spread through the network. The Power-law degree distribution is evident in many real-world networks including wealth distribution network (Sinha, 2006), location-based social networks (Gao, et al., 2012), publication citation (van Raan, 2005), and pagerank distribution (Becchetti & Castillo, 2006). More specifically, a power law distribution states that 20% of the population is responsible for 80% of the information. This means that the influence starts from a small and maybe dense population in the online network and spreads within the network. The path of influence with itself brings and spreads the word-of-mouth through the network, which contributes to the norm formation process.

Bastos et al. (2013) state that Twitter consists of fragmented users, which means a small portion of the network plays a major role in information diffusion in the network. Thus, a majority opinion can be reversed by a small fraction of randomly distributed users with opposing opinions (Xie et al., 2011). They also introduce and challenge the concept of gatekeeping in social media in political networks. The results show that in political networks gatekeeping is not reliant on hub nodes. Instead ordinary active users play major roles in diffusing messages in the digital networks. User influence in information diffusion has been studied in some researches (Veenstra et al., 2014). Cha et al. (2012) investigate the role of types of users in information diffusion in Twitter space. One measure of influence they used is the size of the audience one could reach. To investigate the influence of a group, they tested what fraction of an audience can be also reached without top spreaders. They claim that the importance of grassroots is more significant in the absence of mass media. They figured out that the mass media, in contrast with traditional perspectives, are not necessarily the first ones to reflect on news. Instead, in crisis situations, grassroots are more active in spreading the information at the beginning of an event. Bakshy et al. (2011) point out the difficulty in empirical analysis of diffusion. The goal of their study is predicting the influence. They focus on original posters of URLs and emphasize on predicting influence rather than recognizing it in the aftermath. They track influence by tracking the followers of a person who posts the same URL. They mention that local past influence is the strongest predictor of the influence.

Their prediction works well on average but not at individual level, as they acknowledge. Thus, they suggest targeting influential individuals to measure the average performance instead of relying on individual-level predictions of influence.

Imitation-Status of Individuals. There are studies on the use of social network influence theory to investigate norm formation in a physical environment. Friedkin (2001) used social network influence theory to study norm formation in physical network of workers. The theory they used has three constructs: 1) the initial positions of the individuals; 2) susceptibilities to interpersonal influence; and 3) relative influence of other workers. They track interpersonal influence through the pattern of network ties and centrality of a person's position. They propose that the similarity of network relations indicates shared social positions. Interpersonal relations in this paper are considered as stable and to some extent permanent. I intend to extend the implications of social influence theory to norm formation process in temporary and emergent networks of relations.

Previous studies such as Postmes et al.'s help us understand how norms are formed in a group of people. In my proposed research, I plan to study the norm establishment process as it occurs through the use of social media technology features and how those features are intertwined with norm formation in online crowds.

2.3.3. The Main Theoretical Foundation

Emergent Norm Theory (ENT) may appear as the best theory to explain the crowd behavior. But this theory also has some limitations and cannot adequately explain what is going on in crowds. Emergent Norm Theory is not enough to explain crowd behavior (Snow et al, 1981).

First, ENT supposes that there is a single norm that regulates the behavior in crowd. While it is questionable whether there is one single dominant norm, which is called as “illusion of unanimity” (Turner and Killian, 1972:22).

Second, norms are specific to the various categories instead of the collectivity as a whole.

Third, the behavioral pattern change over time and crowd is not necessarily following a unified pattern through time.

Another critique to ENT from the perspective of Snow et al. (1981) is that the analyses are based on laboratory experiments or post-event interviews with participants. Thus the interaction between different categories of participants, which leads to formation of behavioral regularities, is neglected.

In my study, I will study the emergent norm with respect to different social roles. Using a data driven longitudinal analysis, I go beyond the limitation in ENT and track backs the interactions between different categories of users, which leads to formation of behavioral regularities.

2.4. Theoretical Lenses

To better understand the dynamics of crowd in a sociotechnical system, I present several theoretical lenses, which will give us several different or similar insights and perspectives on how to look at this phenomenon.

2.4.1. Sociocultural Systems as Complex Adaptive Systems

As stated at the beginning of this dissertation, the collective behavior of crowds is not just a set of random acts. This spontaneously formed collectivity of people in a social setting could be seen from a systems perspective. Buckley (1998) classifies the society as a sociocultural system, which shares some characteristics with other systems such as biological or psychological systems. Buckley's perspective on sociocultural systems as complex adaptive systems confirms that even loosely connected social objects in the form of a collectivity move towards a normative stage during several phases of adaptation. This confirms that the main concept of my study, the norm, potentially exists or will emerge at some point during the lifetime of a collective behavior. However, Buckley's perspective is not claiming the ability to explain the process under which the norm forms or predict what types of norms will emerge. The non-predictability of collective behavior has always been a concern of researchers. This uncertainty nature of human collective behavior is well explained by structuration theory.

Buckley (1998) considers sociocultural systems as complex adaptive systems in which the interrelations are less rigid and strong allowing for the system to less directly reflect on the changes in the environment. In other words, such systems are able to resist the changes in the external environment when they are not too demanding. But in cases where the external triggers are strong, these systems are capable of temporary change in their structure to meet the environmental changes. Also, the persistence of a high level adaptive system requires constant change in its structure. However, due to the constant restructuring of sociocultural systems, the reactions of these systems to the external changes are difficult to predict (Buckley, 1998). The perspective of Complex Adaptive Systems has been used in many studies regarding consensus building (Innes & Booher, 1999), economic systems (Tesfatsion, 2003) and organizations (Dooley, 1997; Schneider & Somers, 2006). One of the main features that define complex adaptive systems is that such systems are in constant interchange with their surrounding environment and have the ability to react to external changes. These external changing factors could be changes in the temperature of an ecosystem. Or could be a social incident in a sociocultural system, which triggers the system (the people comprising the system) to react to it. Online crowds could also be perceived as complex adaptive systems. A seemingly small incident could trigger a crowd to react to it in different forms.

Buckley's view tries to demonstrate that there exists a relationship between the micro and macro patterns of behavior in a sociocultural system. The former refers to the interactions among individuals and their patterns of behavior. The latter refers to a higher level of abstraction in the system such as the structure of the sociocultural system. Buckley believes that there is a relationship and an interchange between the micro-processes and the macro-processes in such systems. The patterns of behavior, which are manifested at the macro-level, are mediated by the micro-level (individuals). Thus, there are two approaches to the study of social systems. We can look at the social system from macrosociology and microsociology approaches. The former studies the social system from the level of social structure, while the latter looks into the social system from the level of individuals. The macro approach will allow us to define and identify the norm-sets in my current study context. The micro approach will help us investigate the process of norm formation. Because of the inseparability of the structure and agency, I need to integrate both perspectives in my study. This integration is suggested by Giddens's Structuration Theory.

This changing nature of social systems stems back from anthropology concepts regarding human behavior in social settings. Henry (1959) explains the change in a social system structure by stating that "*the lack of specificity of man's genetic mechanisms has placed* *him in the situation of constantly having to revise his social structure because of their frequent failure to guide interpersonal relations without tensions felt as burdensome…*" (Henry, 1959). The change in the social system usually occurs through "deviation" and "variation" as stated by Buckley (1998). The deviation from the standard values results in variation and consequently in more potential new transformation of structure, which may eventually get us closer to a normative stage and a stable status in the system; but at the same time, it brings up the challenge of "selection" and "systematic structuring". As a result of the selection process, institutionalized normative behavior occurs through a variety of processes, such as power, authority, and collective behavior, which includes mob behavior, opinion formation, and social movements (Buckley, 1998).

2.4.2. Structuration and Adaptive Structuration Theory

Buckley believes that lack of constraints (such as causal relationships) leads to complete randomness in a system where elements are so loosely related that there is equal chance of association (Buckley, 1998). In his theory of Structuration, Giddens suggests that social life is not defined solely based on a mass of random individual acts. Instead, in a social system, micro-level individual actions reflect on the macro-level. In other words, human agency at the micro-level and social structure at the macro-level are in an enduring relationship with each other. This relationship gives a dual structure to such systems. He believes that structure is not the shape but the process, which gives form and shape to social life (Giddens, 1991; Giddens, 2013). Collective constructs acquire meaning and structure at the collective level (Morgeson & Hofmann, 1999). In order to understand the process of collective construct formation, we need to conceptualize the complex relationships between micro-level and macro-level units in organizational settings (House, Rousseau, & Thomashunt, 1995). The basic unit of collective construct is the double interactions among individuals in a collectivity. The interdependence between individuals creates behavior patterns. These actions and reactions determine the structure of the system, which leads to collective construct or "*organizational memory*" or "*collective action*" (Morgeson & Hofmann, 1999). The reality of collective constructs that emerge is independent of the interaction that gave rise to it. This gives a dual structure to sociotechnical systems. Giddens believes that the structure is both the product of the behavior and the constraint on the behavior. The dual nature of the sociocultural systems allows us to describe how normative rules developed over time (Barker, 1993). The norm does not regulate individual or group output; it is the action and interaction of members of the collectivity. They exist even after a member leaves or the context changes because the system of interactions becomes routinized (Morgeson & Hofman, 1999). The context (organizational setting) defines the range of possible interactions, which defines the structure of collective constructs. The collective constructs have some outputs, which are called "*functions*" and have influence through feedback on the way individuals behave and interact. Giddens emphasizes the relationship between the micro-level (individuals' interaction) and macro-level (collective behavior) elements in sociocultural systems from the perspective of Giddens's structuration theory.

With the increasing use of information technology in daily life and in organizations, it sounds reasonable to look at the structuration theory with inclusion of technology as having agency. DeSanctis and Poole (1994) adapted Giddens's structuration theory to include the agency of technology in the sociotechnical systems. They criticize the technocentric approach to study the implications of technology on social life. Instead they argue that people gradually shape their perception of technology through interactions with the technology and other people and learn how to adapt the technology to fit their activities. Thus, depending on the nature of the activity, the same technology may have different outcomes and implications for different groups and organizations (DeSanctis & Poole, 1994).

Adaptive Structuration Theory confirms that a technology platform with the same features might have different implications and outcomes for different contexts of social use (DeSanctis & Poole, 1994). Depending on the context, people usually have uncertainty about the proper use of technology or appropriate behavior, which conforms to the social norms in the related context.

I use Buckley's view, Giddens's structuration theory, and Adaptive Structuration Theory as a lens through which I look at the sociocultural systems from two levels, from the macro viewpoint and micro viewpoint. The theory of structuration can shape our view of the system. However, it does not have the power of prediction. It is not able to predict human behavior in a sociocultural system. I limit my use of structuration theory as a lens to frame my study.

2.4.3. Sociomateriality

In line with previous works, Orlikowski introduces the Sociomateriality perspective, which proposes the inseparability of human behavior and technology in studying social changes (Orlikowski, 2007). In her theory she emphasizes the entanglement of material and social agencies. She argues that neither a techno-centric nor a human-centric view is sufficient to look at the technology and human interaction in a sociotechnical system and both views have limitations if taken solely.

(Orlikowski, 1992) tries to place the technology in a more central position than what it has been in the structuration theory and AST approach. While in AST, the communication among actors is referred to as action, in Orlikowski's sociomateriality perspective, the technology use is considered as action. This micro-level action is aggregated into a macro-level structure. This means that through the use of technology, leading actors are influencing the technology use of other actors through communication. Particular practices gradually dominate the crowd use of technology. Instead of the term "technology", Orlikowski uses the term sociomateriality to emphasize the inseparability of technology use and artifact, and to articulate that the actions in a sociotechnical system are as social as they are material.

Leonardi (2013) recognizes two theoretical foundations for the study of sociomateriality: the agential realisms, and the critical realism. He believes that both approaches for the study of sociomateriality in practice have their own merits, but the practical consequences and the way scholars contribute to theory and practice are different depending on what approach they take as the foundation of their study of sociomateriality (Leonardi, 2013).

According to Orlikowski, there is no material that is not social and there is no social that is not material. None of these two are primary of one another. Indeed there is no primacy of influence between the two. The material is emergently intertwined in the social so that the entanglement between the two creates sociotechnical norms and practices over time. This entanglement causes continuous reconfiguration of the agency.

One of the main differences between the traditional way of doing works and the technology-mediated ways is the stability of structure and agency in the traditional ways.

Scott and Orlikowski (2009) explored the sociomateriality aspects of a Web 2.0 social media website, TripAdvisor, and compared the online hotel ranking schemes with the traditional system (AAA). One of the important outcomes of their study suggests that the ranking configuration in the new method is dynamic and constantly changing over time, while it was relatively fixed in the AAA hotel guidebook (S. V. Scott & Orlikowski, 2009). This continuous reconfiguration of social agency leads to creating practiced behaviors and norms of material use. To study the interrelation between the social structure and the material, it is necessary to identify the technical factors and the social factors. Hauptmann & Steger (2013) studied this interrelation between technology and social structure in in-house social media for organizations and identified these two sets of factors by using Herring (2007)'s classification of factors. The technical factors include mode of communication, synchronicity, and other medium-specific characteristics. The social factors include participation structure, purpose, norms, and codes. Thus, they considered norms as one of the social factors. The focus of my study is on norms as one of the social factors. However, norms in the context of sociotechnical systems are intertwined with what technology provides as features. So technology factors are continuously intertwined with norms of behavior being formed. Figure 4 presents my conceptual theoretical framework based on the related theories discussed in previous sections.

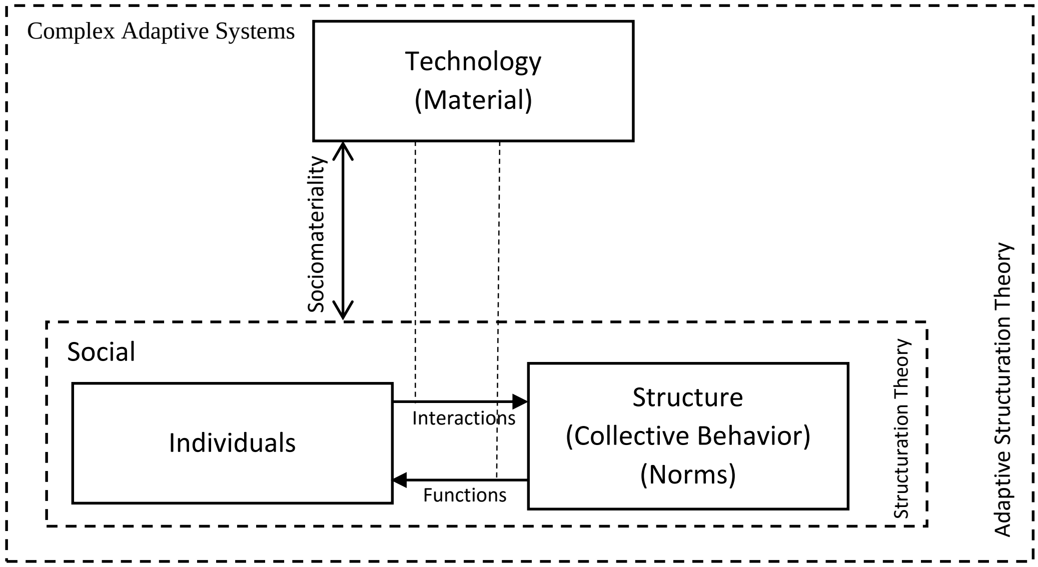

Figure 4: Conceptual Theoretical Framework

3. Research Method

3.1. Context of the Study and Data Collection

The advent of online social media technologies has brought about the era of online societies. It provides us with an abundance of real-life data about the behaviors and interrelations of online actors in online social environments. This abundance of data provides us with a unique opportunity to study and track the underlying process of norm formation in online societies. People use different social media platforms to perform online activities in their daily lives. There are different social media tools employed by online crowds for information dissemination. In this context, Twitter is one of the most widespread social media technologies used in various contexts. Its unique feature of a 140-character limitation in each tweet post makes it a good fit as a means to spread information fast. Also, because of this limitation, users employ creative ways to make best use of this technology. Users in Twitter can follow other users. The concept of friendship in Twitter is not necessarily two directional. Users do not have to follow back their followers. Also users can use other features embedded in the technology, such as including hashtags in their tweets. A hashtag can serve as the topic or category, which a tweet falls into. It is called hashtag because people use hash sign (#) before the tag, which makes it clickable. A clickable hashtag redirects to a list of tweets that contains the clicked hashtag. Hashtags analysis can be used for discovering trends in social media (Huang, Thornton, & Efthimiadis, 2010).

Egyptian 2011 uprising and Twitter. On January 25, 2011, the Egyptian 2011 uprising began with the purpose of overthrowing the regime of Egyptian President Hosni Mubarak. Millions of Egyptians from different political, social, and economic backgrounds participated in the uprising. The protest mainly took place in Cairo, but also spread to other Egyptian cities. Although the actual movement started in early 2011, the roots of this uprising go back to June, 2010 when a political activist, Wael Ghonim, anonymously created a Facebook page in tribute to Khaled Said, the 28 year-old blogger murdered by police officers in Egypt (Vargas, 2012). The result of the protest finally ended a 23-year dictatorship in Egypt.

A reason researchers find this event interesting is the role of social media, especially Twitter's role in the spread of information and in engaging people from outside of Egypt. Twitter was widely used during the uprising to increase public awareness about the social movement and also to connect on-the-ground protesters to the rest of the world (Starbird & Palen, 2012).

I choose the Egyptian 2011 uprising as the context of my research to study the emergence of norm in online crowds. Because with the spontaneous collectivity of online users that participate in the online discussion, it exemplifies an online crowd, which embodies the characteristics, defined in the previous section. The crowd formed around Egyptian 2011 uprising on Twitter consists of people from heterogeneous backgrounds.

I consider Weller and Quarantelli's typology, discussed in section 2.3, to classify the collective behavior in the context of my study. It sounds reasonable for the online collective behavior in a social movement to fall within the space of emergent social relationships and emergent social norms. Because in an emergency situation, as stated previously, individuals from heterogeneous background join the movement with minimum restrictions on the relationships and, also, because of the uncertainty condition and emergence of the situation, norms of behavior are unknown and will gradually emerge over time.

Data Collection. We used a Twitter API to collect our data sets from the network of users in the Egyptian 2011 uprising case. The Twitter data were collected with sufficient days before and after the Egypt revolution time period. The collected Tweets range from January 12^{th} 2011 to March 10^{th} 2011. Twitter does not allow for searching historical data based on keywords. Thus, the individual Twitter accounts were backtracked for archival data dating back to more than eight days. The data collection was a three-step process: (1) Collection of Twitter accounts who might have tweeted around the time period of Egyptian revolution. (2) Tracking back the user accounts in step 1 to collect their tweets over the time period of Egyptian revolution. (3) Using "Egypt" as a filter word to clean out the tweets that are irrelevant to the Egyptian revolution. The twitter data were collected eight times per day from January 12^{th} 2011 till March 10^{th} 2011. Each data collection took one hour to complete. The dominant hashtags used for search keywords include "Egypt" "#Mubarak," "#Jan25," "#Tahrir," and "#Cairo".

After applying the keyword filter on the data, the sample size was reduced to 343,581 tweets posted by 20,565 distinct users, of which 133,743 posts have been retweeted at least once. Each observation includes a tweet message content, the username of the poster of the message, and the date on which the message was posted.

I pre-processed the data to distinguish between an original tweet (a tweet which is posted for the first time by its poster), and a retweet (a tweet which is a repost from an original tweet). If a tweet is a repost from an original tweet, its text starts with "RT" or "via". By processing the tweet contents, I could extract the retweet messages, which also include the original poster of the tweet (which follows a '@' sign after 'RT' or 'via'). After processing the tweets to identify the retweets, 133,743 Retweets could be found in the Egyptian 2011 Social Network. Since I had the user ID of the original poster of each retweet, I could identify the total frequency of retweets each user achieved. The preprocessing steps are explained in more detail later in this chapter.

3.2. Data Analysis

I depict my research model here again (Figure 5), which is a simplified version of the model I presented in section 2.2, with the emphasis on the behavior regularities as the first step of evolutionary norm formation and the influential factors.

