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ICT in Business

Coalition Formation during Technology Adoption

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MASTER'S THESIS

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ABSTRACT

The introduction of a new technology into an organization is often coupled with the formation of opinions of acceptance or rejection by individuals. Given the large costs incurred in implementing the technology, the challenge for organizations is to understand and promote the factors that lead to acceptance. The most prominent framework that addresses this issue is the Technology Acceptance Model (TAM), which takes into account the effect of a number of variables on individuals' acceptance of new technologies. Nevertheless, the role of one of the key factors, namely, social influence, is still not fully understood. Drawing on earlier studies that have mentioned the potential contribution of referent individuals to technology acceptance (i.e. social influence), this research introduces the notion of the "coalition" as a social group that influences the opinion of other, non-coalition members of an organization. This framework is then employed in an empirical study centering on an organization – ING Group (a global financial group) – which has recently decided to introduce Big Data into the organization's formal operations. Through a unique empirical approach that analyzes the sentiments expressed by individuals about this technology on the organization's online forum, which includes 258 meaningful comments from 66 active forum participants, the emergence of a central coalition on the Big Data issue is demonstrated, and the influence of this coalition upon the attitude (i.e. intention to use) of individuals who participated in the discussion forum. This research contributes to existing TAM frameworks by enhancing our understanding of the social influence variable, while offering a methodological tool that can be utilized by organizations to understand the social dynamics that form about a newly introduced technology and accelerate its acceptance by employees.

Keywords: technology acceptance, TAM, coalitions, coalition formation

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Chapter 1

INTRODUCTION

Information Technology (IT) plays an extremely important role in the competitive position of organizations, and yet, many organizations fail to keep pace with and adopt new technological innovations that would otherwise enhance their performance. In 2001, for instance, Nike announced the near $50 million revenue shortfall the company had incurred as a result of failing to successfully implement supply chain software. In fact, a well reported and studied phenomenon is the incapacity of organizations to successfully introduce new innovations into their operations, subject to resistance from individual employees who are required to work day-to-day with the technology (e.g., Davis, 1989). A line of research dedicated to understanding individuals' IT usage behavior has consequently garnered burgeoning interest in the field of technology and innovation management.

1.1 Problem Statement

A framework known as the "Technology Acceptance Model" (TAM) has been offered by scholars to explain the users' acceptance of new technologies, bestowed by a number of key variables, including the technology's perceived ease of use and perceived usefulness, as well as social influence, voluntariness, and image (e.g., Davis, 1989; Venkatesh and Davis, 2000; Venkatesh et al. 2003).

TAM is considered to be the most parsimonious and powerful theory in the literature that has been used to study technology usage behavior (Venkatesh and Davis, 2000). Notwithstanding, Venkatesh and Davis (2000), and Venkatesh et al. (2003), drew attention to two particular weaknesses. Firstly, the studied technologies have been relatively simple and individual-oriented, despite more complex technologies changing the way organizations do business today, as illustrated in IT governance tools and cloud computing. The second limitation underlined by the authors relates to "the continuing trend in organizations away from hierarchical, command-and-control structures towards networks of empowered, autonomous teams". Hence, complex technologies are likely to be confronted by a group of people instead of individuals once they are introduced into the organization. Moreover, an individual's decision to accept or reject a technology will be based upon both his or her own opinion as well as that of the group in which the individual is embedded.

Studies have hitherto come short of providing a comprehensive view that explains these social influence externalities, especially lacking elaboration of the social influence processes from a group perspective. This is a salient topic for organizations given the extensive costs associated with the acquisition and implementation of complex technological systems, and the ubiquity of social media platforms that allow individuals (i.e. employees) to share opinions and coalesce about technological issues in a variety of settings.

1.2 Statement of the Research

In response to this much needed elaboration, this research introduces the notion of "coalitions" to enhance our understanding of the social influence on technology acceptance in organizations. Used extensively in Organization Science, coalitions refer to "temporary, means oriented, alliances among individuals or groups which differ in goals" (Gamson 1961). The potential for coalitional behavior in organizations arises from the multiplicity of organizational goals. When these goals are conflicting, different individuals (e.g., employees, managers, and stockholders) who are motivated to pursue the realization of particular objectives, coalesce about the issues (Cyert and March, 1963; Gamson, 1961; March and Simon, 1958). In turn, the two questions to be answered in this research are as follows:

RQ1. What are the dynamics of coalition formation during the introduction of a new technology in an organization?

RQ2. What is the influence of the coalition, as the referent, on individuals' intention to accept a technology?

Subsequently, a theoretical framework that brings together TAM and coalition theory is developed in this research, whereby the coalition describes the group that forms in response to the introduction of a new technology, and which has the power to act as the referent for other individuals that are not coalition members. Rather than the traditionally studied, simple, individually used technologies, a large, encompassing technological issue that has been used by multiple individuals directly and indirectly is purposefully selected. This research, then, illustrates the applicability of this framework in an empirical study centering on an organization – ING Group (a global financial group) – which has decided to introduce Big Data into the organization's formal operations, based on which they expect creation of business value by using the platforms, tools and software to enhance the use of a large volume, variety and velocity of data. The assumption is that Big Data represents an emergent and important technological issue within the organization that motivates individuals to derive a positive or negative opinion, potentially creating coalitions as individuals converge on similar opinions.

Empirically, this work departs substantially from earlier studies that have traditionally utilized qualitative methods such as interviews, surveys, and questionnaires. Instead, this research undertakes a unique approach to acquiring qualitative data by accessing the written opinions of individuals on the organization's online intranet social media platform, named "Big Data Community". Since its inception in June 2012, this technology–focused forum has encouraged 363 employees to voluntarily join, of which 66 individuals have contributed to the opinion sharing in the community, resulting in 258 meaningful comments. Given that prior research has verified the correlation between "intention to use" (intention of acceptance) and "actual use" (acceptance) of technology, this research focuses its investigation on the former. In this research, intention to use is denoted through the proxy of sentiment, such that, the positive sentiment signals intention to use, while negative sentiment would indicate the reluctance to use. Sentiment analysis of the online forum comments is conducted by using the IBM SPSS Text Analytics for Surveys 4.0.1 software, which is built upon a class of Natural Language Processing (NLP) algorithms. The resulting sentiment data allow us to analyze the employees' shared opinions about the emergent technological issue (i.e. Big Data), the emergence of networks or latent coalitions about this issue, and the influence of the forming coalition upon the attitude of individuals who participant in the discussion forum.

The structure of this thesis is as follows: Chapter 2 gives comprehensive theoretic backgrounds of both TAM model and coalition theory. A combined framework by using the coalition theory to understand the social influence in TAM model is proposed at the end of the chapter. Chapter 3 elaborates the empirical contexts and the designing of this research, followed by the empirical results demonstrated in Chapter 4. Conclusions are drawn in Chapter 5, along with discussions and indications for future research.