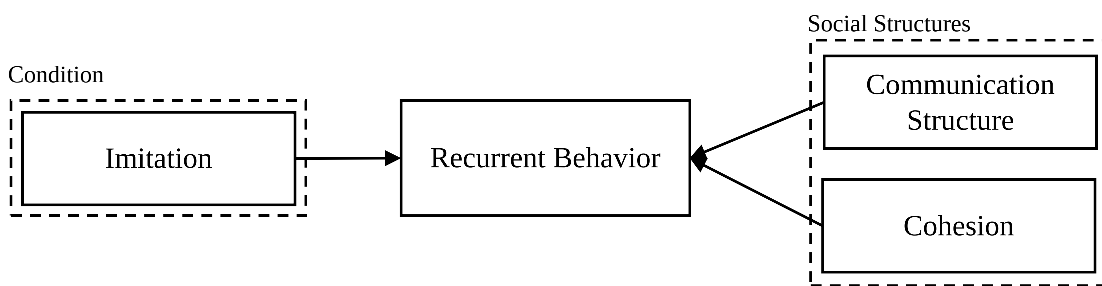

Figure 5: Research Model

Measurement of the Constructs. According to the stages of evolutionary norm formation introduced by Opp (1982), the parameters of social constructs at the macro level which play a role on the recurrent behaviors include two constructs: the communication structure and the cohesiveness of the group. In the following I discuss how I measure the constructs in the model.

Communication Structure. In online social media studies communication structure is measured by constructing a network of relations (which is comprised of edges and nodes) based on the type of communication. The types of communication include: messages, blog comments, conversation and shared media artifact, social actions (such as 'likes' on Facebook), and micro-blogging (De Choudhury, Sundaram, John, & Seligmann, 2010). Micro-blogging is a communication type, which is attributed to Twitter. The specific communication types in Twitter are Tweeting, Retweeting, and Mentioning. In the context of Egyptian 2011 Twitter dataset, different communication networks can be constructed based on different interaction types. The interaction network (also called the dynamic network) represents the dynamic interrelations of the network elements (online users) based on different interaction types. A 'Retweet' network represents all the retweet links between two users; and in a 'Mention' network, the links between any two elements represent the occurrence of mentioning of a user by another user in the network. These two networks in combination define the communication structure of the online crowd in the context of this study. The communication structure is usually measured from the social network perspective.

In a complex graph such a social network graph, nodes are different in terms of their special position in the network, which also is an indicator of their power in the network. Thus, the removal of each node may have a different effect on the overall flow of information in the network. Some nodes are cut vertices, removal of which will result in malfunction of the entire network. The measure of centrality in a network is thus introduced to identify the power of each node in the network. This is of importance in identifying key participants and information producers or community leaders in social network environments, which can be modeled as graphs. There are several measures of centrality, which will be measured in my study. Betweennness centrality refers to the extent to which a node falls on the shortest path between any pairs of nodes in the network (Freeman, Roeder, & Mulholland, 1979). The node at the central position with respect to its betweenness centrality has the influence to withhold information as well as to disseminate information. So removal of such node will result in removing an informational broker. Closeness centrality of a node is the mean of geodistance from the node to other nodes in the network (Newman, 2008), thus the central nodes have lower distance on average to other nodes. Degree centrality measures the number of direct ties of a node to other nodes in a network. While degree centrality stresses on the direct interactions, closeness centrality focuses on both direct and indirect access to other nodes in the network (Irwin & Hughes, 1992). Researchers also use other variations of centrality measures in their studies. For example, Choi and Park (2014) use the concept of flow betweenness instead of Freeman's betweenness and the geodesic distance instead of closeness centrality. They come to the conclusion that denser networks tend to increase norm establishment and collective actions (Choi and Park, 2014). Each of these centrality measures gives us an insight on the network interaction patterns from different perspectives. The distribution of influential power in the network can be investigated through the study of node centrality in the network.

Cohesion. Cohesion can be measured both on the macro-level (a group/network property) and on the micro-level (dyadic or relational). From the former perspective, the cohesion measure of a network defines to what extent the elements of a network are stuck together. From the latter perspective, cohesion refers to the level of interaction and closeness between two elements (Borgatti, Everett, & Johnson, 2013). These two measures are related to each other because group cohesion is built on the dyadic cohesion. Indeed, group cohesion is an aggregation of all dyadic cohesions in a network. Network cohesion is usually measured by dividing the number of all ties in the network by the number of all possible ties. In this study, cohesion can be measured for the dynamic network in each time frame using the same method.

***Imitation*.** I believe that in the context of online social media, imitation is a dominant factor, which drives individuals to act in accordance with others. In the context of an online crowd with minimum coordination and leadership, direct reward is less likely to be a case as a condition that leads to recurrent behavior.

This model provides measurement for network imitation potential at the macro-level, which is the network level. However, individual characteristics of immediate connections are missing from the model. Individual characteristics are expected to affect their position in the network and consequently their influential potentials.

To measure the imitation level, different roles should be identified in the network. Different roles may have different levels of influential power. Thus the roles should be ranked based on their potential influence. From the network structure, we can see how the influential roles are connected to the rest of the population and if it has any correlation with the recurrent behavior. The indicators of recurrent behavior are explained at the end of this chapter.

***Recurrent Behavior*.** Norms are a result of behavioral regularities that can form and be defined in many ways. In microblogging literature the user behavior is usually referred to as the act of posting or reposting microblogs (Wang, Li, Feng, & Feng, 2013; Yan, Wu, & Zheng, 2013; Bild, Liu, Dick, Mao, & Wallach, 2015). Thus the behavior analysis includes the analysis of the changes in the frequency of posting microblogs or reposting a microblog, which is referred to retweet in the Twitter space. The frequency of tweets and retweets can be measured to identify the norms of contribution and sharing. Reciprocity is one of the behavioral regularities that are studied by some authors (Pelaprat & Brown, 2012). Online behavioral regularities such as 'reciprocity' are usually discussed case by case. But in general, reciprocity is explained based on the theoretical foundations such as rational choice theory (J. Scott, 2000) and social exchange theory (Emerson, 1976). Norms of reciprocity in this context can be identified by the usage of mention (@) in Twitter network. Reciprocity practice in Twitter can be identified by the act of replying to each other or retweeting each other reciprocally (Pelaprat & Brown, 2012). Different authors focus on a particular behavior of interest in their studies and each contribute to the body of literature in user behavior studies. However, online social media literature lacks a comprehensive definition of user behavioral regularities. The Tweet and Retweet analyses are useful in creating insights on the aggregated patterns of sharing behavior and reciprocity patterns in Twitter space. However, they do not provide sufficient insight on the contextual characteristics of the Tweets. In this study I fill this gap by incorporating the content characteristics of the Tweets as well, which provides detailed insight on the type of behavior that is existent in the Tweets. Contextual information (linguistic properties) can be extracted from the content and be used to identify the recurrent behaviors, which may lead to norms formation. There are several indicators of recurrent behavior that can be extracted from the dataset. Norms of validation can be identified by analyzing the usage of URL in Tweets. Norms of categorization are identifiable by tracking the usage of hashtag (#).

Pre-Processing. The first step in my data analysis process would be pre-processing the data to get a sense of the overall structure and components of the network. A network component is a group of nodes, which are more strongly connected to each other than to the nodes outside of the group. Considering the biggest connected component may help filtering out the data and increase efficiency.

After removing irrelevant tweets, I came up with 343,581 tweets out of which 202,143 were original tweets. Since the data was being collected at the time of the event and the analysis began after with a time gap in between, some uses' information could not be found which means some users have deactivated their twitter accounts sometimes after the movement. After removing those users and their corresponding tweets, I ended up with 134,541 original tweets.

Role Identification:

As discussed in the literature review, individuals imitate behavior from other individuals of higher status. The flow network gradually forms and its structure changes as users interact over time. From the dynamic/flow network, I am able to see how a message-sharing path emerges and how it gets established as a dominant path through time. From the network structure, I am able to estimate the users' status according to their position in the network. To improve the status measure and obtain a more accurate rank measure, I also consider exploring the users' profile and measure their status based on what they report about themselves on their own profile page. Thus, I need to look at the users' status from a content perspective as well.

Previous studies suggest that both interpretive and structural approaches look at the social systems from different perspectives and thus the combination of both approaches is a better option for studying social systems. The former emphasizes the content of the interaction among different roles while the latter uses social network metrics to differentiate between individual nodes in a network (Gleave, Welser, Lento, & Smith, 2009). Role identification makes it easier to study the social system and creates the potential to answer the system level questions about the impact of different social roles on norm enforcement (Gleave et al., 2009). In order to account for the impact of different social roles in the crowd, I categorize the crowd members and classify them into different pre-identified roles. Identifying roles will help us study the crowd behavior both from the macro level (by identifying the pattern of behavior of each role in the network), and the micro level (by differentiating among the influential power of each role on their neighbors in the crowd).

The users are categorized into two categories of ‘individuals’ and ‘professionals’. ‘Individual’ category includes individual users who are not related to any professional journalism agency or not a freelance journalist. ‘Professional’ category includes user accounts that represent any one of the following sub-categories: mainstream media accounts, correspondents, online individual journalists, professional online journalists, and non-profit organizations. For this part of analysis simple logistic regression was selected and performed on the data in Weka.

The next step in my study will be the content analysis of the tweets. Then the content characteristic measures will be aggregated for each role from these linguistic perspectives. Based on these characteristics, the tweets will be categorized into different types. I will search for the correlations between the roles and the types of tweets each role posts more frequently. But before continuing on the content analysis of the Tweets, an extra step needs to be taken to translate the non-English Tweets to English.

Translating tweets to English:

Not all tweets were is English. Although majority of Tweets in the context of Egyptian 2011 movement are in English, there are few Tweets in other languages such as Arabic, Japanese, and Korean. Accounting for the Tweets in other languages will increase the accuracy of the analysis. In order to account for these tweets, I translate them into English. Since the number of Tweets to be translated is high, it is not possible to do a manual translation. Thus, I will use a programming script to automatically translate the Tweets into English. To verify the accuracy of the translation, I will use the help of an expert in Arabic language (since Arabic is the language of the majority of non-English Tweets) to confirm the accuracy of the translation.

Linguistic Analysis:

Linguistic analysis will serve as a way to extract features from the Tweets. These linguistic features are then used as indicators of behavior regularities. Several studies use different tools for linguistic feature extraction for text. One of the most common tools for this purpose is LIWC. This tool extracts 80 different features of a text section. The features include linguistic characteristics such as ‘word counts’, ‘pronouns’, ‘we’ words, ‘you’ words, ‘positive emotions’, ‘negative emotions’, etc. A complete list of features and their description is available on the LIWC website[5]. In this analysis, the tweets are

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[5] http://liwc.wpengine.com/wp-content/uploads/2015/11/LIWC2015_LanguageManual.pdf

the input to the LIWC tool. The output of the analysis is a table of tweets with 80 linguistic features for each tweet. These linguistic features are used for identification of behavioral regularities. Also the 80 different features along with other variables extracted from the data (which will be described in the following) are serving as predictors for user categories.

Other variables:

Centrality measures: To leverage the accuracy of prediction, users' centrality measures in the network have also been incorporated into the data. Total of six different centrality measures have been calculated for each user. Three for RT and three for Mention network. The three measures for each network include betweenness centrality, closeness centrality, and degree centrality.

Also the ratio of number of retweets made to the number of original tweets posted by the user is calculated. This is an indicator showing how much a user is leaned toward dissemination of information rather than creating original information. The ratio of the number of times the user gets Retweeted to the numbers of user's original posts is also calculated. This ratio indicates that what percentage of a user's tweets is getting notices and republished. It can be also an indicator of effectiveness of the user in terms of sharing valuable information to the community.

Tweet platform-specific features: In addition to the network related measures, the usage of twitter technology-specific features is also measured for each individual user. These measures include: (1) the average usage of urls and (2) the average usage of hashtags.

Longitudinal Study. According to the previous studies (Choi and Park, 2014), network structure seems to have significant influence on the formation of behavior regularities and consequently emergence of norm. Behavioral regularities change over time as well as the structure of the network. To investigate the relation between these changes, I need to take a longitudinal approach to be able to uncover this correlation over time.

Thus, my approach to this problem would be dividing and studying the data in different timeframes along the lifetime of the event. To investigate and study the structure of the interactions at each time period, I will use network metrics that are also used in the prior studies. Potential network measures are discussed in previous sections. Some potential network measures include: group or user properties related to reciprocity (such as mentioning in Twitter), tweet posting pattern, and the number of total retweets received to the number of total retweets made. If the network links represent the retweet behavior, then the number of total retweets can be measured by counting the links going out of a node (outdegree), and similarly, the number of retweets a user receives from others can be measured by counting the links coming in to a node (indegree). In Twitter, the act of mentioning is not necessarily two-directional. This means that users do not need to reply back to other users. But the action of replying back to the users can be an indicator of a reciprocal behavior. Also, the overall network properties such as size, density, or centralization could be potential indicators of network structure.

To better clarify the steps of my dissertation, I simplify them in the following diagram (Figure 6).

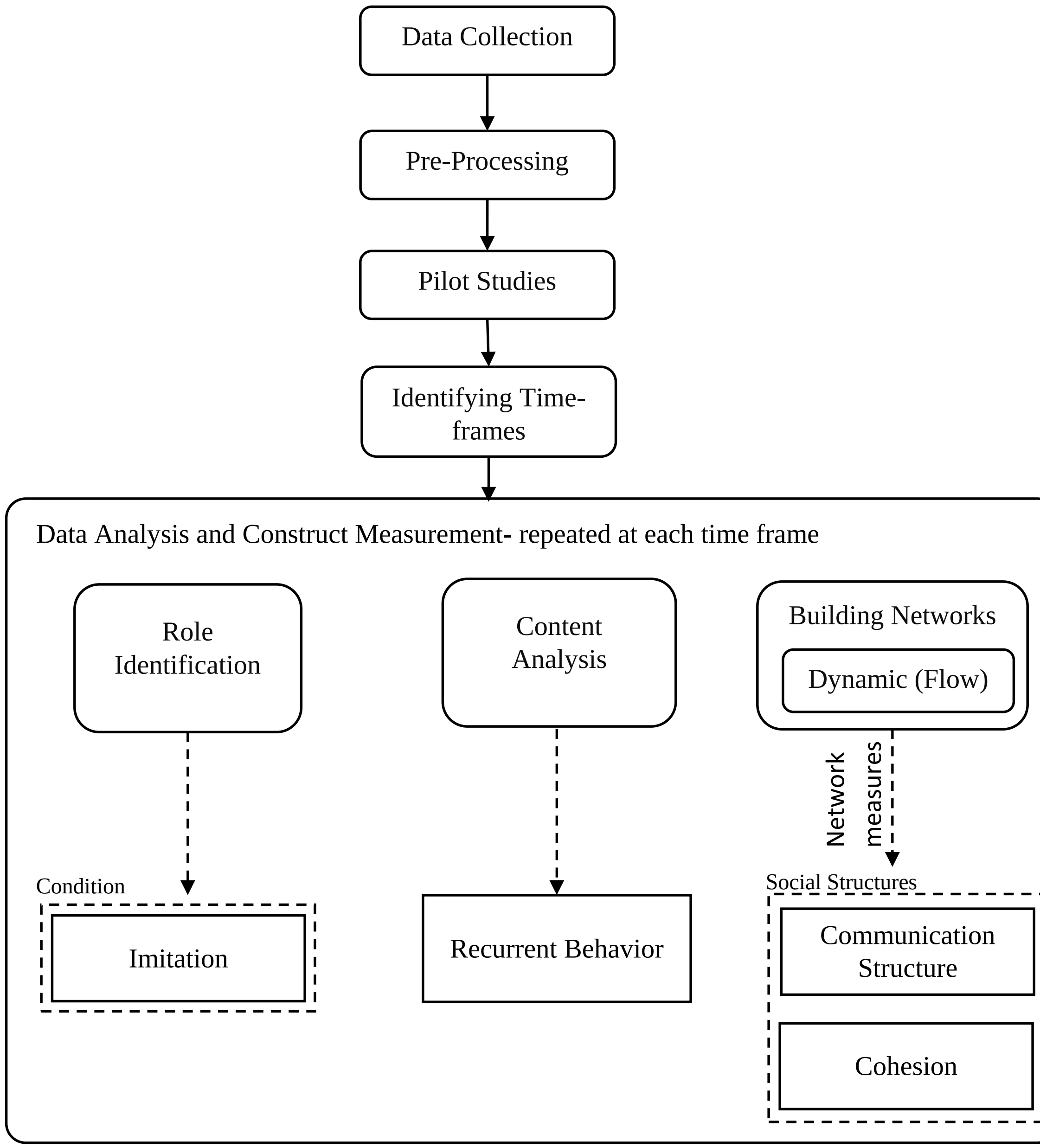


Figure 6: The research method

4. Pilot Studies

This study will make the effort to explore and investigate the process of norm formation in online crowds. Before I start my main study for this purpose, I start with a set of pilot studies, which serve two purposes: before I study the process of norm formation, I need to investigate if there are evidences of such a phenomenon forming in online crowds. In particular, I want to demonstrate through empirical evidences that this phenomenon (emergent norms) exists and the collective behavior in crowds is not a mere set of random actions. Thus I conduct pilot study 1 to identify and investigate evidences of normative patterns in online crowds by studying a real-life data set from the Egyptian 2011 twitter network.

Second, in my main study I am interested to investigate the potential role of structure in the formation of behavior regularities. Thus, I need to figure out if there are any differences in the pattern of changes in the structure in different contexts of collective behavior. As suggested by Modgerson and Hofman (1999), individual actions are limited by the context. Also, the context (organizational or social setting) defines the range of possible interactions, which consequently define the structure of collective constructs. Thus, I need to first investigate if the pattern of collective behavior differs in various social settings and how it is related to the social structure. For this purpose, I identify two different social settings and for each setting, I take two appropriate datasets, which represent their respective social settings. In pilot study 2, I compare and contrast the pattern of structural changes over time between two social events: the Egyptian 2011 and Boston Bombing 2013 Twitter network.

4.1. Study 1: Identification of Normative Patterns in Online Crowds

4.1.1 Data

The dataset contains more than 343,000 tweets posted during January 12, 2011 to March 10, 2011. More than 20,000 unique Twitter users have been contributing to the body of tweets posted during the lifetime of the event. These users posted about 202,000 original tweets and retweeted around 141,400 posts. This dataset has been pre-processed. During the pre-processing task, the network has been cleaned so that the nodes which were not highly connected to other nodes (isolated nodes) have been filtered out for increased efficiency.

4.1.2. Data Analysis

Looking through the lens of the Structuration Theory, I take macro and micro approaches together to study the process of norm formation in the Egyptian movement. These two approaches include: (1) defining and identifying the indicators of the normative behavior, and (2) explaining the underlying processes of norm formation. In the first approach, I need to demonstrate that some forms of norms are evident in the pattern of behaviors extracted from the data. This approach is from a macro viewpoint, which allows us to uncover the emergent and sustainable patterns of behavior, which convert to norms over time. I used a data-driven approach to address this question. In this methodology, I analyze the tweets to identify the normative patterns of behavior during the lifetime of the movement. The second approach is from the micro viewpoint where I identify the influential groups of users at each time frame and study the scope and reach of the audience of each group. The micro viewpoint allows us to figure out how the norms get established through a social process. I will leave the second approach for the main study. The longitudinal study will help us uncover the process of self-organization in the networks and identify the changing patterns of behavior over time.

I take the initial step of my analysis to identify the overall patterns of behavior regardless of the user roles as described in the first approach. The results of this part of the analysis are provided in the following section.

4.1.3. Preliminary Results of Study 1

First of all, I analyzed the frequency of original tweets over time. The graph includes peaks in the frequency at different points of time (Figure 7a). These peak times include January 25, January 28, February 2, and February 11, 2011. Looking back at the pre-revolution events on the timeline of the 2011 Egyptian uprising (Table 1), I found the correlation between the critical points of time and the peak times in the tweet frequency graph. This simply tells us that depending on the nature of the movement, certain triggering events drive people to disseminate a higher number of original tweets to respond to the increasing need of firsthand information. In the first step of my analysis, which is identifying the overall pattern of behavior, regardless of user roles, I extracted the following measures and tracked them over time. I considered two of the main technology features, which are commonly adopted by the users of Twitter. The measures include the number of hashtags per tweet and inclusion of a URL to the source of the content. The usage of the aforementioned tweet notions follows different patterns in regards to the total number of original tweets over time. Regardless of which role posted the tweets, the results show that, in general, when the number of tweets goes up, the average number of urls per tweet drops down (Figure 7b). This tells us that during an event, when an occurrence of an incident triggers lots of discussions in online environments (especially in critical points of time), inclusion of a source of content becomes of less importance. This appears to be when rumors find their way to spread in the network. However, the average number of hashtags per tweet experiences a relatively stable pattern over time, regardless of number of tweets (Figure 7c). The purpose of using hashtags in tweets posts is to group the messages by labeling them. Labeling Tweets makes it easier for future references by making them appear in the electronic searches. The stability and consistency of the number of average hashtags used per tweet in Egyptian uprising could be because of the existence of a potential norm regarding the use of hashtags which puts a limit on the maximum number of hashtags in a single tweet. Especially because of the character limitation in each single tweet (140), the hashtags should be used with caution to make the best use of this limitation.

Table 1: Description of the critical points in the lifetime of Egypt 2011 revolution (Causey, 2012)

Critical Point	**Incident Description**
25 January 2011 ("the Day of Rage")	Ten of thousands protested throughout Egypt
28 January 2011 (The "Friday of Anger")	Hundreds of thousands demonstrated after Friday prayers. Clashes broke out in Tahrir Square
2 February 2011 (Camel Battle)	Mubarak supporters rode camels in Tahrir square as a sign of escalation of violence
11 February 2011 ("Friday of Completion")	Mubarak resignation and nationwide celebration

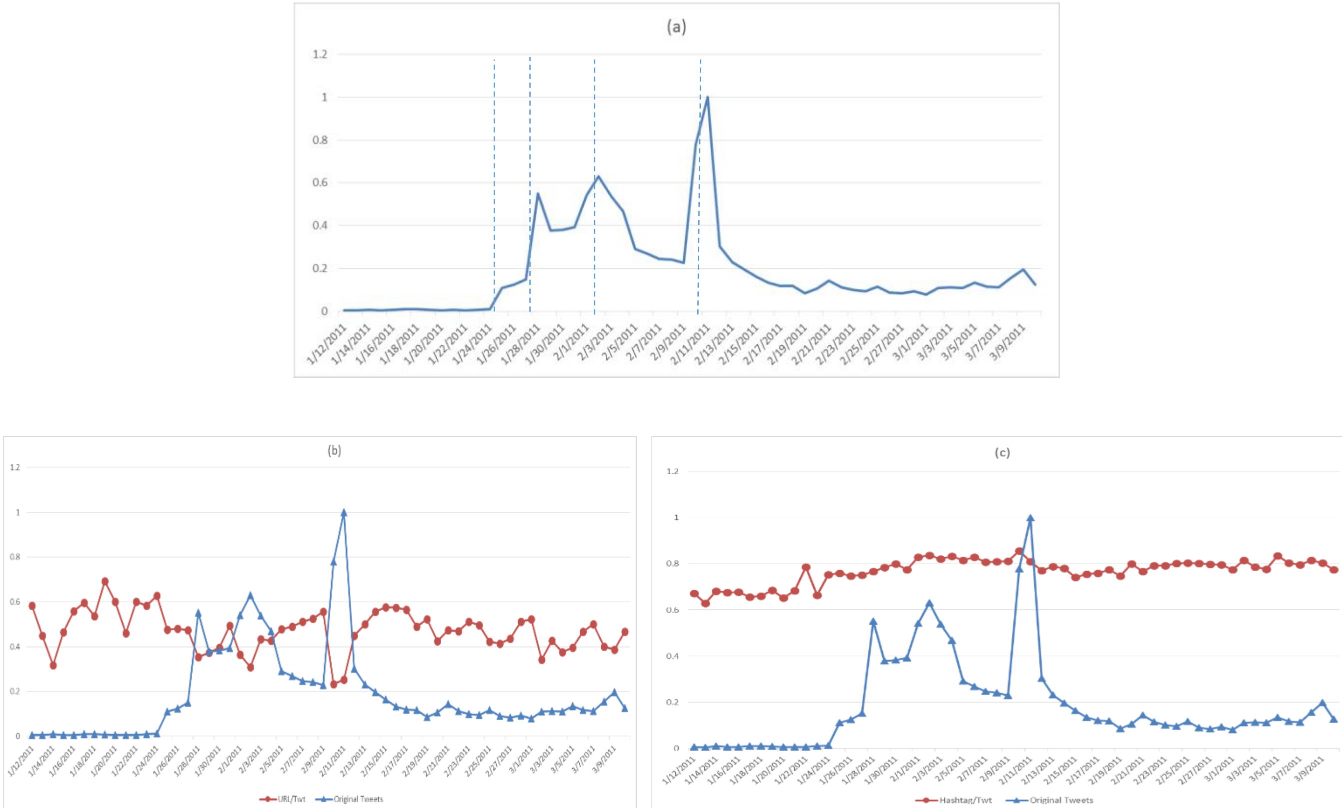


Figure 7: Pattern of original tweet post (a) pattern of URL inclusion (b), and hashtag usage (c) during the lifetime of the Egypt 2011 movement compared to the total number of original tweets

4.1.4. Conclusion of study 1

Considering the context of online crowds, this pilot study makes the effort to extend the application of structuration theory beyond the scope of institutionalized groups with enduring relationships and norms systems. The results suggest that the online crowd follows some sort of behavioral pattern consistent with external triggering events. Further work is required to extend the indicators of normative behavior considered in this pilot study and also account for the potential effects of confounding factors such as the demographic information of the users and the peer social influence. My main study will also include the analysis of other content characteristics, such as linguistic characteristics of the tweets, which will be identified using the LIWC linguistic tool. Then the aggregated values of each of the tweet characteristic measures should be calculated for each role at each time period. The tweets will be categorized based on each identified role. All the tweets are time-stamped so we are able to track the pattern of changes in tweet content for each role over time.

The results of our initial step confirm that the online crowd that formed around the context of the Egyptian uprising in 2011 is not acting randomly. Instead, the collective behavior follows a pattern towards a normative stage. The main study will focus on identifying the process underlying the norm formation in online crowds.

4.2. Study 2: A Comparative Analysis of Collective Behavior Patterns between two Contexts

In this pilot study, I investigate two types of radical[6] social events—*social movements and disruptive events* that have occurred in the Twitter space, in an attempt to better understand the role and the extent of Twitter's potential, as well as similar broadcasting technologies, on influencing the collective behavior during the two social events. Hence, I ask the following research question: "*How do the collective behaviors of the crowd who participate in social movements and disruptive events compare and contrast with each other in regards to the crowd's use of online social networks?*"

In order to explore the data for answers, I compare the evolutionary transformation of two social networks as revealed from two radical social events: (1) the 2011 Egypt revolution (Al Masaeed, 2013), a non-violent civil resistance which evolved over a

[6] To my knowledge, literature does not specify what a radical social event consists of. However, the Merriam-Webster dictionary defines *"radical"* as being *"very different from the usual or traditional; extreme"*. In this study, I use the phrase "radical social events" to refer to social phenomena that are driven by extreme political and social factors, like the Egypt movement in 2011 and the Boston Bombing in 2013.

lengthy period of time, and (2) the 2013 Boston bombings (Volpp, 2014), a terrorist-driven event that triggered extreme, albeit more fleeting, agitation in a massive crowd. By transformation, I specifically refer to the changes in the information diffusion (of tweet and retweet) patterns in the crowd's social networks in temporal and spatial perspectives.

The potential contributions of this pilot study are two-fold. First, by looking at the temporal changes in the information diffusion pattern, I may understand how information is spread in the social network over time. Second, by looking at the spatial changes, I may be able to understand how the power of influence is distributed across the online social network.

4.2.1. Social Movements and Massive Disruptive Events

Drawing the definition of a social movement from various experts and perspectives, Diani (1992) hypothesizes a synthesized definition of social movements as *"networks of information interaction between a plurality of individuals, groups and/or organizations, engaged in a political or cultural conflict on the basis of a shared collective identity"* (p. 13). Social movements, in particular, are characterized as movements which focus on restructuring, instead of incorporating into, the system in which the collective group belongs (Fitzgerald & Rodgers, 2000). A specific type of a social movement is a *revolution* (Aberle, 1967), which is carried out in pursuit of claims of a state or certain portions of it (Tilly, 1978).

In contrast, Diani (1992) explains that disruptive political protests are beyond the inclusive spherical nature of social movements. In this spectrum, Lin (2013) refers to a (massive) disruptive event, related to an emergency situation or a disastrous event, as that which upsets and harms the regular and accustomed day-to-day affairs of a large group of people. These events may include *natural disasters*, like earthquakes and tsunamis, tornadoes, and hurricanes (e.g. the 2011 earthquake/tsunami in Japan and hurricane Katrina in the US, also in 2011), or *man-made*, which are predominantly associated with terrorist attacks (e.g., 9/11 event and the Boston bombing in 2013). The magnitude of these events' impacts extends beyond the people who are directly affected by the events. Such events are classified as "disastrous" or "emergency" (Van den Eynde and Veno, 1999) because various *psychosocial* interactions take place while a disastrous event occurs, or near the time of occurrence of a disastrous event.

An upset in the normal functions of a community induces fear and discomfort in the community (Lin, 2014) that likewise ignites a need for citizens to cope and restore prior functioning levels (Van den Eynde and Veno, 1999). One effect of these coping mechanisms is manifested in the change or upsurge in people's collective communication behaviors. With the ubiquity of technology, the spread of disaster-related news may happen almost instantaneously. This ability is understood as an advantage against unforeseen yet imminent disasters. Through technology, effective and timely dissemination of news helps to avoid or to minimize impacts of disaster-related events (e.g., Fong, 2008; Nacos, 2003; Waldman, 2005).

In this pilot study, I attempt to better understand the differences in the collective behaviors related to these radical social events—the 2011 Egyptian revolution, classified as a radical social movement, and the 2013 Boston bombing, classified as a massive disruptive event. It would appear that there are clear differences in these events' communication patterns. However, I contribute by exploring more deeply how these phenomena differ temporally and spatially by providing empirical evidence drawn from the above-mentioned social events.

4.2.2. Social Movement: The 2011 Egyptian Revolution

The context of Egyptian 2011 uprising has been explained in section 3.1. In this pilot study, I used the same data set as I will use for my main study.

4.2.3. Massive Disruptive Event: The 2013 Boston Bombings

The Boston Marathon is the world's oldest annual Marathon. On the afternoon of April 15, 2013, during the 117th running of Boston Marathon, two bombs exploded near the finish line on Boylston Street, which killed 3 people and injured 261. An investigation was launched on the same day, and thousands of law enforcement officers started searching for the suspects in the neighborhood of Watertown. In less than two days, two male suspects were identified through thousands of images and videos of security cameras. On the same night, a 27-year old police officer was shot and killed in his patrol car. The murder was linked to the suspects found on cameras earlier that day. The 19-year old suspect was found first but ran away after the 26-year-old older brother, a fellow suspect, died of a law enforcement shootout. A day later, April 19, the city was shut down while police conducted searches for the second suspect. The younger brother was found later that day in Watertown neighborhood (History.com Staff, 2014). Twitter feeds that swirled in the Internet became a channel that expressed a multitude of sentiments (Volpp, 2014).

4.2.4. Research Method

In order to answer my research questions I conduct my analysis in two major steps. First, I start by investigating the overall pattern of information contribution (use of retweets) of the two datasets form the two social events. Using power law (Clauset et. al. 2009), I am able to compare the similarities between the two radical social events. The proportion of the top contributors, likewise, allows us to see the dissimilarities between the social events. In the second step, I analyze the pattern of information contribution over time to discover the similarities and dissimilarities of the patterns of collective behavior in a finer granularity over the time dimension, for which I take a longitudinal approach.

Data Collection. I used the Twitter API to collect my data sets from the network of users in the two cases. For the 2011 Egyptian social movement, I used the same data set as I will use in my main study: tweets posted from January 12, 2011 to March 10, 2011 were collected. The Twitter activities of users during the Boston Bombing in 2013 were collected from April 15, 2013 until April 29, 2013. Aggregating of data from this period is equivalent to total of 8 days of tweets and retweets. Because of the interruption in Twitter API functionality at the time of data collection, tweets from some days are missed and the data is collected for 8 days during the lifetime of this event. The Boston Bombing dataset contains 40,806 tweet posts, of which 21,397 have been retweeted at least once. Each observation includes a tweet message content, the username of the poster of the message, and the date on which the message was posted.

Data Analysis. My analysis strategy was a two-step process. First, I identified the distribution of retweet frequency among users of both networks. Second, I explored the pattern of change in the distribution of power during the lifetime of both events. For both of these steps, I defined a measure of power of reach. Power of reach indicates the size of the audience a user can reach. For example, when a tweet from a user gets retweeted multiple times and circulates around the network, it will reach beyond the user's immediate neighbors and, overall, a wider range of audience would receive the original message. The size of the aggregated audience is an indicator of the power of reach of a user.

Calculating the Power of Reach of each User. One indicator of power in the network is the number of attentions a user gets from others. In Twitter space, users express their attention to a tweet by retweeting it. In this study, I consider the retweet counts to measure the size of the audience a user can reach. The larger the audience a user can reach, the more potential the user has to influence other users (Cha et al, 2010). Thus, the number of total retweets a user gets from other users in the network can become a measure of influential power of the user. Hence, I refer to the measure of influential power of the user as the *power of reach of each user*. In aggregation, the power of reach of the users equates the overall information contribution in the network.

Identifying the Distribution of Power of Reach among Users. The next step of the analysis was to identify the distribution of power of reach among users. The distribution of the retweet frequency (power of reach) of users was graphed for both networks (Figure 8). The graphs helped us to get an overall insight on the pattern of distribution of retweet frequency among users, and compared them between the two networks. To obtain an objective measure of comparison, for the sake of accuracy, I used the concept of power-law, which is a common pattern of distribution in real-world networks. The dependent variable can then be obtained from a power function of the independent variable, as presented in the following formula:

$P\ (frq) = K^{-B}$

Where in this case, *frq* is the frequency of retweets for each user, and K is the number of users with the specific frequency of retweets. The power B in the formula above determines the heaviness of the tail in the distribution graph. Thus, by identifying the value of B for both networks, a comparative measure for identifying the difference in the heaviness of the tails of the two networks can be obtained. By applying a log-based transformation on the two sides of the formula above, a new equation was derived:

$\text{Log}\ (frq) = -B \log (k)$

Then by applying linear regression analysis, I obtained the coefficient in the equation, which is the value of B. I took a random sample of 20% of the population for both networks and performed a regression analysis on the natural log transformed equation to obtain the value of B. Figure 8 shows the Retweet frequency distribution diagrams and the sample network graphs for the two radical social events. For simplicity and improved visualization, the network graphs are representing a random sample of the same amount of information contribution in both datasets. I refer to ‘information contribution’ as the ‘retweet’ concept in technology terms. A retweet in the network graphs is presented by an edge. The reason I considered the same number of contributions (same number of edges) for the two datasets is to compare the percentage of top contributors in the two datasets. In the Egypt case, the number of edges shown in the network accounts for one percent of the total contributions, whereas in the Boston case, the same number of edges are representative of 20 percent of the total contributions. However, the proportion of the top contributors (the bigger darker spots in the network graphs) seems to be the same for both networks.

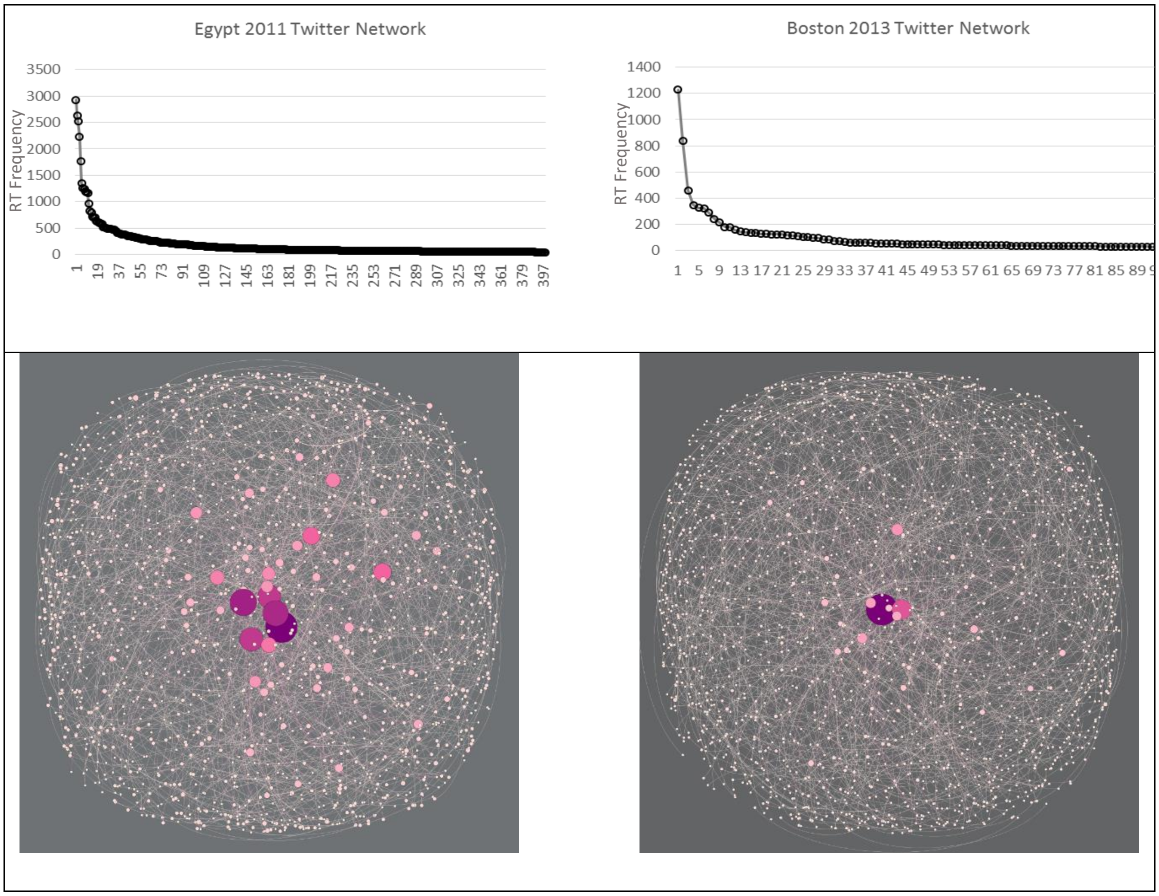


Figure 8: Retweet Frequency Distribution in: Egypt 2011 Twitter Network (left), Boston 2013 Twitter Network (right)

Exploring the Pattern of Change in the Distribution of Power over Time. The contribution of the top portion of the users in terms of the number of retweets they gain in comparison to the total number of Tweets was calculated for the two data sets during different time frames on a daily basis. The lifetime duration of my Egyptian uprising network and of the Boston Bombing network is 57 days and 8 days respectively. The overall frequency of Retweets of the top fraction of contributors is then calculated for each day in each network. For the Egyptian network, the top 1%-5% of users is considered in the analysis. For the Boston network, the contribution of the top 10%-50% of the users is taken into account. These percentages were chosen so that the top portion of users in both networks contributed to the same percentage of contents. Figure 9 shows the percentage of users contributing to more than 50% of the contents during the lifetime of both networks.

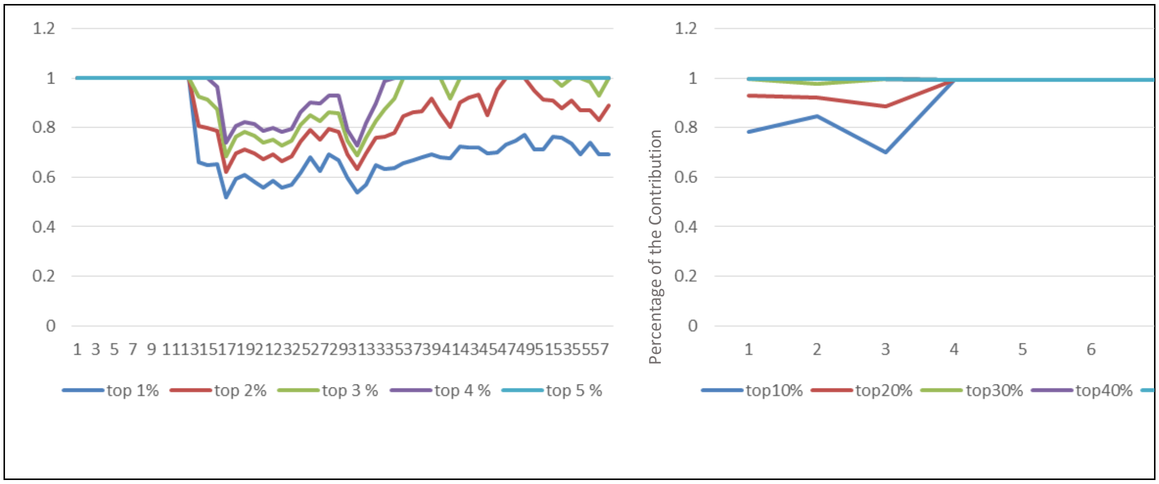


Figure 9: Percentage of users contribute to above 50% of the contents during time: Egypt Social Movement: 1%-5% (left), Boston bombing: 10%-50% (right)

4.2.5. Preliminary Results and Discussion

According to the ANOVA tables resulted from my regression analyses, my model for both networks fits well with R-square > 0.7.