Chapter 2

THEORETICAL BACKGROUND

Information Technology (IT) plays an extremely important role in today’s organizations. A variety of new technologies ranging from incremental innovations to disruptive innovations, such as, the Internet and mobile telephony appear from time to time. There are many cases about the failure of organizations or industries that do not keep pace with technological development, while other cases portray the success of organizations that are able to change the way they do business as new technologies appear. One example is the replacement of traditional “brick and mortar” business (e.g., bookstores and retail outlets) by online e-commerce companies such as Amazon and eBay, utilizing the Internet as an enabling, intermediary technology.

However, the adoption of new technologies by an organization is not always effective, as showed in the research of the “Productivity Paradox” phenomenon. Landauer (1995) argued that individual utility and usability are the main reasons that result in the declining productivity rate in service industries. In the meanwhile, mismanagement, organizational barriers, learning curves, hardware and software incompatibilities are all possible factors that can hinder technology adoption and sometimes even cause disastrous losses to the company.

Therefore, it is of great importance for a company to know the nature of the technologies and facilitate the successful adoption of them in the organization. During more than two decades of research on the IT organization's adoption of new technological innovations, several models have been developed on both the individual level and firm level to better understand how technologies are adopted by an organization. This research emphasizes on technology adoption by employees in the organization, therefore, a literature review on the individual level of technology adoption models is studied in the following section.

2.1 Individual Level Models of IT Acceptance

The literature about technology adoption by IT organizations has afforded substantial attention upon the acceptance of the technology by its users, in other words, the individual members of the organization. A review of the literature highlights eight models that have been developed to understand individual's IT adoption intention: Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT). Among them, Davis was the first scholar who introduced the concept of "user's acceptance of IT" in 1989. He identified two measurements, perceived usefulness and perceived ease of use, to build the Technology Acceptance Model. Over the two decades following Davis' contribution, TAM has been extended a few times with the introduction of specific factors to predict users' acceptance. Rooted in the realms of information systems, psychology, and sociology, these extensions of TAM routinely explain over 40% of the variance in individual's intention to use a technology (Davis et al, 1989; Venkatesh and Davis 2000). In the recent development of TAM, these eight models have been combined into a Unified Theory of Acceptance and Use of Technology (UTAUT) model. Collectively, TAM is considered as the most parsimonious and powerful theory that explains the technology usage behavior (see Appendix I: TAM Model's Recent Usage Frequency in TIM Field).

At the same time, an impressive number of context-specific studies have been conducted that have led to the model's development through comparison with a variety of technologies. From Chuttur's (2009) historical overview of TAM, which incorporated a summary of six meta-analysis studies centering on TAM, in which a list of the most popular technological application arenas including Email, voice mail, fax, dial-up systems, e-commerce, the word processor, and database programs.

However, Venkatesh and Davis (2000) and Venkatesh et al. (2003) draw our attention to two weaknesses in the studies that have employed TAM as a theoretical lens. Firstly, the technologies that have been studied are relatively simple and individual-oriented. In today's rapidly changing world, more complex technologies are changing the way organizations do business, as illustrated in IT governance tools and cloud computing. The second limitation underlined by the authors relates to "the continuing trend in organizations [moving] away from formal hierarchical, command-and-control structures towards networks of empowered, autonomous teams", in which complex technologies are likely to be confronted by a group of people instead of individuals once it is introduced to an organization. As for an individual, it is more likely that decisions of acceptance or rejection of a technology will be based upon both his or her own opinion as well as that of the group to which the individual belongs. This phenomenon used to be studied as the social influence factor in TAM model.

Inspired by the above two points and to further understand how "social influence" plays a role in the individual's acceptance of a technology, this research provides an in-depth literature review to explore the state-of-the-art of this factor in the TAM model.

2.1.1 Overview of the Development of "Social Influence" in TAM

The original TAM model was built upon the "Theory of Reasoned Action" (TRA) (see Figure 1), through which the correlation between the intention of use and actual acceptance of the technology that has been demonstrated in prior studies. The TRA model suggests that the Subjective Norm (SN) of an individual as a social factor results from the multiplication of normative beliefs (i.e. perceived expectation of specific referent individuals or groups), and his or her motivation to comply with these expectations. Therefore, the TRA model also suggests that SN influences Behavioral Intention, which leads to Actual Behavior. In the research of Fishbein and Ajzen (1975), the authors theorized normative beliefs form through two ways: "First, a given referent or some other individual may tell the person what the referent thinks he should do, and the person may or may not accept this information. Second, the person may observe some event[s] or receive some information that allows him to make an inference about a given referent's expectations." However, in his research, the author used questionnaire as the research methodology, which is a relative static approach aiming to test the relationships between different variables. Little information about the referent, either individuals or groups, was gathered from reporters in the questionnaires. Also, the authors suggested that SN is one of the least understood aspects of TRA.

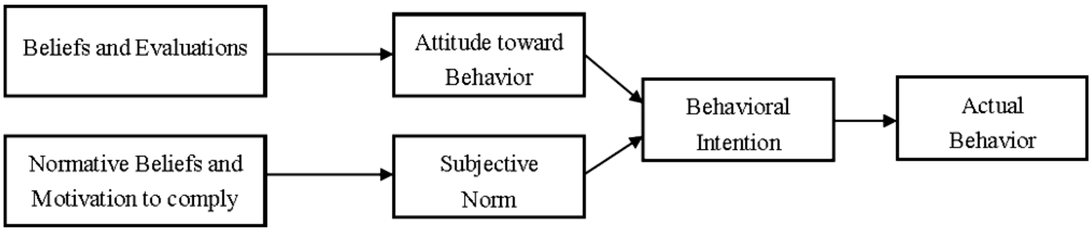

Figure 1. The TRA model (Fishbein and Ajzen, 1975).

In the validated TAM model (see Figure 2) created by Davis et al. (1989), SN did not appear to have explanatory significance in his research and was removed from the TRA model which he used as a premise.

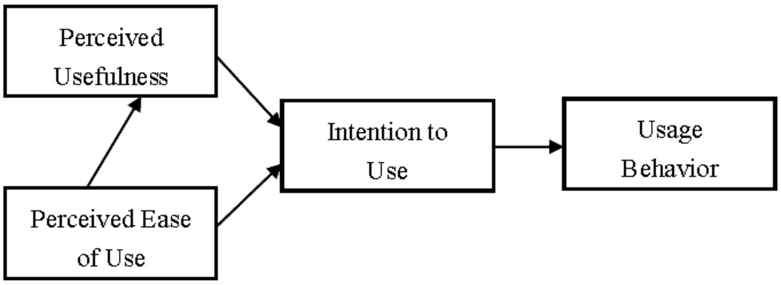

Figure 2. Original validated TAM model (Davis et al, 1989).

The follow-up research conducted by Hartwick and Barki (1994) identified "mandatory setting" as a variable that determines the significance of the "subjective norm" in technology acceptance. The authors concluded that, subjective norm has a significant effect on the intention to use a technology in mandatory settings but not in voluntary settings. This find validated the non-significance of subjective norm in the TAM model (Davis et al., 1989; Davis, 1989).