The power of the distribution is indicated by the coefficients of the regression analysis. The power B for the Egyptian 2011 network equals -.995, and -.884 in Boston 2013 network. This difference in the power tells us that the Egyptian 2011 network has a more heavy-tailed power distribution than the Boston 2013 network, means that although both networks follow a power-law distribution, the power of reach in the Boston 2013 network is more widely distributed among all individual users, while in Egypt 2011 network the power of reach is more densely distributed among top contributors.

My results show that Twitter as a social medium is being used differently in the two contexts. There are two main differences in the pattern of collective behavior in terms of information contribution evident from my results: 1) the distribution of retweets among users is more heavy-tailed in the Egyptian 2011 network, which can be an indicator of the presence of a small fraction of influential users as information contributors. 2) The amount of contributions by top influential users over time, experiences a different pattern in the two networks. In the Egyptian 2011 network, the top 1% of the population is contributing to 100% of the Tweets during the initial days of the movement, and after that, more users are joining the influential set of users. Thus, we see that in the following days after the start of the movement, the influence of the top 1% is spread throughout the top 5% of the population, while in the Boston Bombing 2013 network; this change appears in the opposite direction. At the beginning of the event, the power of reach is more widely distributed than in the final days of the event. At the beginning, the top 50% of the population have the influence to contribute to the entire content. But at the following days, the power of reach is shifting toward a smaller fraction, which is top 10% of the population. Another result of this study is that the percentage of top contributors is significantly different between the two networks. In the Egyptian 2011 network, 1%-5% of the population are responsible for more than 50% of the total Tweets, while in the Boston 2013 Network, 10%-50% of the population are contributing to the same percentage of the Tweets; this indicates that the power of reach is more equally distributed among the users in the Boston 2013 network than in the Egyptian 2011 network. This is also consistent with the distribution of power in the two networks and with the difference in the heaviness of the Retweet frequency distribution tail of the two networks.

The heavy tailed power law distribution of the Egyptian 2011 Twitter network can be explained according to the essence of this particular type of movement. Noting the first 10 time periods in the lifetime of the movement in Twitter (Figure 9), 5% of the population is enough to contribute to the total content of the network around this topic. This tells us there have been initially influential individuals who could manage to capture the attention of the crowd. These individuals may be experts in the domain of social or political science. They may be well known and familiar with the particular situation. In contrast, the Boston Bombing incident was totally unpredictable. Nobody was aware of this event in advance and nobody had any plans for contributing to the event beforehand. The crowd who contributed to sharing information throughout the network immediately after the incident seemed to come out of nowhere. They spontaneously formed and responded to the emergency situation by trying to contribute to helping and informing people as much as they could. There was no norm or any pre-established rules for dealing with this situation. As described in Turner & Killan's (1957) book, *Collective Behavior*, the spontaneous crowd starts with a milling process, in which everybody seeks information from their immediate neighbors. If the event is long enough, then the crowd gradually enters the keynoting phase, in which particular norm around the situation are established. Having said this, in a disaster such as the 2013 Boston Bombing, there were no pre-known experts or influential individuals who could lead the crowd; users on social media shared any new piece of information regardless of the background or identity of the source of information. Because of the lack of information in that particular situation, and delays in mainstream media in sharing the verified information, the crowd will buy any message that has new informational content. Thus the network structure of this type is more widely distributed in terms of power distribution.

4.2.6. Conclusion of study 2

In this pilot study, I used a collective behavior perspective to compare the pattern of information contribution between two radical social events in respect to the use of social media. I started by pointing out the similarities and dissimilarities between the two types of radical social movements; the Egyptian 2011 as a social movement and the Boston Bombing 2013 incident as a massive disruptive event. Then using a longitudinal approach, I made the effort to highlight the difference in the pattern of behavior between the two events. The results show that despite the similarity of the broadcasting technology used in the two social events, different patterns of collective behavior emerge.

This pilot study acknowledges the important role of technology in empowering social change, but at the same time suggests that technology is not a restricting factor that dictates the pattern of collective behavior. It would appear that social phenomena play a significant role in shaping the social change. A potential contribution of this study is opening the door to more research avenues to extricate the entangled relationships between technology and social factors.

According to AST, it is obvious that same technology may bring different outcome for different contexts. Thus difference in the pattern of the power distribution over time might be expected between the two contexts. From this view we are looking at the dissimilarities from a macro viewpoint. But if we break the crowd down to different roles, we may be able to see similar patterns between the two contexts. From another viewpoint, we may see how different roles behave similar to others in their roles and different to the ones in other roles. The consistency of this difference between the roles is a hidden similarity that could be investigated by accounting for the different roles. In the main study the role identification is accounted for and the results are presented and discussed.

5. Results

Tweet Translation:

In total 13,255 tweets were found in other languages such as Arabic, Korean, Russian, and Japanese. Majority of non-English Tweets were in Arabic. I used an Excel VBA script to use the Google Translate API and translate Tweets from other languages to English. A graduate assistant who was fluent in Arabic confirmed the accuracy of translation. A random sample of 100 translated Arabic Tweets were shown to the graduate assistant and the accuracy of the automatic translation was approved at 99% rate. Table 2 shows a sample of original Tweets and their translation.

Table 2: A sample of Original Tweets and their translations

Original Tweet	**Translation**
“@masri_7orr: ليتجه الكل إلى ميدانـ التحرير، اليوم يوم جمعة الرحيل، اليوم الأخير لمباركـ، مصر #Egypt انـشروا رجاء”	"@ Masri_7orr: Everyone is heading to Tahrir Square, on Friday to leave, the last day of Mubarak, Egypt Post please #Egypt"
“@youm7: كاتب أمريكى: الـ "CIA" فشلت فى فهم المتظاهرين المصريين http://t.co/R7ZDQy5 #Egypt” Whats New heh?!	"@ Youm7: American writer: the" CIA "failed to understand the Egyptians demonstrators http://t.co/R7ZDQy5 #Egypt" Whats New heh ?!
ومازال البحث جارى عن ملف القذافى....بس بسرعة قبل ما يبعتلنا مرتزقة #gaddafi #libya #egypt	The search is still underway for Gaddafi .... Bs file quickly before what Abatlna mercenaries #gaddafi #libya #egypt
今晚必须非常productive，根本没时间关注 #egypt 了，遥祝埃及人民胜利！！	Tonight to be very productive, no time to concern #egypt, the Remote Blessing Egyptian people win! !
반정부운동연합체가 엘바라데이에게 임시정부 구성을 요청하는 성명을 발표했다는 소식. BBC 보도. #Egypt #jan25	News that anti-government movement coalition has issued a statement requesting the interim government to ElBaradei. BBC reported. #Egypt # Jan25

Role Identification:

The following section is dedicated to the understanding of the imitation effect on the formation of behavioral regularities. I believe that the existence of different social roles leads to the formation of specific behavioral regularities, which is facilitated by the imitation effect inside the community (the users who are of the same role). To study the formation of emergent norm, it is not sufficient to only look at the overall behavioral pattern in the crowd, but also the potential differences in these regularities between different roles is an identifier of norm formation. These differences are identifiable by comparing the different roles in terms of the specific behavioral regularities. Thus the first step towards this goal is to identify different roles and influential actors who are the role models. First I do preliminary analysis of the overall distribution of the influence among the crowd members. Then I explain the method of role identification in this crowd.

Testing Power-Law Structure to Identify Influential Voices

As the first step to identify the different influential roles in the Egypt Revolution, I identified those Twitter users whose Tweet messages were most frequently retweeted by other Twitter users during the time period of the event.

Barabási & Albert (1999) formulate the power-law distribution as follows:

$$P(k) \sim k^{-r}$$

P(k) is the accumulated number of retweets that k number of Twitter users receive in total. P(k) follows a power law with exponent -*r*. This distribution can be represented on a log-log scale. If the distribution is a negative linear line, then the original distribution is the power-law distribution:

$$P(k) = ak^{-r} \rightarrow lnP(k) = \ln(a) - rln(k) \qquad (1)$$

The above equation shows a log-transformed formula which shows the relationship between the log-transformed value for the number (k) of individual Twitter users and the log-transformed value for the frequencies of retweets for each individual, k, which is $P(k)$.

This relationship is tested and indicates that a significant negative linear relationship exists between the k and $P(k)$ with $R^2 = .755, F(1, 227)$=701.229, $\beta_1 = -.690$[7], at p<.001. Thus, the existence of a power-law distribution is supported which suggests that a tiny fraction of Twitter users' messages are extremely frequently retweeted by a large number of other Twitter users. This also means that during the Egyptian Revolution, a few Twitter users were opinion leaders (keynoters, according to the theories of collective behavior) whose ideas were highly noticed and redistributed by a large number of other Twitter users. Figure 10 and Figure 11 visualize the power distribution. By looking at these two figures we see that majority of people get minimal number of retweets while very few people are very powerful in terms of the amount of attention they get from others. In Figure 10 we can find out that there is one Twitter user with almost 3000 retweets in total while 226 users received no retweets during the lifetime of the event.

[7] $\beta_1$is equivalent to –*r* in the above formula (1).

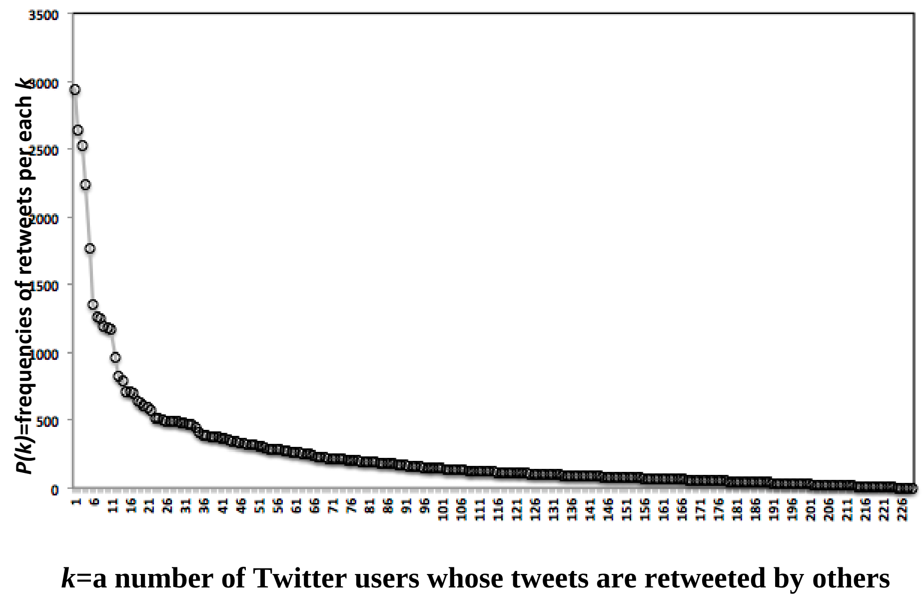


Figure 10: A power-law distribution of the retweet frequencies per each number of Twitter users

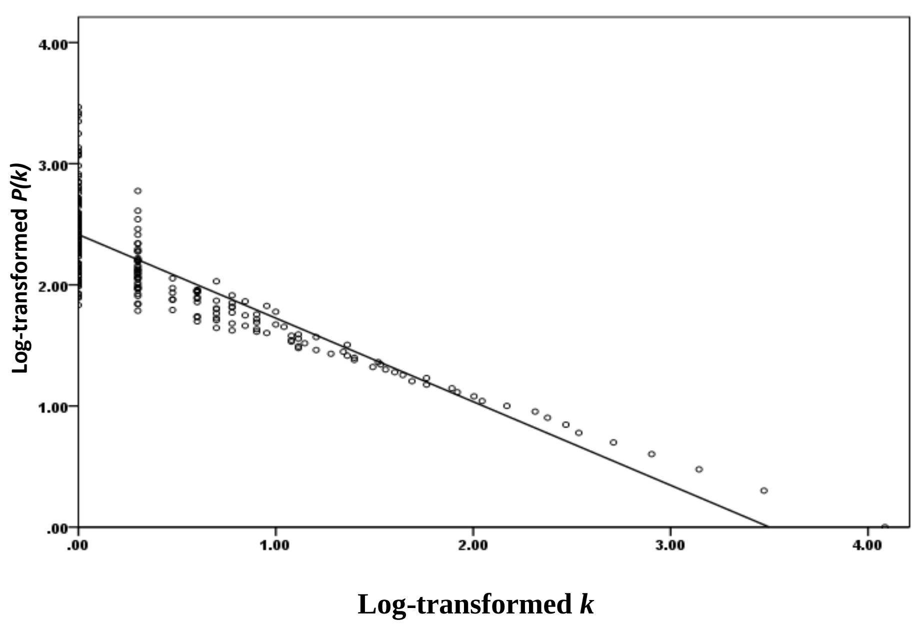


Figure 11: A negative linear line represented on a log-log plot

In Figure 12, the distribution of influence (retweets) of the top 20 most frequently retweeted users (the area in black) is compared to the total retweeted users (the white and black area).

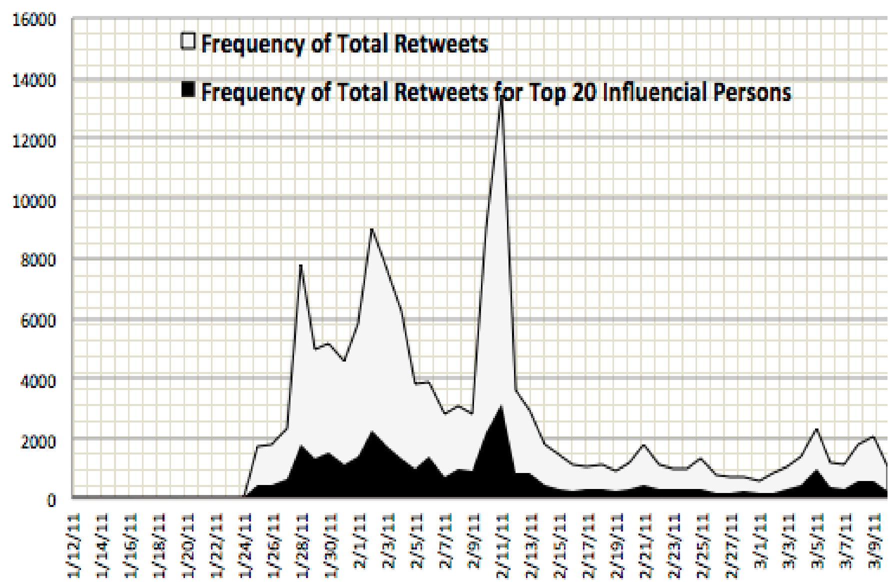


Figure 12: Distribution of Twitter users whose tweets are retweeted by other Twitter users

The results of this section reflect that the modern social media (specifically Twitter in the context of social changes) has become more institutionalized that allows for heterogeneous coexistence of opinions (in the form of Tweets) originating from diverse entities. These entities may include individual users, mainstream media, online journalism or other professional organizations institutions. To account for the diversity of user roles in the Twitter space during the Egyptian 2011 movement, I present a coding scheme based on which I categorize the users into different roles. The data selection, coding scheme, and the outcome of coding process are presented in the following sections.

Data Selection:

The top 10% of the users, which account for 65.68% of total retweeted messages (87,837/133,743) are selected for the purpose of role identification. The criteria for this selection was to have at least 10 Retweets from other users. At the time of coding 237 user Ids were found suspended which were removed from the analysis. Thus our selection is comprised of 1,376 user IDs.

Data Coding:

I initially coded the Twitter users into one of six categories shown in Table 3. The coding scheme is adopted from Kwon et al. (2012) to fit this context. To identify the user's code, we investigated the user's publicly available information on the user's profile. If this kind of information was not publicly available, we read through the user's Tweets to decide on the role that fits the user according to the type of information the user posted on the social media. For the coding, a graduate student assisted me. We started with a random set of 100 users as the pilot data and ensured that it does not come from the sample data. The inter-coder reliability test for pilot coding was satisfactory (Cohen's Kappa k=.794, p<.001)[8]. The inter-coder reliability confirms that both coders had a substantial understanding of the coding scheme presented in Table 3. We proceeded with the actual coding of the users with one coding 806 users and the other coding 807 users. After the coding 237 suspended user IDs were removed (the users have deactivated their accounts by the time of coding).

[8] Landis & Koch (1977) suggest that kappa value .20-.40 is fair, .41-.60 moderate, .61-.80 substantial, and .81-1.00 almost perfect agreement between coders.

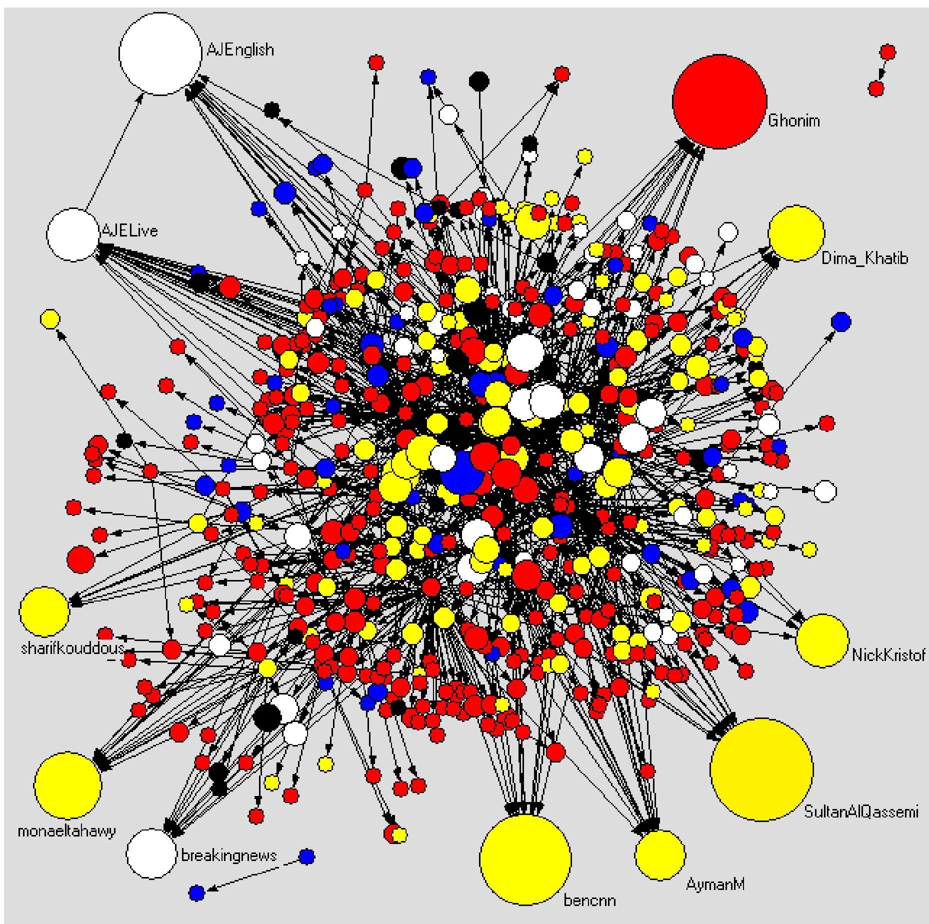
Table 3: Coding scheme adopted from Kwon et al. (2012), p. 212.