Rooted in the realms of information systems, psychology, and sociology, these extensions routinely explain over 40% of the variance in individual intention of using technology (Davis et al, 1989). Over the two decades following Davis' contribution, TAM has been extended several times with the introduction of specific factors to more accurately predict users' technology acceptance behavior. Venkatesh and Davis (2000) subsequently extended TAM into TAM2 (see Figure 3), reflecting the impacts of two social forces: subjective norm and image, and two moderators: voluntariness and experience.

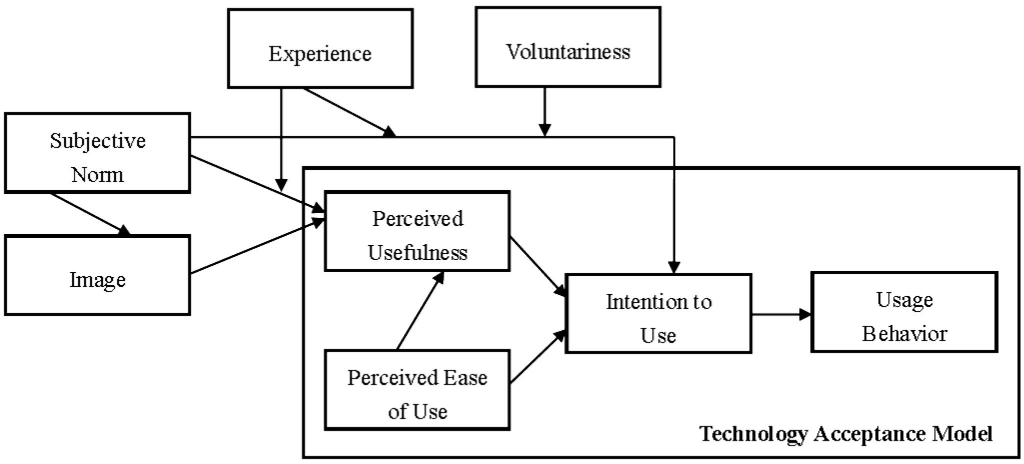

Figure 3. "Social Influence" determinant in the TAM2 model (Venkatesh and Davis, 2000). (Note: This model is without other externalities: Job Relevance, OutPut Quality, and Result Demonstrability.)

Subjective norm is seen to be synonymous with "social norm" (Fishbein and Ajzen, 1975), while the image is defined by Moore and Benbasat (1991) as "the degree to which use of an innovation is perceived to enhance one's status in one's social system." Voluntariness acts as a moderating variable and is defined as "the extent to which potential adopters perceive the adoption decision to be non-mandatory" (Agarwal and Prasad, 1997; Hartwick and Barki, 1994; Moore and Benbasat, 1991).

Venkatesh and Davis (2000) tested the role of voluntariness in moderating the technology acceptance by comparing two sites where the system was mandatorily used and two sites where the system was voluntarily used. As the results showed, subjective norm was significant in the mandatory setting and its effect got weaker as time passed by, thus verifying Hartwick and Barki's (1994) earlier finding. In voluntary setting, subjective norm significantly influenced intention to use via the belief construct of "perceived usefulness". The influence of image on perceived usefulness was significant during the experiment in both settings. Three underlying causal mechanisms from Kelman (1958) were mentioned in his research, namely, compliance, internalization, and identification, as the explanation of the three social forces. The other moderating variable is experience, which governs the effect of subjective norm on both perceived usefulness and intention to use. Specifically, the TAM2 model suggests that as the user experience increases, the effect of subjective norm on both perceived usefulness and intention to use will become less significant.

More recently, the preceding models centering on TAM have been consolidated to form the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003), TAM3 (Venkatesh and Bala, 2008) and UTAUT2 (Venkatesh et al, 2012). The models were developed to combine variables from various theories to achieve a comprehensive prediction scope and a high prediction rate.

For instance, the UTAUT model incorporates eight models in the IT acceptance research, where the social influence determinant encompasses variables of subjective norm, social factors, and image, which are influenced by the four moderators - gender, age, experience, and voluntariness of use (see Figure 4). The model has been shown to predict 70% of the technology use behavior, compared with the previous models' 40% (Davis et al, 1989; Venhatesh and Davis 2000; Venhatesh et al, 2003).

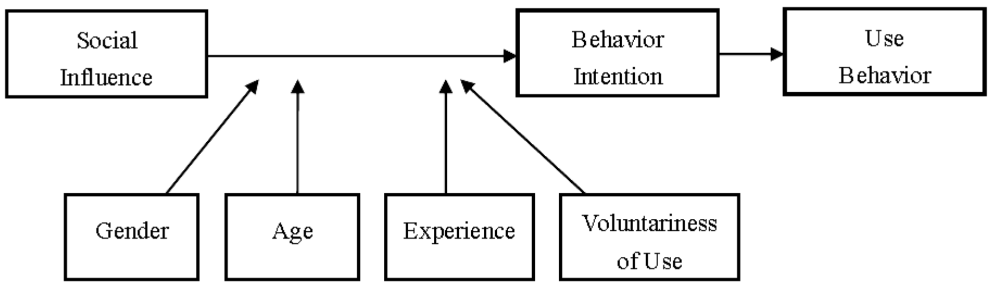

Figure 4. "Social Influence" determinant in the UTAUT model (Venkatesh et al., 2003).
(Note: This model is without other externalities: Performance Expectancy, Effort Expectance, and Facilitating Conditions.)

However, as the models had been broadened, not too much detailed explanation about the interrelation of factors in each determinant was given. Therefore, the descriptions of the three forces in social influence factor was inherited from TAM2, these remain without further elaboration.

Kelman (1958) proposed that “differences in the nature or level of changes that take place correspond to differences in the process whereby the individual accepts influence”. In other words, even though the resulting behavior identified from individuals may appear the same (e.g., having intention to use a given technology), the underlying mechanisms which determine the individual’s induced behavior may be different.

Compliance is manifest when “an individual adopts the induced behavior, not because he or she believes in its content, but because he or she expects to gain specific rewards or approval and avoid specific punishments or disapproval by conforming”. Many of the IT acceptance research had incorporated this mechanism under the label of subjective norm for predicting individual’s intention to use IT.

Identification occurs when “an individual accepts influence because he or she wants to establish or maintain a satisfying self-defining relationship to another person or a group”. That is to say, an individual obtains social support, membership, and goal attainment from another person or a group by behaving consistent with a group norm. The social support depends upon the extent to which the membership affords, and goal attainment occurs only through group activities (Pfeffer, 1982).

Internalization occurs when “an individual accepts influence because he or she is content that the induced behavior – the ideas and actions of which it is composed – is intrinsically rewarding”. In other words, an individual tends to be satisfied with the induced behavior when it is aligned and integrated with the individual’s existing values.