Entity Type	Description	Examples
Individuals	• Twitter accounts of individual users. • Does not belong to or is not affiliated with any formal organization.	Twitter.com/Ghonim Twitter.com/SultanAl Qassemi
Individual journalists	• Identify themselves as professional journalist or correspondent	twitter.com/bencnn twitter.com/jonjensen
Mainstream Media	• Newswire, broadcasting, or print mass media. • Must have offline presence (e.g. offline-based headquarters or offline edition of newspapers). • Should target mass audiences, including a broad range of topics as listed on their websites.	Twitter.com/cnn Twitter.com/ajenglish
Professional Online Journalism	• Journalistic writing style yet no offline edition. • Have its own independent domain name	twitter.com/HuffingtonPost twitter.com/alternet
Organizations or Institutions	• Any organizational / institutional / community twitter account that was not categorized in any category above. This may represent governmental, corporate, educational, research, or organizational advocacy websites.	twitter.com/wikileaks twitter.com/meedan
Others	• Twitter user IDs that do not belong to any of above categories or are not identifiable.	

The results of the coding are summarized in Table 4 and also visualized in Figure 13. Table 4 shows the population densities of each role and the total number of Retweets that each role has received. The population density in Table 4 and the number of red circles in Figure 13 show that the ‘individual’ role has the densest population (60.83%, red color). ‘Individual Journalists’ with 19.19% density shown in yellow are the second densest population. And ‘other Organizations’, ‘Mainstream Media’ and ‘Professional Online Journalism’ roles are next densest population in a decreasing order.

Table 4: Frequency of user Roles and number of retweets received

Entity Type	Color code in Figure 4	Population Density for Each Entity	Total Number of Retweets Received
Individuals	Red	837 (60.83%)	30,869 (35.48%)
Individual Journalists	Yellow	264 (19.19%)	32,532 (36.70%)
Other Organizations	Blue	122 (8.87%)	5,675 (6.5%)
Mainstream Media	White	91 (6.61%)	14,973 (17.05%)
Professional Online Journalism	Black	62 (4.51%)	3,788 (4.3%)
Sum		1,376 (100%)	87,837 (100%)



* red – individuals; yellow – individual journalists; white – mainstream media; black – professional online journalism; blue – other organizations

Figure 13: Retweet networks during the 2011 Egypt Revolution.

Although the population density of each role gives us useful insight on the distribution of different roles in the population of Twitter users in Egyptian 2011 movement, it is not revealing all the facets of retweet dynamics. By comparing the third and the fourth column in Table 4, a different story is revealed. Individual users account for a significantly higher population density than other roles, but they only receive 35.48% of the total retweets. In Figure 13, each circle represents a user and the size of the circle is proportional to the number of retweets the user receives from others. As this figure also represents, a very small portion of the population receive the majority of retweets. We can see that the red circles (individuals) are of the smaller sizes but in a higher density than the circles of other colors.

In Figure 13 we see many small red circles and a few bigger red circles. The most dominant red circle belongs to 'Ghonim', a user in the 'individual' category who received a high volume of retweet attentions. At the same time there are 836 other individual users (small red circles) who received a few retweets and are considered as peripheral supporters. Similarly, we can spot seven big yellow circles in the graph that represent the 'individual journalist' category. These seven users include 'SultanAlQassemi,' 'Dima_Khatib,' 'NickKristof,' 'AymanM,' 'bencnn,' 'monaeltahawy,' and 'sharifkouddous') who received a high volume of retweet attentions. There also exist 257 other small yellow circles (individual journalists) that do not receive much retweet attentions. The big white circles in the graph represent the most influential users in the 'mainstream media' category. The three mainstream media users are 'AJEnglish,' 'AJElive,' and 'BreakingNews' who receive a dominant amount of retweet attentions.

Other than these seven users, there are 88 other mainstream media user accounts that do not receive high amount of retweets.

The amount of retweet attention received by these eleven dominant user IDs is summarized in Table 5. The 1,613 users, which were initially selected for coding, comprise top 10.3% of the retweet sample (133,743 retweets posted by 15,636 Twitter users). These users account for 65.68% of the total number of retweets (=87,837/133,743). If we consider the top 11 users (top 0.07% users =11/15,636), they account for 14.59% (=19,510/133,743) of the total number of retweets. Among the 11 users demonstrated in Table 5, there are one individual, three mainstream media, and seven individual journalists received a comparatively extremely large volume of retweet attentions. This shows that, the types of entities involved are diversified while role of institutional organizations (e.g., mainstream media) are more prominent.

Table 5: Number of Retweet frequencies of Top 11 Twitter users

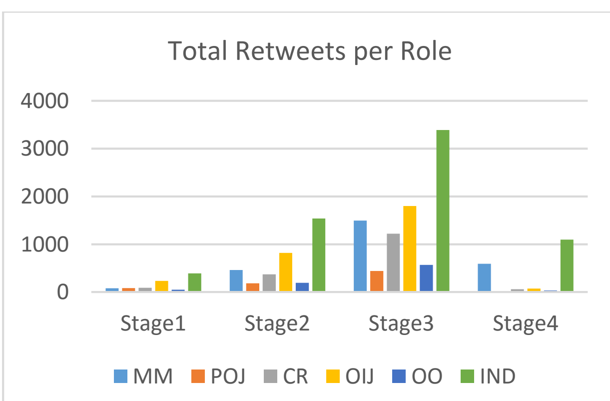
Rank	**User IDs**	**Entity Type (Color code in In Figure 13)**	**RT frequency (%)**
1	SultanAlQassemi	Individual Journalist (yellow)	2,933 (2.19%)
2	Ghonim	Individual (red)	2,636 (1.97%)
3	Bencnn	Individual Journalist (yellow)	2,521 (1.88%)
4	AJEnglish	Mainstream Media (white)	2,236 (1.67%)
5	monaeltahawy	Individual Journalist (yellow)	1,771 (1.32%)

6	Dima_Khatib	Individual Journalist (yellow)	1,358 (1.02%)
7	NickKristof	Individual Journalist (yellow)	1,264 (0.95%)
8	AJELive	Mainstream Media (white)	1,247 (0.93%)
9	BreakingNews	Mainstream Media (white)	1,196 (0.89%)
10	sharifkouddous	Individual Journalist (yellow)	1,181 (0.88%)
11	AymanM	Individual Journalist (yellow)	1,167 (0.87%)
Total			**19,510 (14.59%)**

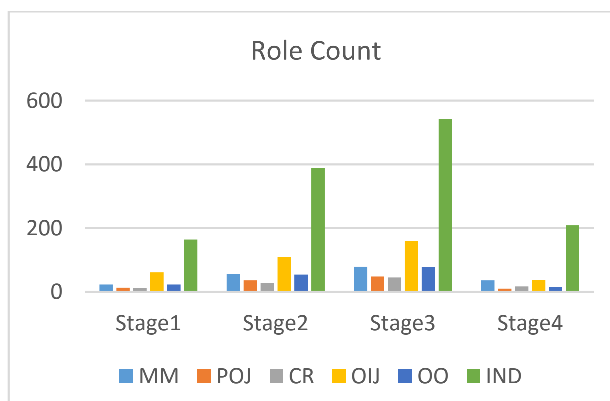
To demonstrate this concept in more detail I have delved into the dynamic pattern of retweet and analyzed the Retweet pattern in each role over the time. The results presented in the next section give us an overview of the different Retweet patterns among different roles.

Dynamic analysis of Retweet in each role:

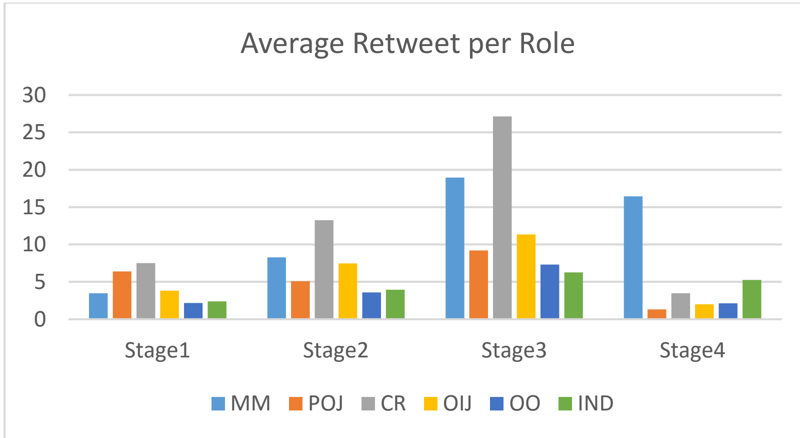
After studying the lifetime of the Egyptian revolution in Twitter and the micro-events during this time frame, four critical stages have been identified. These critical stages are shown in the pilot study 1 section in Table 1. The four different time frames include the period before January 25 (stage 1), January 26-28 (stage 2), January 29-February 2 (stage 3), and February 3-11 (stage 4). In each of these time frames the frequency of Retweets received by each role are analyzed. Figure 14 shows the total retweets received by each role (a), the role population (b), and the average retweets received by each role (c) at each stage. From these diagrams it is evident that the 'individual' users still account for the majority of the population and total retweets received over time and this pattern is preserved during the four stages. However, looking closer to the average retweets per role (Figure 14c), we can see that the average number of retweets per role does not follow the same pattern among all four stages. 'Mainstream Media' and 'Correspondents' gradually take over during the first three stages with the 'correspondents' receiving continuously more retweet average than the 'mainstream media'. However, after the end of stage 3, the rate of average retweets received by the correspondents experiences a sudden decrease alongside 'POJ', 'OIJ', and 'OO' roles. At the same time, 'individuals' stand out as the only competitors to the 'mainstream media' roles. This pattern shows that at the end of the final critical point in time, after the 'correspondents' (the professional witnesses of the event) have been dismissed from their reporting duties and seemingly left the location of the events, few individuals filled this power gap and gained more power reflecting on their opinions on the social media while mainstream media accounts remained relatively powerful in reporting on the aftermath of the event.



(a)



(b)



(c)

Figure 14: Pattern of Retweets received by each role over time.

The dynamics of retweet pattern over time reflects on the fact that the relative influential power of the different roles in the Egyptian revolution on Twitter follows a relatively consistent pattern over time. Since this analysis focuses on a single pattern of behavior (retweet action), I was intended to take a step further and delve into more detail of the potential differences in the pattern of other behavioral regularities among different roles. To simplify the process and the representation, in the next step, I consider a higher level of categorization and reduce the number of roles into two roles: ‘individuals’ and ‘professionals’. ‘Individuals’ preserve the same definition as before; and all other categories are integrated into a single category (‘professionals’).

This time I included more users to the analysis to not only cover the most influential users and instead include the entire population for more accurate results. But coding the entire population was not possible manually. 8,882 unique users were found who at least posted one original Tweet about the Egyptian revolution. To code the entire population I used a classification method by using the already coded data from the previous stage as the training set and applying the fitted model to the rest of the population. The results of the classification were satisfactory and the model could successfully code the users with a reasonable accuracy. The model is trained according to the variables obtained for each user from the linguistic analysis of the user's original tweets. The linguistic analysis will be explained later in this chapter. But first the classification process is explained in the following.

The train set includes 459 random users, which have been labeled. The user classification is performed using a simple logistic regression with stratified 10-fold cross-validation. The `AttributeSelectedClassifier` with `Best first` search method in Weka is used to select the influential features. After the feature selection method we ended up with 22 variables out of 92 attributes.

The list of influential variables and their coefficient in the regression is shown in Table 6.

Table 6: The list of influential variables and their coefficient in the regression

Class 0 :	Class 1 :	Description
1.1 +	-1.1 +	--
[RT/twt] * 0.48 +	[RT/twt] * -0.48 +	The ratio of Retweets to the original tweets posted by the user
[URL avg] * -1.29 +	[URL avg] * 1.29 +	The average usage of url in the tweets
[pronoun avg] * -0.13 +	[pronoun avg] * 0.13 +	Function Words
[ppron avg] * -0.09 +	[ppron avg] * 0.09 +	Personal Pronouns
[i avg] * 0.83 +	[i avg] * -0.83 +	1st Person singular
[they avg] * 0.34 +	[they avg] * -0.34 +	3rd Person singular
[article avg] * 0.04 +	[article avg] * -0.04 +	Articles
[negate avg] * 0.05 +	[negate avg] * -0.05 +	Negations
[quant avg] * -0.04 +	[quant avg] * 0.04 +	Quantifiers
[swear avg] * 2.61 +	[swear avg] * -2.61 +	Swear Words

[affect avg] * 0.05 +	[affect avg] * -0.05 +	Affect words
[cogmech avg] * 0.03 +	[cogmech avg] * -0.03 +	Cognitive
[body avg] * 0.19 +	[body avg] * -0.19 +	Biological processes
[assent avg] * 0.67 +	[assent avg] * -0.67 +	Informal Speech
[Period avg] * -0.03 +	[Period avg] * 0.03 +	Period
[Colon avg] * -0.07 +	[Colon avg] * 0.07 +	Colon
[QMark avg] * 0	[QMark avg] * -0	Question marks

Several classification models have been trained and the model fit was evaluated for each method. A comparison among the evaluated classification methods is presented in Table 7.

Table 7: A comparison among the evaluated classification methods

	Simple Logistic	Logistic Regression	RandomTree	RandomForest
Correctly Classified Instances	396 86.2745 %	393 85.6209 %	362 78.8671 %	395 86.0566 %
Incorrectly Classified Instances	63 13.7255 %	66 14.3791 %	97 21.1329 %	64 13.9434 %
Kappa statistic	0.5174	0.5015	0.3092	0.4724
Mean absolute error	0.1958	0.1926	0.2113	0.2124
Root mean squared error	0.3201	0.3278	0.4597	0.3236
Relative absolute error	62.9859 %	61.9561 %	67.983 %	68.3124 %
Root relative squared error	81.3155 %	83.2575 %	116.7724 %	82.2074 %
Total Number of Instances	459	459	459	459

Among the classification methods used to train the model, SimpleLogistic works best. The model has the accuracy of 86.27%.

The detailed accuracy of the model and the confusion matrix is presented in Table 8.

Table 8: Confusion Matrix and the Detailed Accuracy of user categorization by class

```
  a   b   <-- classified as
346  25 |   a = IND
 41  47 |   b = PRO
```

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.933	0.466	0.894	0.933	0.913	0.856	IND
	0.534	0.067	0.653	0.534	0.587	0.856	MM
Weighted Avg.	0.856	0.390	0.848	0.856	0.851	0.856	

The ROC graph for both Individual and Professional roles prediction are shown in Figure 15.

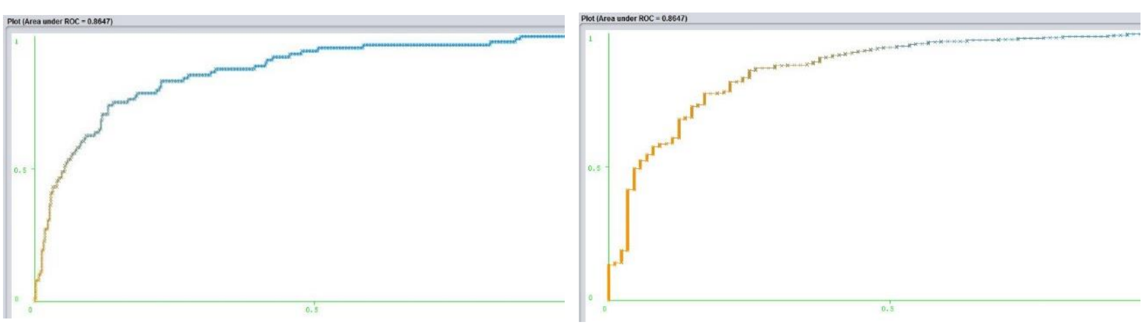
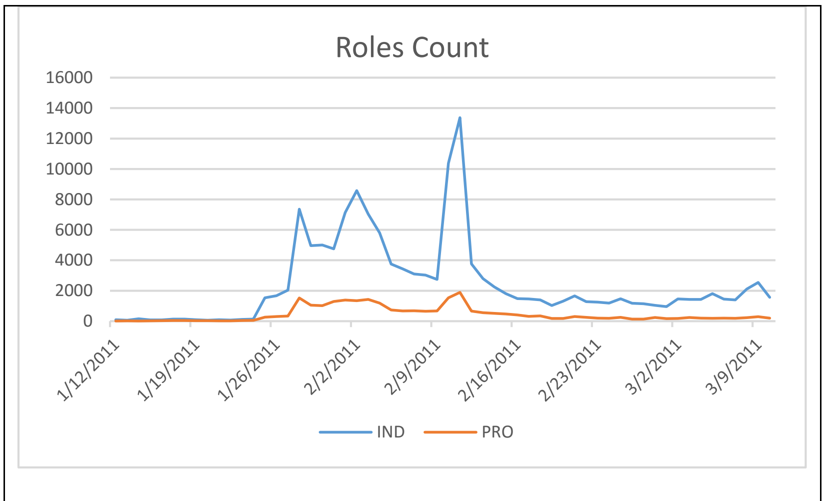


Figure 15: ROC graph for Individual (right) and Professional (left) roles prediction

Prediction Result:

After removing suspended users ids, total of 8,411 distinct users (who have posted at least one original Tweet) were identified and the trained model was applied to the data to predict the roles of unlabeled users. The prediction identified 7,321 users as 'Individuals' and the remaining 1090 users as 'Professionals'.

Figure 16 shows the number of each role per day and per stage. As we see in these diagrams, the number of individuals is always more than the number of professionals at each time frame. The frequency measures are also calculated and shown after stage 4 to reflect the aftermath of the event. Thus, I added another stage to the diagrams as stage 5 (after February 11, 2011).



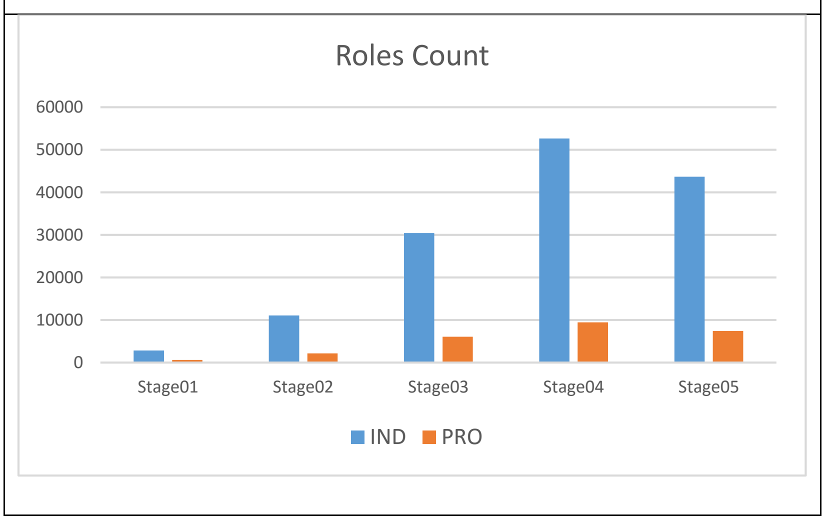
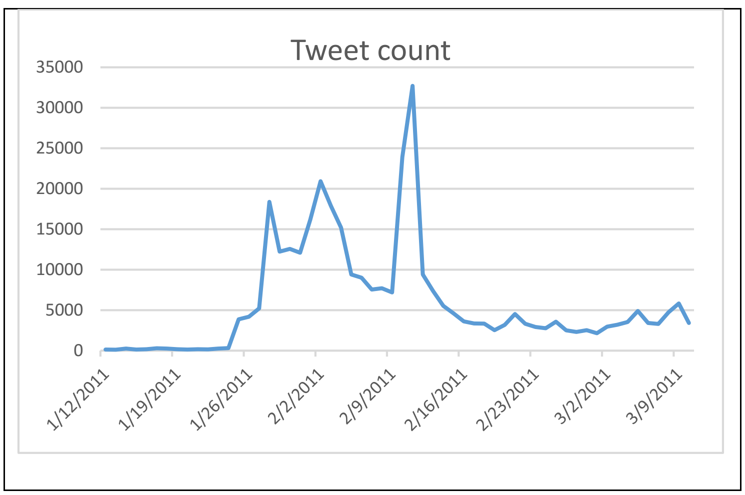


Figure 16: Number of roles over time shown on a daily basis (top) and a stage basis (down)

A comparison of behavioral regularities between the two roles:

Figure 17 shows the number of original Tweets posted over time (for each day (left) and each stage (right)). The number of Tweets increases through each stage, decreases after stage 4 when no triggering event is present anymore. The daily based tweet count graph shows a detailed frequency of Tweets per day. The Tweet counts increases significantly on the critical days of the movement (January 25, January 28, February 2, and February 11).



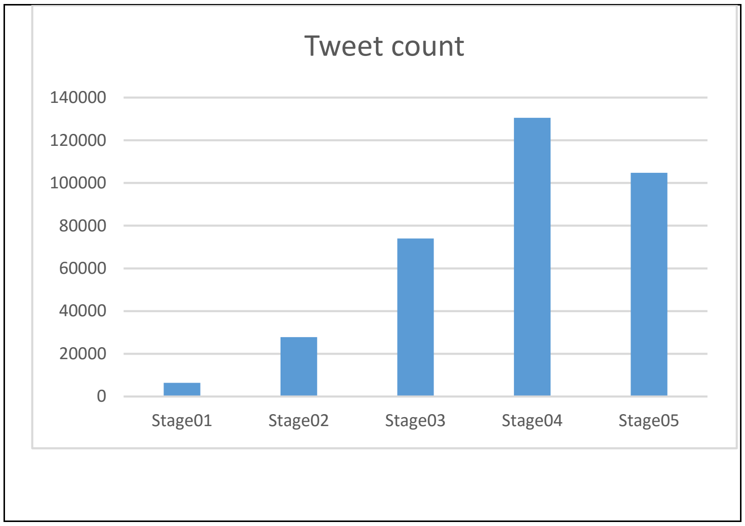


Figure 17: Number of original Tweets over time

After identification of each user's role, a comparison graph based on the aggregation of variables for each role is created. Each graph serves an exploratory purpose to identify the differences in the usage of a specific Tweet feature by the two different roles. The results indicate that the two roles act differently in the usage of URL and linguistic features in their tweets. For instance, Figure 18 shows that the 'professional' users tend to practice the URL inclusion behavior more regularly than the 'individual' users in all stages. This is a testament to the fact that 'professional' users are concerned more about associating their message to an external resource, which potentially increases the perceived reliability of the tweets. Similarly, the graph for the usage of 'Exclusive' words shows that individuals use more exclusive words than professionals over time (Figure 18).

Tausczik and Pennebaker (2010) state in their paper that exclusive words are indicators of complexity of the speech. This complexity is less evident in false statement because of the high cognitive load required to convince someone of the validity of the false statement. However, in this case, the usage of higher rate of exclusive words among individual users does not indicate that the professional users use less trustworthy statements; it simply indicates that individual users incorporate more complexity in their communication with each other. They use exclusive words particularly to make distinction and decide what is inside a category and what is not.

In the study conducted by Gunsch and colleagues, it was evident that the usage of past tense verbs was associated with negative political ads (Gunsch, Brownlow, Haynes, & Mabe, 2000). As Figure 20 shows, the average usage of 'past' words among individual users is higher than that of professional users. This trend is similar for the usage of negative emotions as well (Figure 21).

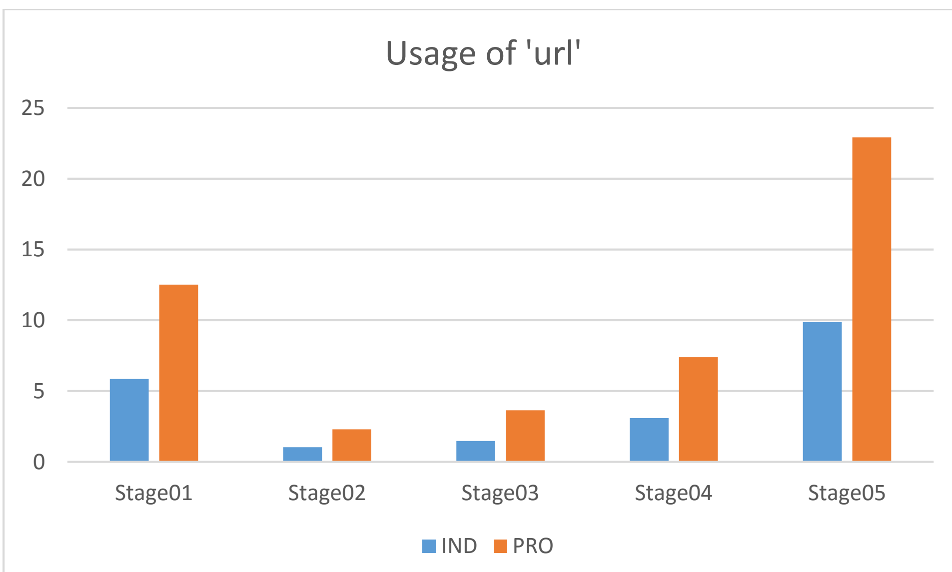


Figure 18: Usage of URL in 'individual' and 'professional' tweets over time.

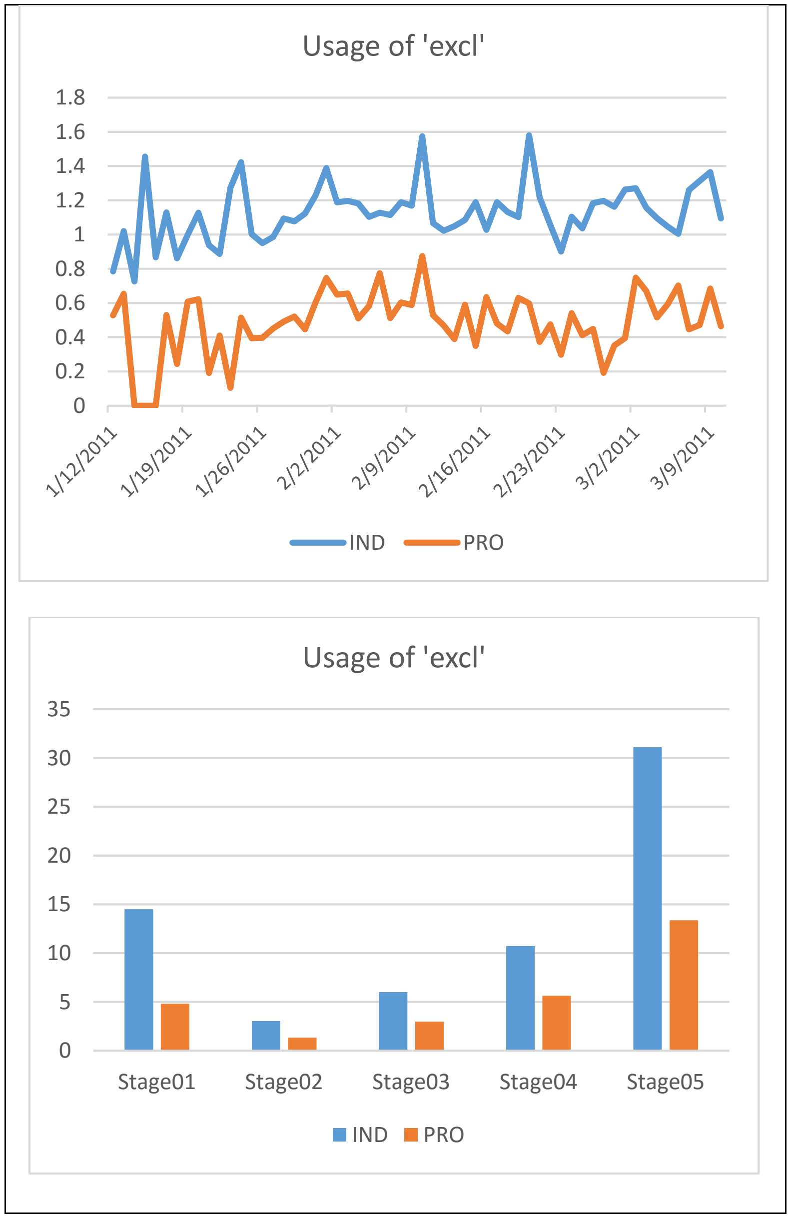


Figure 19: The usage of exclusive words among Individual and Professional roles

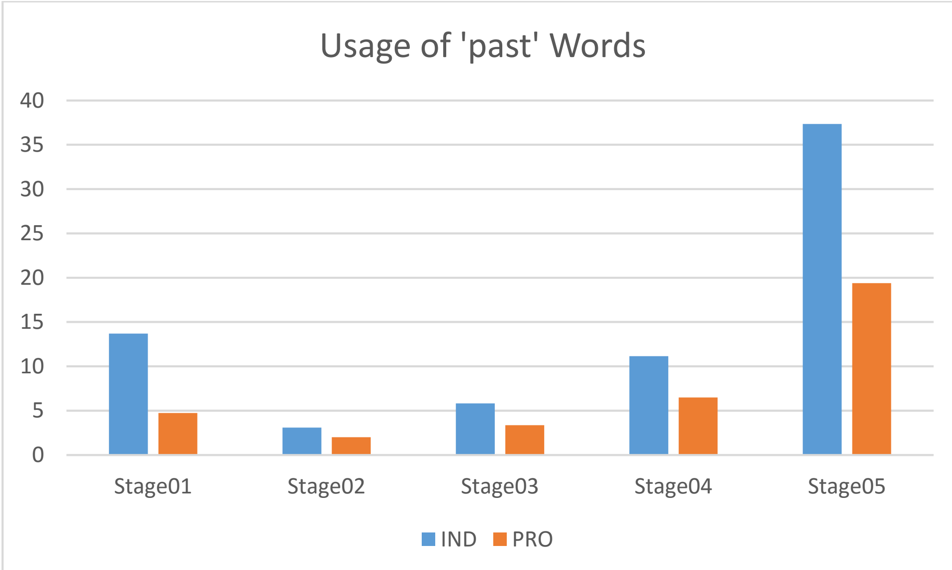


Figure 20: Usage of 'past' words among individual and professional users

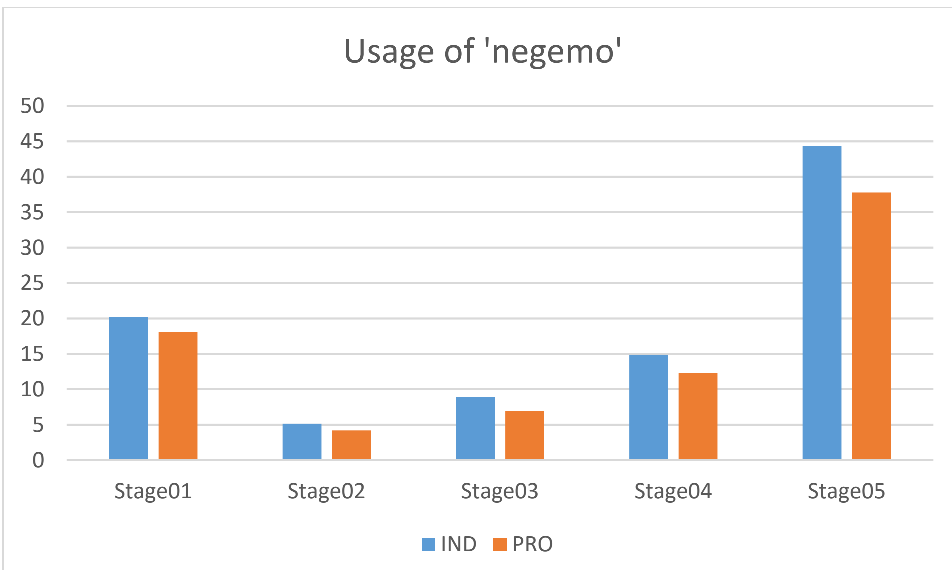
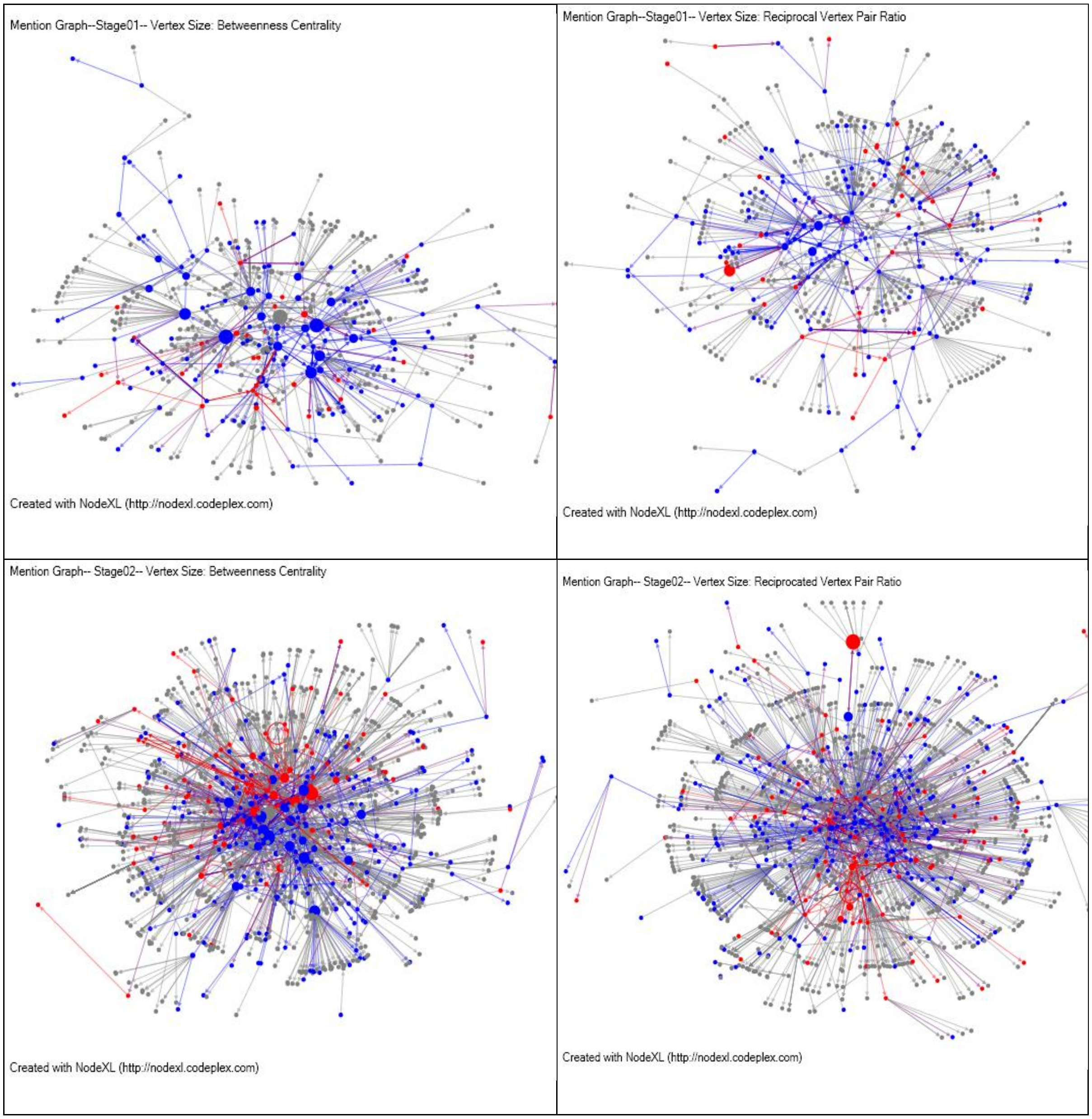


Figure 21: Usage of negative emotions among individual and professional users

Reciprocity Pattern:

Figure 22 shows the mention graphs of the four critical stages. The blue circles represent the individual users and the red circles represent the professional users. In the left side graphs, the size of a node is proportional to the node's betweenness centrality value. The blue edges represent a Tweets mention between two individuals and the red edges represent a Tweet mention between two professionals. For some users, the role could not be identified, because those users were only mentioned by other users and an original Tweet could not be found in the collected data set. I showed those nodes with gray color. Similarly the edges corresponding to any of these nodes are shown as gray. For the simplicity of the visualization I ignored the color of the gray edges in stage 4 and stage 5 as the graphs become denser.

In the right side graphs, the size of a node is proportional to the node's reciprocated vertex pair ratio. The reciprocated vertex pair in this case is a measure that reflects how frequently a user gets reciprocated when making Tweet mentions to other users. The betweenness centrality as explained earlier shows how frequently a user is positioned in a path between two other users. In this case the users who make or receive mentions to/from the users that are not connected otherwise have high betweenness centrality. In Figure 22, at each stage we see that the density of nodes with high betweenness centrality is higher than the density of nodes with higher vertex pair reciprocity. This tells us that making/receiving Tweets mentions or a central position in the mention network does not guarantee a reciprocal action. The reciprocal mention is more dependent on the specific role a user has in the network. For example, it is evident from the network graph in Figure 22 that the professional roles tend to receive more reciprocal mentions when making a Tweet mention. The difference in the density of vertex pair reciprocity and betweenness centrality are easier to grasp from the networks of the first two stages as the networks are less dense. To illustrate this concept in another way, histograms of betweenness centrality, vertex pair reciprocity, and out-degree per role are provided for each stage in Figure 23.



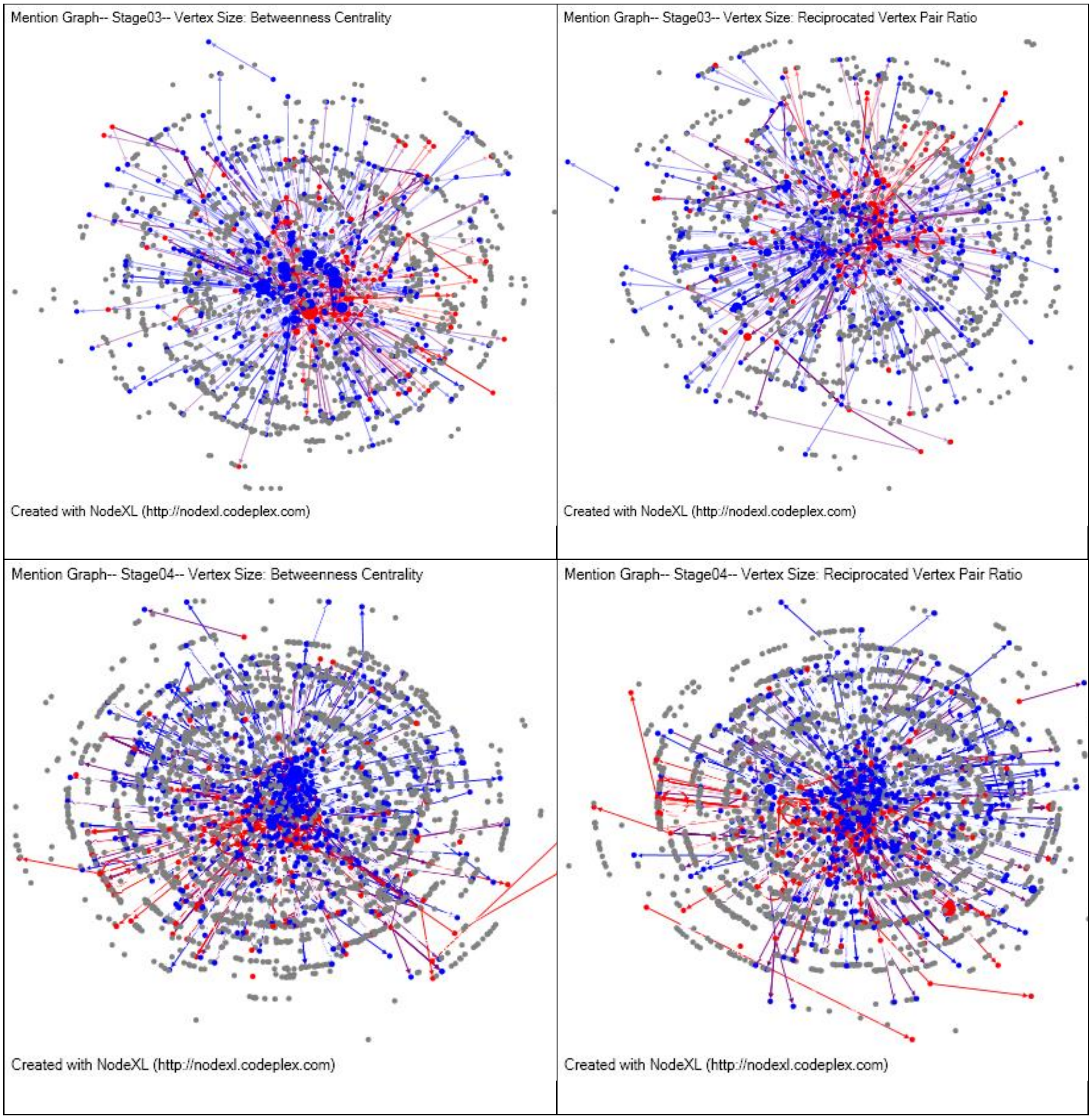


Figure 22: Mention Graphs of the four critical Stages.