However, these three underlying mechanisms are not always clearly distinguished with each other in real life cases, the complexity of the interrelations makes them hard to be measured (Davis, 1986). Only in the TAM2 model, Venkatesh and Davis (2000) theorized that subjective norm can positively influence the image.

In the meanwhile, French and Raven's notable study (1959) deepen our understanding from another approach by explaining five separate forms of power. "Coercive power" is used to pressure individuals to align with a certain directive. "Reward power" and "punish power" are considered as legitimate power - normally an individual owns this type of power based on his position or role in an organization. Therefore, if an individual's decision making is affected by these three types of power, the main underlying basis is compliance.

"Referent power" is defined as "the ability to administer to another a sense of personal acceptance or personal approval". An individual or a group who has this power is likely to act as a role model and others are attracted to their personality and charisma. Therefore, it is likely that the decision made by an individual will be inclined to the referent's opinion and build up a similar image. It fits the underlying process of identification.

The most interesting point about "expert power" is that the power is awarded to the individual by his subordinates. That is to say, subordinates are convinced by the expertise or knowledge of the individual who owns the power. They are willing to trust the expert and make decisions accordingly. Therefore, the underlying basis for this process is similar to internalization.

Applied to the TAM model (Venkatesh et al., 2003), Kelman's (1958) three causal mechanisms can be used to interpret the three social influence constructs which are subjective norm, social influence, and image. Subjective norm aligns with the compliance process in the mandatory setting as individuals make decisions based on other people's expectations of them. It is an outside-in approach, whereby people are not forced by their own willingness but by others'. In voluntary contexts, by contrast, “internalization” plays the most powerful mechanism in explaining the “social factor” which is defined by Thompson et al. (1991) as “the individual’s internalization of the referent group’s subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations.” In this process, the individual is expected to change attitudes from within according to their own beliefs. Finally, the image fits with the identification process, whereby the user makes a reasoned decision under group influence because he or she expects a greater payoff, even though it is not demanded by others.

The contribution of later technology acceptance models to the social influence factor was rather limited. For instance, Venkatesh and Bala (2008) developed the TAM3 model by extending TAM2, combining the determinants of perceived ease of use (Venkatesh, 2000). This new model focused on the intervention of IT implementation, thereby, tested a few relationships moderated by experience. With regards to the social influence determinant, these factors were fully adopted from TAM2. In the most recent UTAUT2 model (Venkatesh et al, 2012), the model is expanded to the consumer context, which already stepped out the study scope of this research.

In retrospect, the development of TAM over the past 20 years has had huge advancement in identifying comprehensive predictors and improving the predictive rate. Most of the TAM studies were employed with a variance theory approach, where conclusions are drawn from the statistical analyzing of the relationships among different variables. Although previous research emphasized on what factors lead to technology acceptance, very few researchers have paid attention to the in-depth analyzing of detailed events and corresponding action sequences to answer how these factors lead to the individual’s acceptance of a new technology in an organization. Studies so far do not provide a comprehensive view that explains these social influence externalities, especially lacking elaboration of the social influence processes from a group perspective.

To gain a more comprehensive picture of the employment of social influence factors in technology acceptance, especially in more recent work, a systematic literature review was conducted in the following section.

2.1.2 Literature Review of the "Social Influence" Factor in TAM Empirical Studies

This literature review is conducted by using the Web of Science database[1], which identified five articles that had specifically conducted empirical research on this topic within the organizational context[2] (see Table 1). All of these empirical studies attempt to verify a relationship between social influence and one of the main constructs of the TAM model: perceived usefulness, perceived ease of use, intention to use, and usage. Three moderating factors - voluntariness, experience, and gender - are identified as having an effect on these relationships. For instance, two of the studies, Venkatesh and Davis (2000), and Wu and Li (2009), show that social influence has an indirect effect on the main constructs of the TAM model via the variables of attitude or image. Furthermore, Karahanna and Limayem (2000), and Wu and Li (2009), use social influence as a moderator to explore the causal relationships of "perceived usefulness and attitude", "attitude and behavior intention", and "belief and usage". In the development of a theoretical framework, Yang and Lin (2012) as well as Karahanna and Limayem (2000) attempt to explain the referent, which the authors identify as peers and supervisors. However, the questionnaires employed in these studies have not explicitly explored social influence from a group perspective and the corresponding dynamic behavior of the referent group, thus leaving this as an open issue for future studies to disclose.

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[1] From an inquiry using the search terms "TAM" and "social influence" in the title, abstract, and keywords of published work, we acquired a total of 51 journal papers. However, as the research focus of our paper is on the organizational adoption of technology, in particular IT adoption, we refined this selection to those that fall into the "Management" and "Computer Science Information Systems" categories, leaving a total of 23 articles for analysis.

[2] Venkatesh and Davis (2000); Venkatesh et al. (2000); Karahanna and Limayem (2000); Wu and Li (2009); Yang and Lin (2012).

This focused literature review suggests that recent research has not provided a comprehensive picture of social influence on technology acceptance in organizations. This supports Bagozzi's (2007) call for needed elaboration of the TAM model's constructs by "reconceptualizing existing variables in the model, or introducing new variables explaining how the existing variables produce the effects they do." In this light, this research aims to introduce a coalitional view, which may bolster the explanatory power of social factors in the TAM model.

Table 1. Studies of the TAM model with "Social Influence" determinant as an extension[3].

Studies	Research Purpose	Dependent Variable	Moderator	Independent Variable	Results
Venkatesh and Davis (2000)	Extend TAM to TAM2 by combining with social influence and other factors	Subjective Norm	Voluntariness; Experience	Image; Perceived Usefulness; Intention to Use	Subjective norm -> Intention to use (mandatory, experience); Subjective norm -> Percieved Usefulness (experience); Subjective norm -> Image; Image -> perceived usefulness
Venkatesh et al (2000)	Extend TAM with moderator "gender"	Subjective Norm	Gender; Experience	Intention to Use	Subjective norm -> Intention to Use (Female, Experience)
Karahanna and Limayem (2000)	Extend TAM with social influence and theories of communication choice and use	Social Influence; Belief	Social Norm	Perceived Ease of Use; Perceived Usefulness; Use	Email: Social Influence-> Peceived Ease of Use; Social Influence -> Use Vmail: Social Influence -> Peceived Usefulness; Social Influence -> Perceived Ease of Use; Belief -> Use (Social Norm)
Wu and Li (2009)	Extend TAM with social influence and other factor to understand user behavoir of KM system	Social Influence	Social Influence	Perceived Usefulness; Behavior Intention; Attitude	Social Influence -> Attitude; Social Influence -> Behavoir Intention; Perceived Usefulness -> Attitude (Social Influence); Attitude -> Behavoir Intention (Social Influence)
Yang and Lin (2012)	Extend TAM with scoial influence and other theories to understand the usage behavior of Facebook in the organization	Social Influence		Perceived Usefulness	Social Influence -> Perceived Usefulness

[3] In the last column, the content in the bracket is moderator in the relation. For instance, Subjective norm -> Intention to Use (female, experience) means subjective norm affect female's intention to use a technology and the impact changes along with the experience gained.