By looking at the mention graphs we might be able to compare the density of blue edges (mentions between individuals) and red edges (mentions between professionals). This comparison is also represented in Figure 24. As the histograms show, the rate of mentions among individuals is higher than that of professionals. But we see in Figure 23 that the reciprocity rate is higher in professional users. In other words, while professionals practice less mentions than the individuals, they tend to reciprocate this action more than the individuals users.

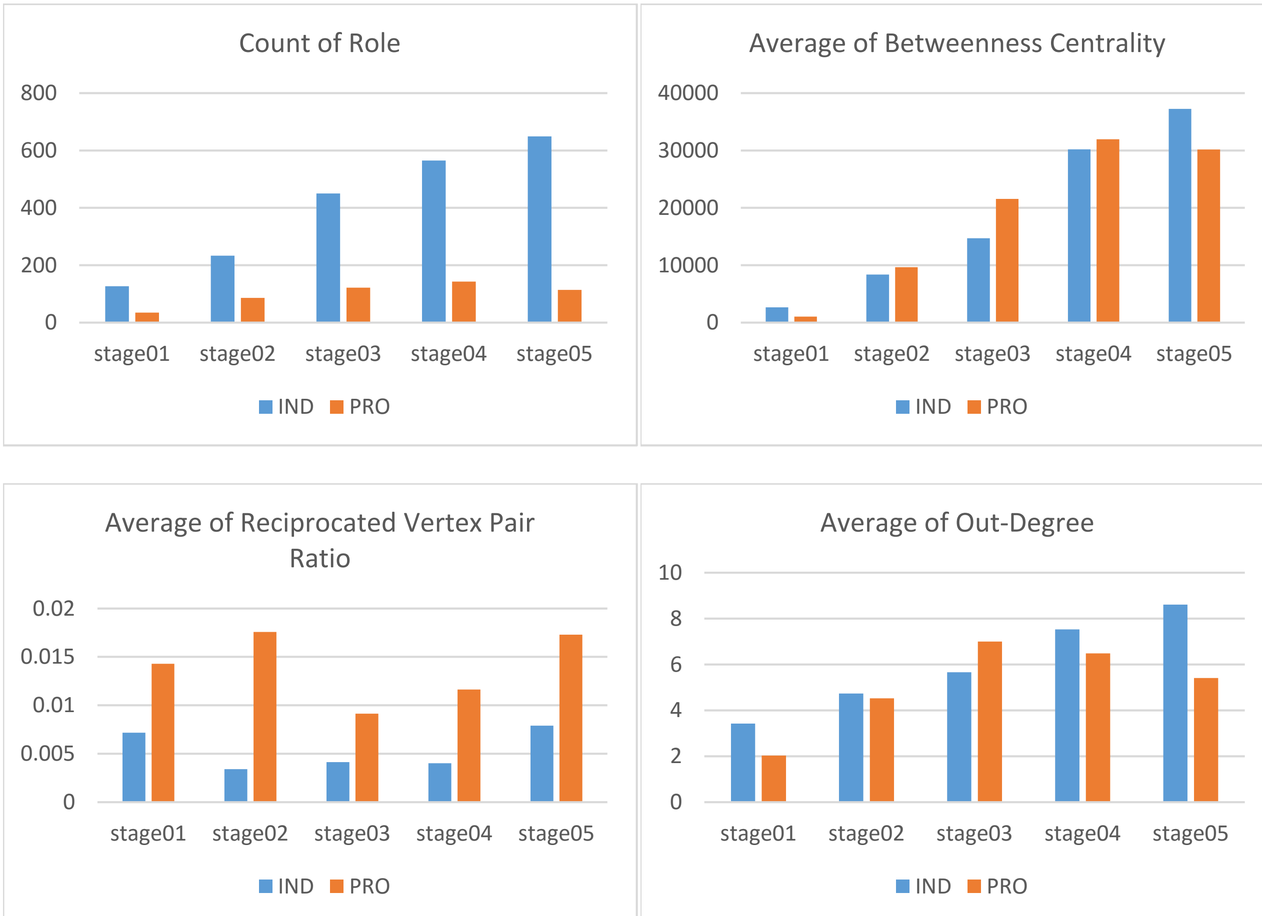


Figure 23: Average of reciprocated vertex pair vs. average of out-degree per role over time

Another insight on the comparison of different roles is understandable from Figure 24. The right side histogram compares the frequency of between-role and in-role mentions. There are of course Tweets mentions that are made between users from two different roles. But at each stage of time the in-role mention rate dominates the between-role mention rate.

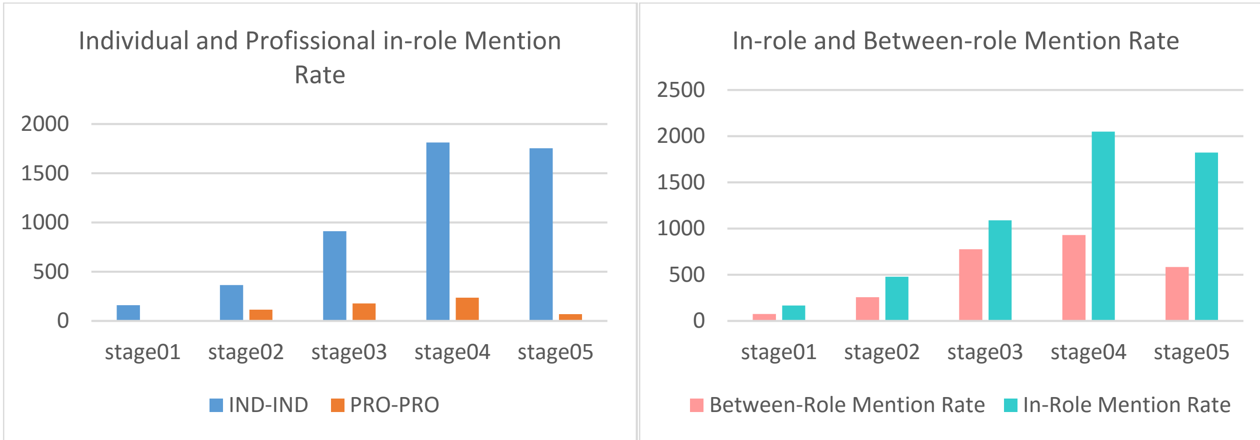


Figure 24: The comparison of in-role and between-role mention rate over time

The results of this section confirm the differences in the behavioral patterns of the two main roles in the Egyptian 2011 Twitter dataset: individuals and professionals. We see more similarities among the users of the same role while collectively they are acting differently than other roles. A potential reason for this observation can be explained by the existence of imitation condition, which leads to consistencies in the differentiated behaviors in the two roles. As mentioned before, norm is about how each social role is supposed to behave rather than how the society should behave as a whole in each situation. The differentiated behavioral pattern in the two main roles and the existence of several roles with a few keynoters in each role are indicators of the existence of an emergent norm caused by the imitation effect.

In the next section, I analyze the communication structure and its effect on the behavioral regularities formation.

Communication Structure:

The communication structure of the network is measured by three network centrality indexes.

The three measures include betweenness centrality, closeness centrality and degree centrality. As the initial analysis step, the tweet features were investigated for correlation with the centrality measures. Among all three centrality measures, the degree centrality has the most correlations with the tweet features. Appendix I shows the correlation of tweet features with the degree centrality of network over the time period of this study. The features also have correlations with each other.

The results show that there are some features that are intensified when the degree centrality increases. This is an identifier of an intensified practice of a particular behavioral regularity as a result of increased degree centrality in the network. A factor analysis using PCA method was applied to the tweet features. Two main components were identified as a result of the analysis. The degree centrality was later served as an independent variable in a regression model to estimate the two factors. The results of the factor analysis are shown in Table 9. Six variables are loading into the first component. These variables include urlCnt, Dic, funct, negate, cogmech, and Colon. According to the description of linguistic features provided by LIWC website[9], these variables are classified into the main categories of function words, language metrics and cognitive processes. I label this component as 'Cognitive & Function'. The second component includes Qmark and AllPct variables. These features are categorized as punctuation variable. Thus, I label this component as 'Punctuations'. The regression results for the 'Cognitive & Function' component including the summary of the model and the ANOVA and coefficients table are represented in Table 10 and Table 11 along with the histogram

[9] http://liwc.wpengine.com/wp-content/uploads/2015/11/LIWC2015_LanguageManual.pdf

and P-P plot of the residuals in Figure 25. The results of the regression for the ‘Punctuations’ component are presented in Table 12, Table 13, and Figure 26.

Table 9: The result of the factor analysis and regression analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.855
Bartlett's Test of Sphericity	Approx. Chi-Square	791.100
	Df	66
	Sig.	.000

Rotated Component Matrix[a]

	1	2
Dic avg	.723	
funct avg	.785	
negate avg	.709	
cogmech avg	.746	
Colon avg	-.844	
QMark avg		-.880
AllPct avg		-.970
% of Variance	87.332	7.027
Cumulative %	87.332	94.359

a. Factor loadings less than .70 have not been printed

Table 10: Regression analysis results for Cognitive & Function

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.664[a]	.441	.431	.75766895

a. Predictors: (Constant), Average of degree

b. Dependent Variable: REGR factor score 1 for analysis 2

Table 11: ANOVA and coefficients table for the regression analysis for Cognitive & Function

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.318	1	25.318	44.104	.000[b]
	Residual	32.147	56	.574		
	Total	57.466	57			

a. Dependent Variable: REGR factor score 1 for analysis 2

b. Predictors: (Constant), Average of degree

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.080	.327		-6.364	.000
	Average of degree	.979	.147	.664	6.641	.000

a. Dependent Variable: REGR factor score 1 for analysis 2

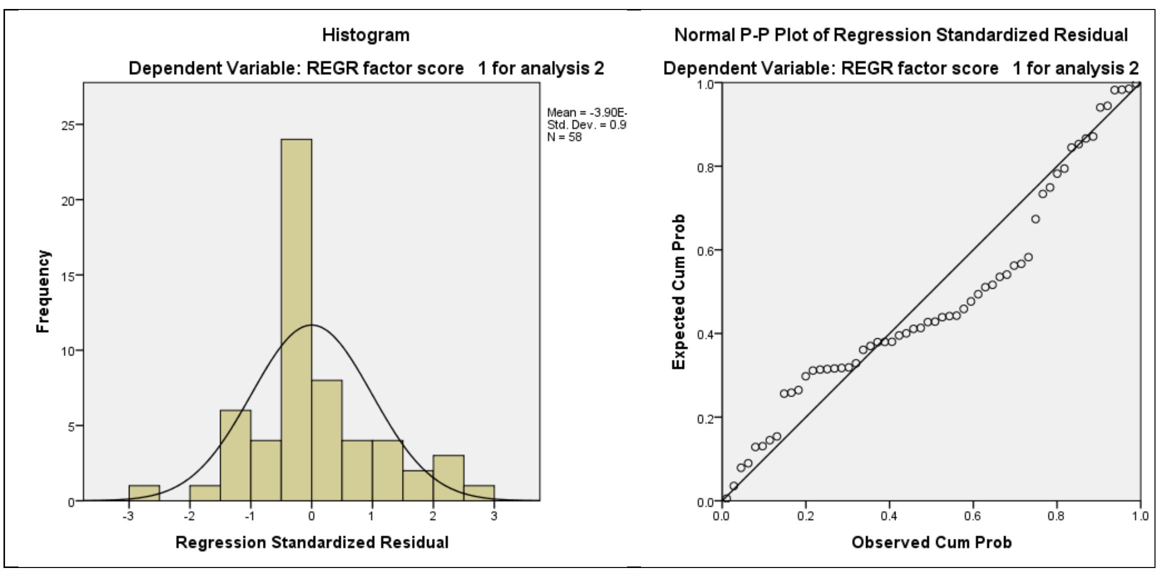


Figure 25: Histogram and P-P plot of regression standardized residual for 'Cognitive & Function'

According the ANOVA table presented in Table 11, the regression model for Cognitive & Function is significant (p-value=0.000, alpha=0.05). R=.664 and R-square=.441 mean that 66 percent of the variance is explained by this model. The result of the regression for the component is more promising with R=.776 and R Square=.602 (Table 12), 77 percent of the variance of ‘Punctuations’ is explained by the model. Figure 25 and Figure 26 show the histogram of the standardized residuals in both cases the residuals seem to have a normal distribution, which confirms the validity of the model. The results of the regression for the two components are thus satisfactory. The results show that the degree centrality of the network, which is an identifier of the network structure, is a predictor of behavioral regularities in terms of frequent linguistic features used in Tweets.

Table 12: Regression analysis results for ‘Punctuations’ (RT Degree)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.776[a]	.602	.595	.63870962

a. Predictors: (Constant), Average of degree

b. Dependent Variable: REGR factor score 2 for analysis 2

Table 13: ANOVA and coefficients table for the regression analysis for ‘Punctuations’ (RT Degree)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.600	1	34.600	84.813	.000[b]
	Residual	22.845	56	.408		
	Total	57.445	57			

a. Dependent Variable: REGR factor score 2 for analysis 2

b. Predictors: (Constant), Average of degree

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.430	.276		-8.819	.000
	Average of degree	1.144	.124	.776	9.209	.000

a. Dependent Variable: REGR factor score 2 for analysis 2

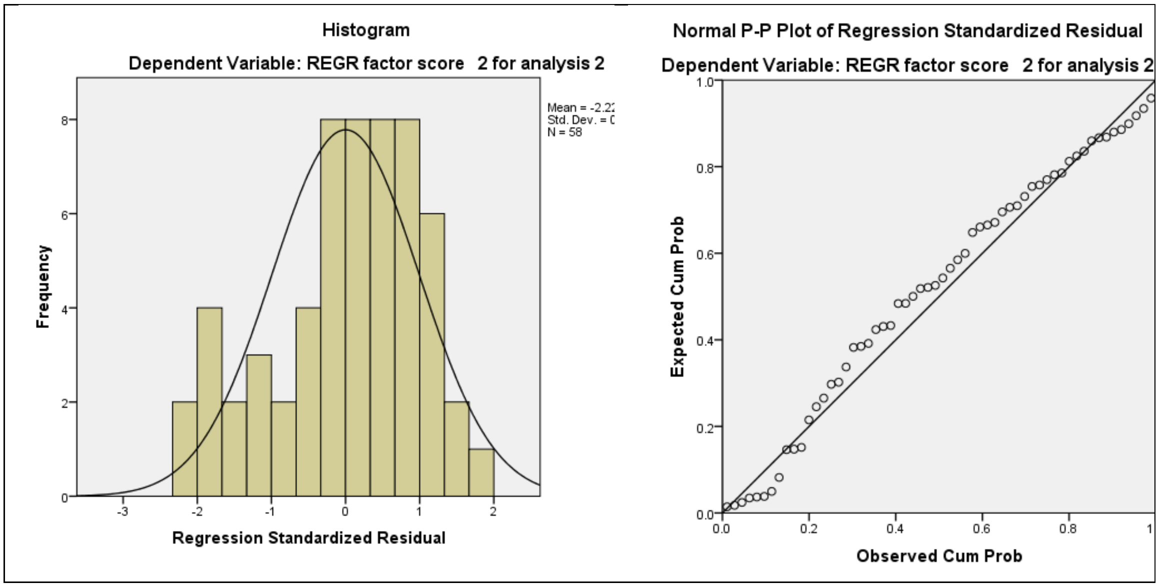


Figure 26: Histogram and P-P plot of regression standardized residual for 'Punctuations' (RT degree)

Cohesion:

From the Retweet graph, which is constructed for each day of the movement, a cohesion measure is calculated. As explained in the research method section, cohesion can be measured by calculating the ratio of the existing ties in the graph to the total number of possible ties in the graph. In the Retweet graph, cohesion is measured by dividing the Retweet counts of each day by the count of potential Retweets that could be made (according to the number of users in each day). The following equation shows the cohesion at time *t* (C_t) is measured:

$$C_t = \frac{RT_t}{N_t*(N_t-1)}$$

Where RT_t is the count of Retweets at time *t*, and N_t is the number of users who made/received at least one Retweet mention at time *t*.

Figure 277 shows the pattern of Retweet count and the user count over the lifetime of the movement.

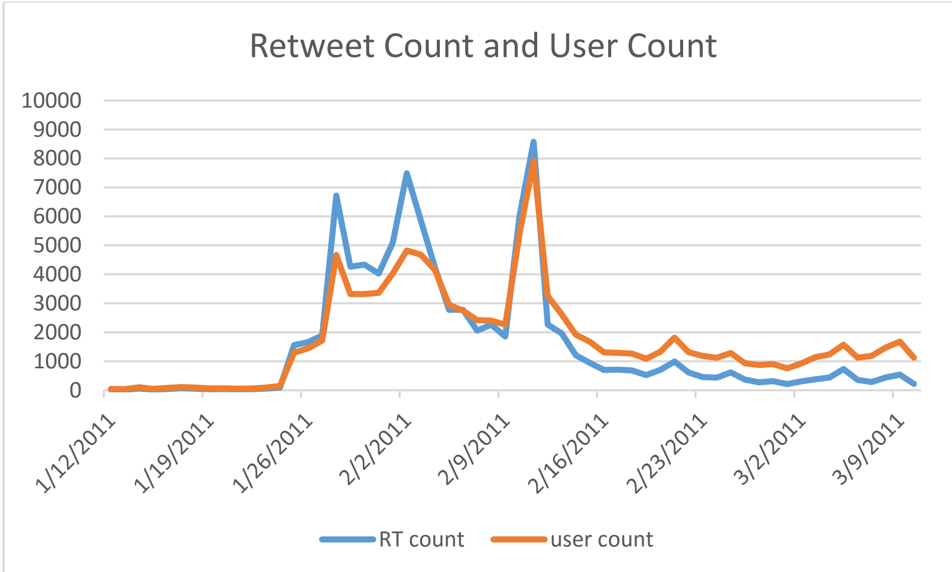


Figure 27: Patterns of Retweet count and the user count over time

A linear regression analysis is performed on the components extracted from the correlation analysis. This time, the cohesion of the Retweet network is considered as the predicting variable, and the regression analysis is performed on both components. The results of the regression analysis for 'Cognitive & Function' is presented in Table 14, Table 15. Figure 29: Histogram and P-P plot of regression standardized residual for 'Punctuations' (cohesion)

8 shows the histogram and Q-Q plot of the standardized residuals. The model is significant with R=.449 and R-Square of .202. For 'Punctuations', the results are more promising as shown in Table 16 and Table 17. The R-Square for 'Punctuations' is equal to .605, which means that about 60 percent of the variance in 'Punctuations', is explained by this model. However, if we look at the coefficient of the independent variable in Table 15 and Table 17, we notice that the effect is negative.