In the following section, the notion of coalitions within organizations is introduced as a theoretical frame to describe groups that form in response to the introduction of a technological innovation and therefore have the power to act as a referent for other individuals.

2.2 Coalition Theory

2.2.1 Overview of Coalition Theory

The breadth of the term "coalition" is rather wide due to many branches of organizational theories that have utilized this notion. Among them, political science and social psychology are the two fields of science which have studied coalitions the most.

In political science, coalition behavior in organizations is seen to arise from the multiplicity of organizational goals where power acquisition (e.g. Pfeffer and Salancik 1978; Cobb 1986; Brass and Burkhardt 1993), and political dynamics (e.g. Cobb 1986; Eisenhardt and Bourgeois III, 1988; Gargiulo 1993) play a central role. By joining with other individuals or groups to form a coalition, an individual can increase payoffs (Kelly, 1968), which include the allocation of rewards and access to organizational resources (Gamson, 1961). At times, opposing coalitions are generated due to the conflict of goals in the organization, which compete and bargain for payoffs. Classical research has subsequently implied "Game Theory" to predict potential coalition behavior by calculating the maximum possible payoff. For instance, Gamson (1961) and Caplow (1956) have predicted coalitions in triads of varying initial strength in their experimentations. Modern politicians have also applied game theory to simulate coalition bargaining and predict the formation of government after elections (e.g., Netherlands election in 1952 and Geman election in 1987). The winning coalition is what is able to control the decision concerning the central issue. However, the predictions were conducted in the experimental setting where specific assumptions were required. For example, in the game theory experiments, players needed to be aware of the resources owned by every other player. Even under such restricted conditions, the experimental results were at times not significant, let alone in the real organizational setting where the situation is far more complex. Therefore, the applicability of the predictive experiments has strong limitation, as also echoed by Narayanan and Fahey (1982).

With regard to the field of social psychology, early theorists and modern sociologists have emphasized the "unanticipated consequences of purposive social action" (Merton, 1936; Cyert and March, 1963) while more researchers have increasingly attempted to incorporate ideological diversity in coalition research (Axelrod, 1970; Rosenthal, 1970). For instance, researchers have predicted that parities with similar ideologies or with less conflict of interest were more likely to join forces (Axelrod, 1970). More recently, along with the increasing popularity of open innovation and knowledge sharing, researchers have drawn conclusions that coalitions are related to interpersonal ties and networked innovations (Brass et al, 2004; Sie et al, 2010), where actor's similarity, personality, and reputation act as important antecedents of coalition formation.

Since the 1980s, researchers have also started to pay more attention on the development of intra-organizational coalition theory. In one of the early contributions, Narayanan and Fahey (1982) criticize Mintzberg's rational model (1977), which describes the strategy formation as a set of procedures, an objective framework, but without the consideration of the state of affairs within the organization. In other words, in the organizational environment, decision making is not always centrally coordinated and cannot be decided by a single "decision-maker", but rather more often decided by a set of actors. Moreover, he argued that individual's decision making on whether to accept, modify, or reject a strategy or its alternatives relies on the power or influence distribution within and across the relevant coalitions. Therefore, he emphasized internal dynamics, such as, the evolution of coalitions in his research and proposed a framework that includes five stages of strategic decision making - Activation, Mobilization, Coalescence, Encounter, and Decision - and gave implications of how the coalition behaves in each stage and when it transits to the next stage.

Stevenson et al. (1985) provide a comprehensive review of the literature studying intra-organizational coalition and clarify the differences between coalitions in an organizational context and others. The authors present eight characteristics in defining a coalition as: (i) an interacting group, that (ii) is deliberately constructed, (iii) is independent of formal structure, (iv) lacks formal internal structure, (v) consists of mutually perceived membership, (vi) is issue oriented, (vii) focuses on a goal or goals external to the coalition, and (viii) requires concerted member action (to be elaborated in the following section). Additionally, the authors suggest a model portraying a whole process of coalition development, from the stage of "antecedent conditions" till "formalization".

Murnighan (1985), in his article, gives readers explicit examples of organizational coalitions. He views the formation of coalition from a network perspective, starting from one actor's first move, and then expanding successively to a pair and in turn to a group. The author also describes many key concepts, such as, resource distribution and dominant coalition.

Researchers (Stevenson et al., 1985; Murnighan, 1985) have also been concerned with the way that coalitions may be considered illegitimate or even threatening for the formal structure of the organization. However, whether the coalition is seen to be detrimental or beneficial depends on the issue at hand. In some cases, the coalition offers a more effective way of working and is recognized by the organization, such as, coalition for knowledge sharing.

More recent research describes people's interaction in the networked innovation as a coalition (Sie et al., 2010). The research focuses on building a variable model where antecedents are identified to predict the formation of a potential coalition. The amount of time, emotional intensity, intimacy, and reciprocal services are the key characteristics that have been proposed to define the interaction between different individuals (Granovetter, 1973).

2.2.2 Intra-organizational Coalition Definition

Even though the coalition has been talked about for over half a century and received notable attention in the area of organization theory, the definitions of coalition appear differently across studies. Cyert and March (1963), for instance, have viewed the organization as a coalition of individuals, and some of them are organized into sub-coalitions. In the organizational context, the coalition members can include managers, workers, stockholders, suppliers, customers, lawyers, tax collectors, regulatory agencies, and so on. Even though the authors simplified the conceptualization by focusing on the participants in a particular "region" – either temporal or functional, their definition still remains board, robbing its meaning and leaving readers without a clear understanding of the differences between a coalition and a collective of stakeholders (Stevenson et al, 1985).

With regard to intra-organizational coalitions, the definition of a coalition provided by Stevenson et al. (1985) is the most comprehensive. To this end, the authors list eight characteristics that distinguish the coalition from other types of collectives.

Firstly, the independence of the coalition from the formal organizational structure enables it to collect a greater amount and a higher variety of resources. In formal departments, committees or task forces, and the resources they own tend to be solo and limited to the unit's function. Moreover, it takes a lot of effort and time to join together the resources from different organizational units. And yet, Tsai and Ghoshal (1998) show that business units that exchange resources with many other units tend to produce a higher amount of product innovations. The formation of the informal coalition provides an effective way to erase the difficulty. However, in practice, the formally mandated objectives and coalitional goals are sometimes mingled together and might be hard to distinguish with each other, because the issue could be work-related. Thus, the membership in the coalition and formally designated groups are not necessarily mutually exclusive with the other.

Secondly, the coalition is deliberately constructed. As previous research assumes (Murnighan, 1985), organizational actors will be reasonably aware of their own interests and will attempt to further enhance them whenever possible, to the best of their ability. The rational way of thinking and the self-interested nature make actors seek the best possible strategy. Related to the coalition, if an actor decides to join in, it means the decision follows his or her own willingness. Compared with the formal workforce, coalitional way of working is more self-motivated and effective, since the actor's work is self-determined.

Thirdly, the lack of internal formal structure offers a more flexible and extensive channel of internal communication. People's interaction resembles a network with a potentially exponential growth in the amount of communications compared with the formal tree-structure of the hierarchical organization. According to Hansen (1999), strong ties between business units facilitate the transfer of complex knowledge, whereas weak ties are sufficient for less complex knowledge. That is to say, especially, when a company is confronted with complex technology, frequent communication within the coalition enables the generation of a larger number of new ideas, new perspectives, and new solutions for problem solving.

Beside the above characteristics, a coalition also needs to be an interactive group, which requires the joint efforts of its members. This characteristic is necessary because it excludes individuals that are in an autarchic organization or department independently seeking to influence events. Therefore, such groups comprising individuals who have the power to make decisions alone are not coalitions. However, since the coalition has an informal structure, it is not mandated that all of the members should participate in every coalition-related conversation.

A further characteristic that differentiates a coalition from a group of individuals acting independently, but toward achieving the same goals, is that the coalition consists of mutually perceived membership. The boundary of a coalition can be ambiguous. However, individuals in the coalition should have a sense about others who are also interacting around the same issue and contribute to or have the potential to contribute to the same coalition. In fact, it is normal that some of the coalition members are perceived as the "core" while other memberships may be less obvious.

The coalition is often formed when change happens, and members interact around a specific issue. Issue orientation as a characteristic implies that a coalition is a temporal group. When members are less likely to interact around an issue, the coalition loses its meaning, although the group may still exist for social purposes. When the original issue is replaced by another, the existing coalitions can serve as latent coalitions and develop into a new coalition. The issue discussed here must be exogenous to the coalition, which means coalitions have an external focus.

And finally, the coalition requires concerted member action. The actions can be both proactive and reactive, in other words, either they can originate proposals related to a focal issue, or they can organize in reaction to the proposal. The joint action of members in the coalition distinguishes the coalition from some other groups that might only appear in the situation of commiserating with a common problem.

Some of the characteristics listed by Stevenson et al. (1985) are also reflected in the definitions given by different scholars. For instance, Murnighan (1985) offers the concept of “Fortuitous Coalition”, which is created when “two or more individuals may discover that they have mutual interests that could be better served by concerted action”. It nonetheless differs from an issue oriented coalition due to the lack of emphasis on the dynamic of resources needed for purposive coalitions. While fortuitous coalitions are long-term oriented and built upon common interests among members (e.g., two individuals) working on the same issue in parallel, these members benefit from reducing duplication in their work. Purposive coalitions, by contrast, have more dynamic characteristics, and their issue orientation makes the coalition a fluid group, resulting in rapidly changing membership and amount of resources held by the members.

The burgeoning complexity of technologies implemented in organizations requires greater collaborative effort of the individuals that constitute the organization. Moreover, it is not unusual to notice, the formation of interactive groups of organizational actors around this emergent issue, which are at the same time independent form the formal organizational working structure. These, at times implicit collaborative groups are referred to as coalitions. By joining a coalition, an organizational actor can exert more power and influence and mobilize more resources than acting as an independent individual (Stevenson, 1985). Furthermore, the interaction process strengthens the coalition's capacity to engage in cooperative problem solving (Roberts-DeGennaro, 1997). Therefore, this organizational behavior is defined as coalition formation. Coalition formation is an indispensable theme that has been studied by various coalition theorists discussed above (e.g. Gamson 1961; Narayanan and Fahey 1982), and will be discussed in detail in the following section.

2.2.3 Coalition Formation

Kahan and Rapoport (1984) suggest that "Whenever three or more parties get together to jointly decide an issue of substantive interest to all of them, it is likely that at least two of them will at some point in time combine forces to their mutual advantage. When this combining of forces is deliberate, done with the full awareness of all joining parties, and binding upon the joiners, we speak of a coalition being formed." Classical models (such as those, based on game theory) on this theme were mostly statistic, based on the assumption that organizational members are rational players and will do their strategic best. However, the fundamental assumptions of these models are not always accurate. In real organizations, individuals cannot always form the optimal coalition due, for example, to the lack of information or so. This research, thus, focuses on the process models which describe the underlying mechanisms of how a coalition develops and evolves in the dynamic organizational environment.

Three schools have tried to map out the coalition formation processes, albeit from different vantage points. Stevenson et al. (1985) propose an empirical model – "The Process of Coalition Development" – which focuses more on the macro-level sequences of cause relationships between different stages. Narayanan and Fahey (1982) have, in turn, employed an approach aligns with decision making processes in identifying the mirco-political dynamics of each stage during coalition formation. And thirdly, Murnighan (1985) and later scholars (e.g., Sie et al., 2010) use network integration to plot the dynamics of coalition formation and described the evolving coalition as the network grows. Actors in the coalition are identified and assigned different roles, which gives more implications of how to manage the coalition.

2.2.3.1 Macro Process of Coalition Formation

Stevenson et al. (1985) firstly proposed an empirical model – "The Process of Coalition Development" – which focuses on the macro-level sequences of causal relationships between different stages. These authors suggested that in the organizational context, antecedent conditions can facilitate the formation of coalitions through a series of stages (see Figure 5).

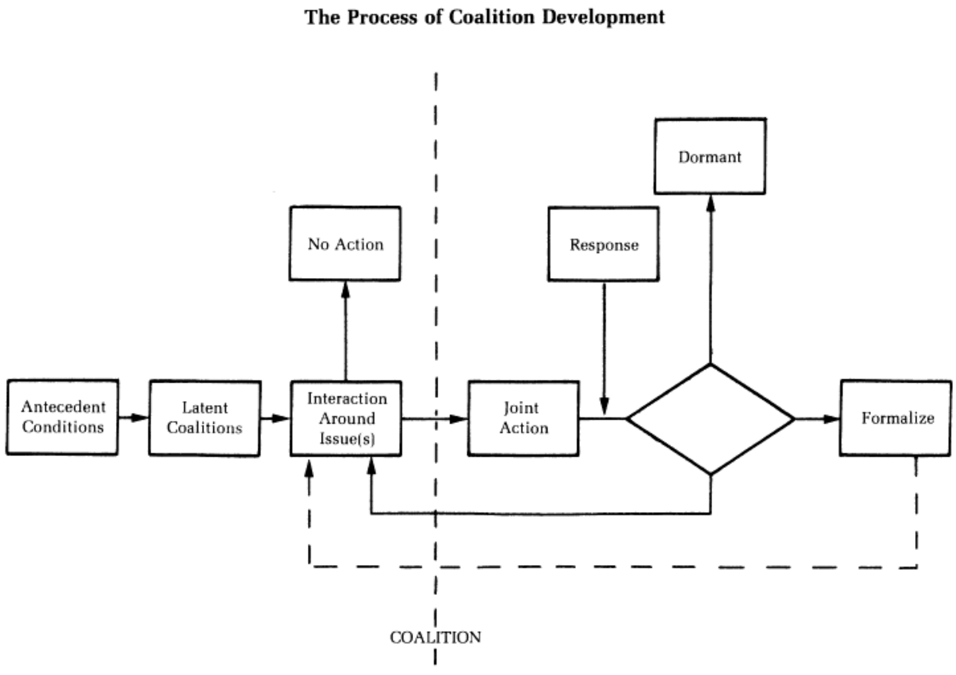

Figure 5. The process of coalition development (Stevenson et al., 1985).