Table 14: Regression analysis results for 'Cogntive & Function' (cohesion)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.449[a]	.202	.187	.90514125

a. Predictors: (Constant), cohesion

b. Dependent Variable: REGR factor score 1 for analysis 2

Table 15: ANOVA and coefficients table for the regression analysis for 'Cogntive & Function' (cohesion)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.586	1	11.586	14.142	.000[b]
	Residual	45.880	56	.819		
	Total	57.466	57			

a. Dependent Variable: REGR factor score 1 for analysis 2

b. Predictors: (Constant), cohesion

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.247	.137		1.799	.077
	cohesion	-111.252	29.584	-.449	-3.761	.000

a. Dependent Variable: REGR factor score 1 for analysis 2

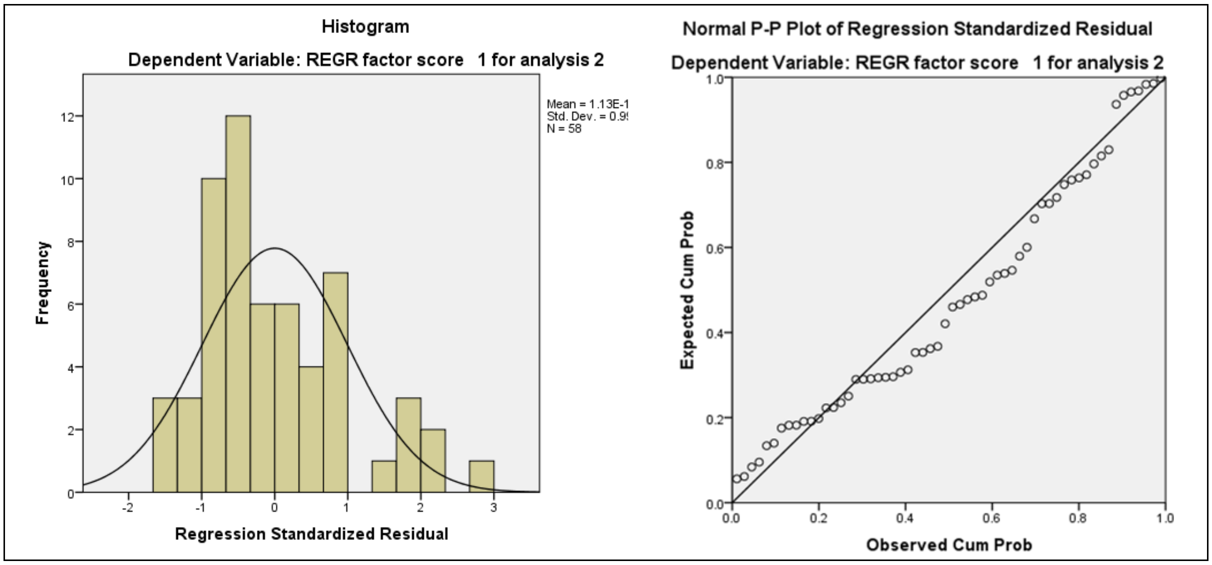


Figure 28: Histogram and P-P plot of regression standardized residual for 'Cogntive & Function' (cohesion)

Table 16: Regression analysis results for 'Punctuations' (cohesion)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.778[a]	.605	.598	.63659094

a. Predictors: (Constant), cohesion

b. Dependent Variable: REGR factor score 2 for analysis 2

Table 17: ANOVA and coefficients table for the regression analysis for 'Punctuations' (cohesion)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.751	1	34.751	85.752	.000[b]
	Residual	22.694	56	.405		
	Total	57.445	57			

a. Dependent Variable: REGR factor score 2 for analysis 2

b. Predictors: (Constant), cohesion

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.437	.097		4.521	.000
	cohesion	-192.672	20.806	-.778	-9.260	.000

a. Dependent Variable: REGR factor score 2 for analysis 2

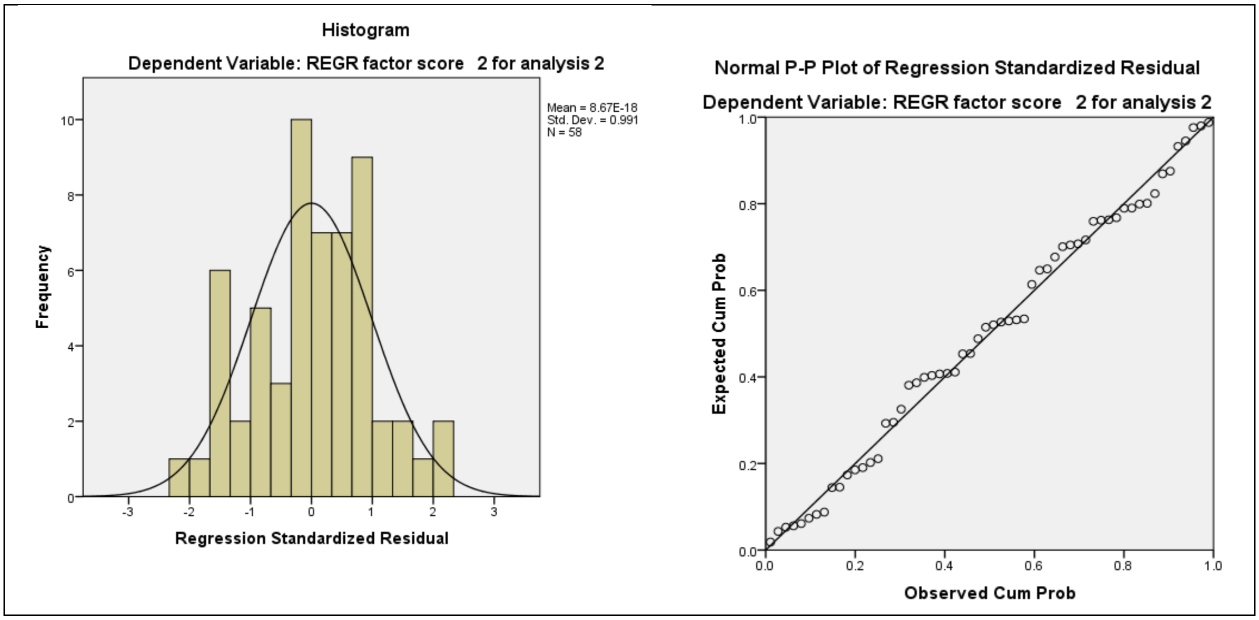


Figure 29: Histogram and P-P plot of regression standardized residual for 'Punctuations' (cohesion)

It is worth to mention that the network graph constructed by the mention interactions was not cohesive. Table 18 shows the descriptive statistics of the cohesion measure over the period of 58 days. The average value of the cohesion is .0023 with the maximum of .02 which indicates that the network is not cohesive enough. One explanation for this observation is that due to the lack of the presence of the independent variable, the results are not telling us much about the potential effect of network cohesion on the formation of behavioral regularities even though the regression model is significant.

Table 18: Descriptive statistics of the Cohesion measure

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
cohesion	58	.02	.00	.02	.0023	.00405	.000
Valid N (listwise)	58						

6. Conclusion

This dissertation addressed our research question on the dynamics of norm formation in online crowds. According to the results of this study, several implications can be derived to explain the dynamics of norm formation in this particular setting. First it is implied that a norm is formed through the imitation between individuals of a social role in the crowd. Second, a norm is affected by the fluctuations in the social structure measures such as the distribution of aggregated users' centrality measures over time. Third, the crowd behavior is not affected by a single unified norm. Rather, different behavioral practices can be observed depending on different social roles. Finally, according to the results, a norm can be defined from a different perspective. A consistent difference between behavioral regularities in different social roles over time can be the identification of norm.

In summary, the results of this study confirm the existence of behavioral regularities as the first step of norm formation in a particular case of an online crowd, the Egyptian revolution in 2011. This study based its theoretical foundation of the evolution of institutional norms introduced by Opp (1982) in an effort to investigate the phenomenon in the context of online societies. The effect of online social media technology in specific events such as a social movement is claimed to exceed the traditional communication tools both in speed and scale (Oh, Eom, & Rao, 2015; Oh, Tahmasbi, Rao, & Vreede, 2012). The results of this study show that although the online crowd in the Egyptian 2011 movement does not constitute an institutional structure, they still show evidences of norm emergence through communications. A structure emerges from the crowd though technology enabled communications and interactions that determine the extent of behavioral regularities in terms of linguistic features or technology-specific features such as URL inclusion or reciprocity. The behavioral regularities formation however is not simply identified by investigating the behavioral patterns of the crowd as a whole. A macro-level analysis may give us an overall view of the crowd. But a single norm or a specific trend may not be simply evident at this level. Theories of Emergent Norms point out the different types of crowd and the processes under which norms emerge. However, they do not specifically recognize the different social roles in the crowd and their unique patterns of behavior compared to other roles. The crowd does not necessarily behave in unity as a whole entity. But what defines norm in this context is the consistency of behavioral pattern differences among different roles in the same crowd. This study puts its emphasis on the application of the theories of emergent norm formation (ENT) on the contemporary online social media by incorporating a micro-level analysis. The main emphasis of this study is to fill the gap that is merely discussed in the ENT. This study suggests a different perspective on how the norm is defined. Studying the behavioral regularities in a macro view is useful to give us an overview of what is going on in the crowd. However, a consistent trend in the behavior might not necessarily be identifiable. But a trend may be identifiable if different roles are accounted for and are compared in terms of the behavioral regularities they follow. What defines the norm in this context is the differential behavioral patterns evident between different roles. In this study I have identified several roles and for the simplicity of the representation of the results, I later combined several roles into one overall category and ended up with two roles of ‘individual’ and ‘professional’. Then the behavioral regularities in terms of linguistic characteristics of the Tweets are compared between two roles over time. Also, the influential parts of each group and the distribution of influence over time is analyzed and compared over time. The results show that the two roles act differently and although the behavioral trend fluctuates over time in each role, but the difference between the two roles are consistent over time.

6.1. Challenges

There are some challenges and limitations in our study. First, external influential factors such as those in physical environments will have effects on network influence. These factors are difficult to control. Media is difficult to be detached from the online network, especially when the Social Media accounts of the news media are core for online information flow. Second, only reposting content from someone else or mentioning others in a Tweet may not fully reflect the influence. And analysis of click-through data may help resolve this limitation. Another limitation of this study is that the role identification is studies in a high level and accounts for two roles. Future studies may include more detailed analysis of several roles as we had identified initially.

The sample size of the collected dataset may not be sufficient and complete. Twitter API faces limitations in terms of the number of Tweets it can collect in ach specific period of time according to the restrictions set by Twitter policy. A complete dataset may help increase the accuracy of the results or reveal more information about the structure and cohesion of the network.

Finally, this study is limited to a specific case of an online crowd using a specific social media technology, and the results may not be generalized to other contexts. To confirm the results using the same approach for other contexts, future studies are needed to investigate the method for other types of datasets.

6.2. Outcome and Contribution

The idea of this study stems from a theoretical foundation from Emergent Norm Theories and the model of norm formation introduced by Opp (1982). Understanding the nature of human behavior in sociotechnical systems gives us insights on how a collectivity of people acts spontaneously. This study contributes to the theory by applying the norm formation model (which was originally introduced for traditional social settings) to the contemporary settings of online crowds. The results show that although there are fundamental differences between organizational groups and spontaneous crowds, the model works for the online crowd as well. However, the constructs in the original model are adopted to meet the specifications of the online settings. Thus, another contribution is the introduction of new methods for measuring the conventional constructs in the Opp's norm formation model in the context of online crowds.

Moreover, this study provides a guideline for a data-driven quantitative approach to investigate the norm formation dynamics in Twitter. The methodology used in this dissertation is shown to provide insightful results and can be used in future studies in the similar area. The challenges that have been faced regarding the data collection and analysis of such dataset are also pointed out in this dissertation, which provides future directions to the researchers. The steps of the methodology including data collection and pre-processing and the tools that are used in the analysis are clearly detailed in Appendix II.

Moreover, other benefits from this study relate to organizations that do viral marketing in social media, and need to know how to target users which lead them to an efficient and faster spread of their intended word-of-mouth. If an agency seeks to establish a norm, they need to know where to start and which group to target. In other words, they need to target the users who are influential enough to establish a particular norm of interest. While this study acknowledges the contribution of the emergent norm theories to the current context, it suggests the recognition of different social roles in the crowd and use of a micro-level approach to investigate the formation of behavioral regularities in each category. This approach resulted in the introduction of a new perspective on the emergent norm as suggested by the ENT. The new definition thus emphasizes on the different behavioral regularities according to the social roles rather than the behavior regularities of the entire crowd as a single unit.

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Appendix I: Correlation of tweet features with the degree centrality of network over the time

		Average of degree
Sixltr avg	Pearson Correlation	-.618**
	Sig. (2-tailed)	.000
	N	58
Dic avg	Pearson Correlation	.442**
	Sig. (2-tailed)	.001
	N	58
funct avg	Pearson Correlation	.582**
	Sig. (2-tailed)	.000
	N	58
pronoun avg	Pearson Correlation	.416**
	Sig. (2-tailed)	.001
	N	58
ppron avg	Pearson Correlation	.349**
	Sig. (2-tailed)	.007
	N	58
we avg	Pearson Correlation	.429**
	Sig. (2-tailed)	.001
	N	58
they avg	Pearson Correlation	.358**
	Sig. (2-tailed)	.006
	N	58
ipron avg	Pearson Correlation	.370**
	Sig. (2-tailed)	.004
	N	58

verb avg	Pearson Correlation	.790**
	Sig. (2-tailed)	.000
	N	58
auxverb avg	Pearson Correlation	.650**
	Sig. (2-tailed)	.000
	N	58
past avg	Pearson Correlation	.313*
	Sig. (2-tailed)	.017
	N	58
present avg	Pearson Correlation	.746**
	Sig. (2-tailed)	.000
	N	58
future avg	Pearson Correlation	.399**
	Sig. (2-tailed)	.002
	N	58
adverb avg	Pearson Correlation	.602**
	Sig. (2-tailed)	.000
	N	58
negate avg	Pearson Correlation	.532**
	Sig. (2-tailed)	.000
	N	58
quant avg	Pearson Correlation	.281*
	Sig. (2-tailed)	.033
	N	58
swear avg	Pearson Correlation	.498**
	Sig. (2-tailed)	.000
	N	58
social avg	Pearson Correlation	.475**

	Sig. (2-tailed)	.000
	N	58
affect avg	Pearson Correlation	.342**
	Sig. (2-tailed)	.009
	N	58
negemo avg	Pearson Correlation	.262*
	Sig. (2-tailed)	.047
	N	58
cogmech avg	Pearson Correlation	.443**
	Sig. (2-tailed)	.001
	N	58
discrep avg	Pearson Correlation	.307*
	Sig. (2-tailed)	.019
	N	58
tentat avg	Pearson Correlation	.320*
	Sig. (2-tailed)	.014
	N	58
certain avg	Pearson Correlation	.314*
	Sig. (2-tailed)	.016
	N	58
inhib avg	Pearson Correlation	.316*
	Sig. (2-tailed)	.016
	N	58
excl avg	Pearson Correlation	.479**
	Sig. (2-tailed)	.000
	N	58
percept avg	Pearson Correlation	.420**
	Sig. (2-tailed)	.001

	N	58
see avg	Pearson Correlation	.663**
	Sig. (2-tailed)	.000
	N	58
hear avg	Pearson Correlation	.304*
	Sig. (2-tailed)	.020
	N	58
bio avg	Pearson Correlation	-.430**
	Sig. (2-tailed)	.001
	N	58
health avg	Pearson Correlation	-.328*
	Sig. (2-tailed)	.012
	N	58
space avg	Pearson Correlation	.276*
	Sig. (2-tailed)	.036
	N	58
time avg	Pearson Correlation	-.270*
	Sig. (2-tailed)	.040
	N	58
leisure avg	Pearson Correlation	-.524**
	Sig. (2-tailed)	.000
	N	58
money avg	Pearson Correlation	-.498**
	Sig. (2-tailed)	.000
	N	58
relig avg	Pearson Correlation	-.368**
	Sig. (2-tailed)	.005
	N	58

death avg	Pearson Correlation	-.305*
	Sig. (2-tailed)	.020
	N	58
assent avg	Pearson Correlation	-.455**
	Sig. (2-tailed)	.000
	N	58
Comma avg	Pearson Correlation	-.419**
	Sig. (2-tailed)	.001
	N	58
Colon avg	Pearson Correlation	-.617**
	Sig. (2-tailed)	.000
	N	58
Quote avg	Pearson Correlation	.384**
	Sig. (2-tailed)	.003
	N	58
OtherP avg	Pearson Correlation	-.555**
	Sig. (2-tailed)	.000
	N	58
AllPct avg	Pearson Correlation	-.335*
	Sig. (2-tailed)	.010
	N	58
urlCnt avg	Pearson Correlation	-.623**
	Sig. (2-tailed)	.000
	N	58

Appendix II: Methodological steps

Data Collection:

Twitter API: Twitter API is publicly provided by Twitter. It is an interface to the Twitter data source, which can be accessed with a server side scripting language like Python, PHP, or Ruby. The programmer can identify the search keywords in the program and receive the Tweet results in a program readable format. Also, a programmer can create a user interface, which takes search keywords as a user input and passes it to the Twitter API and converts the program readable results to a human-readable text file (plain text, csv, etc.). In this study a graphical user interface was used and the search keywords were provided as the user input. The results were stored in plain text format. A pre-processing step was needed to transform the textual data into a relational database format.

The Twitter data policy imposes limitations in terms of the amount of information that can be downloaded in a specific amount of time. Since the Tweets were collected at the time that the movement was happening, data collection needed to be done in several rounds per day to ensure that the maximum amount of Tweets containing the search keywords was captured. The frequent collection of data also resulted in some duplicate Tweets that were collected more than once. Yet there still is a possibility that some Tweets were missed because of the service interruption. Thus the pre-processing step needed an extra step of duplicate removal.

Pre-Processing:

Pre-Processing was mostly done in R and partially in Excel. I used the R scripting language to remove the duplicates (this step can be also done in Excel, but since R is more capable of handling large datasets and due to the amount of memory space required to handle this dataset, R was used in this case). The R scripting language is also used to differentiate Tweets containing Retweets and mentions from original Tweets and to extract the user id associated with the retweeted or mentioned user from the text. The Retweets usually started with RT or via followed by '@' and a user id. The mentions contained '@' and the user id usually at the beginning of the message. After this step, the results were transformed into a relational database (Excel datasheets). The Tweet and Retweet frequencies for each user id were handled in Excel using an Excel formula. The aggregated measures including aggregated frequency of Tweets and Retweets per day were also handled in Excel using Pivot Tables.

Network Analysis and Visualization:

In the pre-processing step, by identifying the mentions and Retweets and extracting the user ids, a list of 'from id' and 'to id' and 'date' triples was created for each communication type (mention or Retweet). This list was served as an edge list for the particular communication network. By filtering the list based on the date (indicating the day on which the Tweet was posted), several networks (one for each day=59 networks) could be created for that particular communication type.

The resulting edge list could be served as a graph input for several network visualization tools. Both Pajek and NodeXL were used in this study as visualization tools. In both tools various metadata can be added to the input. For example, after identifying the social roles for each user, the roles were color-coded and the colors were provided in the input file as an extra feature, which can be used to define the color of the node representing the associated user. Also, Retweet, or mention frequency of each user was served as another feature that was represented as the size of the node associated with the user.

Centrality measures in this study are calculated in R using the ‘sna’ package. The centrality measures can also be obtained from NodeXL results. For each user, the centrality measure is calculated according to the user’s position in the network, which included the interactions in a specific time period (stage). The measures are then aggregated in Excel Pivot Tables, which can be later used in the regression analysis.

Tweet Translation and LIWC Linguistic Analysis:

Excel provides a developer tool to write scripts in the VBA language and automate excel processes and modify excel sheets by assigning the results of a formula to a cell in the program. This allows for automation of the processes and the reduction of manual tasks. The Egyptian 2011 Tweets dataset contains some non-English Tweets most of which are in Arabic language. Manual translation of more than 13,000 Tweets seemed impossible. Thus, an Excel VBA script was used to automatically translate all the Tweets and store the resulting translation in a new cell next to the original Tweet text. This script uses a Google Translate API. The script first creates a connection to this API and provides the original Tweet as the input data and then stores the output of the API (translated text) in a new cell, which is associated with the original Tweet.

Though the translations may not always follow a proper English grammar, the key terms in the translated text seem to convey the main message of the Tweet. Thus, a linguistic analysis, which works based on the types of words and pronouns and sentiment part of the speech is expected to provide relatively accurate results even for machine translated Tweets.

LIWC is a linguistic analysis tool. The input to this tool can be a single line of text or a multi-line text document. The outcome of LIWC is a list of linguistic features for each line provided in the input. The list of features that are extracted and produced by LIWC can be found in the following link: http://liwc.wpengine.com/wp-content/uploads/2015/11/LIWC2015_LanguageManual.pdf

In this study, a document containing all original Tweets, each starting at a new line, was provided as input to LIWC. The result was a .dat file containing a list of linguistic features for each Tweet. This file was later imported into an Excel sheet and then merged with other Tweet data so that other Tweet features (including url inclusion) were also part of the dataset along with all the linguistic features. These features were then aggregated for each day using Pivot Tables in excel. They served as indicators of behavioral regularities in terms of contextual characteristics, which varied over time.