Starting with a set of antecedent conditions, so-called "latent coalitions" are identified as the collective of individuals interacting around a particular issue. People who are not active in the interaction are not part of this preliminary coalition. However, it can be hard to identify these interactions, since individuals can choose to be active in some settings but not in others. For instance, an individual who is inactive in real life social networks can be very active in online social networks. Therefore, coalitions often have fuzzy boundaries.

The authors suggested that, for a coalition formation there are two conditions that need to be taken into account. Firstly, participants need to perceive the issue as requiring their attention. That is to say, on one hand, the issue should not be dealt with individually; on the other hand, such individuals tend to cooperate according to their own willingness if they perceive the issue worthy of their attentions. Secondly, the authors have pointed out that potential coalition participants need to believe that they can form a successful coalition. It means that the coalition is formed to meet the external goal (e.g., gain a better payoff for the individuals). These two antecedents are the foundations of coalition formation. However, there is likely to be a slight difference in the timing of applying these antecedents. For instance, "perceived neediness" requires from the very beginning of the coalition formation process (see Figure 5). The "antecedent of belief of success" is only necessary when individuals are not only active in the "interaction around issues" phase, but also willing to take "joint action" (i.e. transgress across the dotted line in Figure 5). Nonetheless, coalition formation needs to meet both of the two antecedents, but is not a necessity in "latent coalitions". However, the literature has not provided an answer for defining the transition conditions to promote the latent coalition changing into a real coalition.

The most essential part of Stevenson et al.'s framework of coalition formation is nonetheless the interaction of individuals around an issue and the undertaking of joint action. It reflects the key characteristics defining a coalition: an interactive group with external focus and concerted members' action. During the interaction and concerted action phases, the coalition will receive responses from the external environment, such as the organization, either encouragement when successes have been achieved or promoting adjustment for coalitional failures. Responses can also be from other individuals or coalitions, where new members or even coalitions can join together. The coalition can have two outcomes, either persisting in actions over time and formalizing into the organizational structure or disbanding, which is also known as a "dormant coalition".

With the emergence of future issues, formalized coalition can start from the "interaction around issues" phase, since antecedent conditions and latent coalition phases can be inherited from the current issue. And for disbanded coalitions, since individuals have the experience of joining in a coalition already, they can be mobilized with less effort when the next relevant issue appears.

2.2.3.2 Micro Political Dynamics in Coalition Formation

Narayanan and Fahey (1982) divide the whole strategic decision making of a coalition formation into two meta-level phases: "gestation" and "resolution". Gestation is also called "problem formulation", while resolution accordingly is alternatively called "problem solving". The gestation phase is a period of time spent on selecting members and making decisions of alternatives in order to prepare for the resolution phase, where actions are taken and alternatives are adopted (As seen in Figure 6 below).

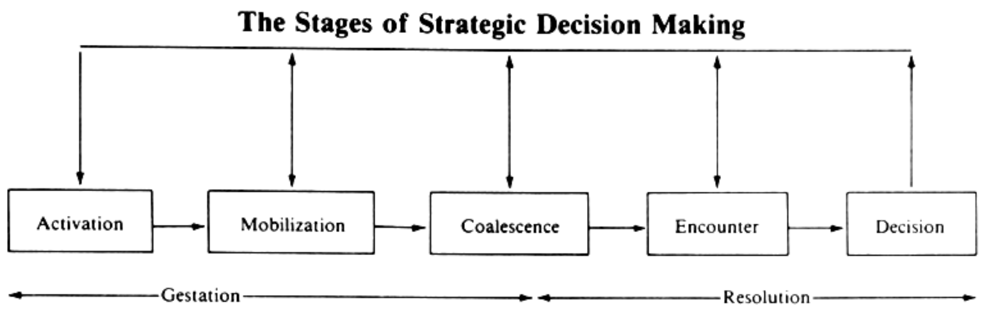

Figure 6. The stages of strategic decision making (Narayanan and Fahey, 1982).

To be specific, the gestation phase is further divided into 3 steps: activation, mobilization, and coalescence. Activation occurs to develop individuals with a clear understanding of the issue, mobilization builds up political commitment and a network of interrelationships among individuals develops around the issues, and coalescence aims to achieve the integration of efforts and the specification of intention internally.

Similarly, the resolution phase has two steps: encounter and decision. Actions are expected to be taken in this phase, for instance, negotiation with external individuals, groups, or organizations in order to sponsor the coalition's preferred alternatives, while the decision is an end when the agreements and disagreements are achieved and cleared out.

The authors comprehensively explained the underlying strategic decision making processes in each stage. The model allows the steps in the process to be repeated if necessary.

2.2.3.3 Network Evolution as a View of Coalition Formation

Murnighan (1985) and later scholars (e.g., Sie et al., 2010) use network integration to plot the dynamics of coalition formation and describe the evolving coalition as the network grows.

According to Murnighan (1985), the essence of coalition formation is the accumulation of interconnecting dyads. Approaching this issue from a game theoretic point of view, a coalition starts with a pair that negotiates the payoff. It is assumed a similar process in the organizational context, where a pair of individuals start the discussion around an issue, no matter whether the issue is from within or outside of the organization, attracting more people to follow the interactions, over time.

In line with this network perspective, individuals can be considered as nodes, and the links between nodes as interpersonal connections. In effect, the coalition essentially starts about a single individual, which may in fact be seen as a "one-person coalition". If two individuals decide to cooperate, a coalition establishes a dyadic connection between these two nodes and grows over time by accumulating further dyad connections. In figure 7, before a coalition starts, single individuals are assumed to be one-person coalitions. If two of them decide to cooperate, such as in the middle picture, where a two-person and a one-person coalitions have developed. Afterwards, dyadic connections may merge into a network. The last picture is an example of the simplest network, which contains a three-person coalition.

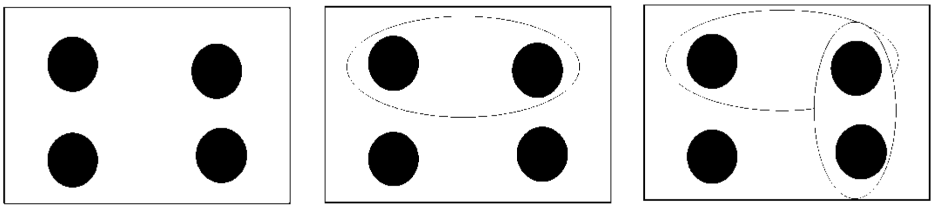

Figure 7. The evolution of a coalition (Sie et al., 2011).

As the amount of nodes and links grow, some of the characteristics in the network start to become obvious. Clusters are formed since some individuals have more mutual interactions as a group compared with people outside of the group. Individuals who share the most links with others are most likely be in the center of the network and are known as the “focal nodes”. Individuals who act as an important connection between different clusters within the whole network scope are named as “boundary spanners” and individuals who have few ties connecting them to others are usually located at the edge of the network, surrounding the network.

Based on the theoretical discussions in the above two sections, the next section focuses on the technology acceptance process by taking a coalitional view of the social influence highlighted by Venkatesh et al. (2003).

2.3 Coalitions as Social Influence in TAM

The aim of this section is to propose a framework that can theoretically explain the social influence in technology acceptance in an organizational setting, through coalition formation. While TAM forms one of the fundamental models in the technology and innovation management literature, the extent of use of the coalition theory in the same field of inquiry was unknown. Furthermore, this research aims to gain an overview of the prior use of a coalitional approach to study social influence in technology acceptance.

To these ends, a structured review of the literature was undertaken by selecting articles from the top 10 journals in the field of TIM (Linton, 2012) using the search term "coalition" in the title, abstract, and keywords of the publications. In total, 32 publications[4] were collected, and after reading through these publications, only two articles – Macri et al. (2001) and Walter et al. (2011) – were found to be relevant to the topic of technology adoption in an organizational setting. Nevertheless, these publications do not link the coalitional view of social influence with TAM, therefore giving some level of confidence that this research may fill a gap in the literature, by contributing a new perspective of technology acceptance within organizations.

The fundamental argument is that, the coalition, whether latent or real, has the power to act as a referent once having formed around an issue. In this manner, this research aims to further elaborate the work of some prior TAM scholars who have noted the potential influence of groups on IT acceptance. However, more than mere groups, a coalitional view is suggested to provide greater accuracy in reflecting such

[4] Technology Analysis and Strategic Management (11), Technological Forecasting and Social Change (8), Research Policy (5), Technovation (4), Journal of Product Innovation Management (2), Industrial and Corporate Change (1), Journal of Technology Transfer (1).

No articles citing the search term could be found from the R&D Management, Journal of Engineering and Technology Management, and we were unable to access IEEE Transactions on Engineering Management.

collectives, especially given their issue orientation and capacity to deliver concerted actions (Stevenson et al. 1985), which must be inherent to a group that can exert influence on individuals' acceptance of new technologies. In this light, Narayanan and Fahey (1982) suggested that "the nature of coalition decisions and the extent to which they are accepted, rejected or modified by an individual relies on the influence of relevant coalitions". With regards to the technology-related issues, coalitions as the referent groups have the power to affect an individual's attitudes with respect to a technology which will lead to his or her intention to use this technology. In fact, the literature shows when individuals (especially females) come across a new technology, they tend to seek information from a referent group (Venkatesh et al, 2000). Additionally, concepts, such as "we think" and "group norm", proved that people tend to comply with a prominent referent.

This framework further elaborates on the role of a coalition in technology acceptance from the vantage point of two individuals – the "influencer" and the "influencee" – whereby the influencer is an individual who can affect the influencee's opinion concerning a certain technological issue. With respect to the former, Walter et al. (2011) stress the impact of the championship in the process of innovation adoption in the organization. Two behavioral characteristics identified in this study that positively affect the innovation success are adopted in this research, namely, pursuing the innovative idea, and network building.

Champions are defined as individuals who firstly pursue their innovation ideas and get other individuals to agree and cooperate with these ideas (Keller and Holland, 1983). It is important to note that, for intra-organizational coalitions around technological issues, the "core" (an individual who is most active or plays an important role in the coalition) faces the challenge of getting his or her idea accepted. Therefore, the core needs to sell his or her idea and garner more supporters. Network building, as the second characteristic, supports this effort by allowing the core to access more supporters. In the coalition context, the core often refers to the centrality of the network, possibly a single individual or multiple individuals dispersing to the center of sub-networks, who are the most influential individuals. From the influencee's point of view, by contrast, attitude change subject to a referent individual or group can occur in three ways, as discussed above: compliance, internalization and identification (Kelman, 1958). However, given that coalitions are formed deliberately, internalization and identification are tentatively anticipating to be more powerful explanations of the social influence factor than compliance, which also echoes with Venhatesh et al (2000), Venhatesh et al (2003), and Wu and Li (2009).

By adopting this empirical framework, a case study is deployed in this research to explore the applicability of coalition view of technology acceptance in an organization.

Chapter 3

EMPIRICAL STUDY

3.1 Empirical Context

Data, exploding at an exponential rate nowadays, leave "information overload" not unfamiliar to ordinary people any more. In April 2012, Information Management reported: "We create 2.5 quintillion [10^{18}] bytes of data every day, with 90% of the data in the world created in the last two years alone... Every hour, Wal-Mart handles 1 million transactions and feed a database of 2.5 petabytes [10^{15} bytes], which is almost 170 times the data in the Library of Congress. The entire collection of the junk delivered by the U.S. Postal Service in one year is equal to 5 petabytes, while Google processes that amount of data in just one hour. The total amount of information in existence is estimated at a little over … A Zettabyte [10^{21} petabytes]."

Big Data, a new term, has been hyped for years and still in the up way of Gartner's hype chart. Many companies believe that data are the new driving force as they have begun to recognize the importance of knowing their business as well as knowing their customers. In a recent research conducted by researchers at IBM (Devlin et al., 2012), financial industry, as the early adopters in the Everett Rogers's Diffusion of innovation curve, follows the Big Data implementers: Media, Public Relations, Retail, and Leisure industries.

Particularly in financial organizations, more than 50% of the data collected is unstructured, which makes the traditional information management approach a hard time to keep pace with the data generated. Big Data, such as the open source software framework Hadoop, will certainly offer financial firms a new approach to handle the large volume, variety and velocity of data for enhanced insight and decision making.

As a global financial institution, ING Group offers a range of banking and insurance services in more than fifty countries. When Big Data popped up in 2012, there was a discussion which lasted for more than 1.5 years in the company's intranet, where members in the "Big Data Community" discussed issues related to whether ING should develop the Big Data competence or not.

3.1.1 Big Data Definition

The concept of "Big Data" started over seventy years when the first attempt was made to quantify the growth rate in the volume of data which is known as the "information explosion"(Oxford English Dictionary, 1941). Over these years, the data counted was first from paper and articles, and later on, increasingly more from digital data ranging from telecommunication to mass media. The key milestones of Big Data definition in pure academic publications are the following: the first "Big Data" term was in the article of Cox and Ellsworth (1997), where they stated the "problem of big data refers to when data sets do not fit in main memory (in core) or when they do not fit even on local disk, the most common solution is to acquire more resources."; the generally-accepted "3Vs" (volume, velocity and variety) dimensions of describing Big Data was defined a decade year ago by Laney (2001); Most recently, Boyd and Crawford (2012) define Big Data as "a cultural, technological, and scholarly phenomenon that rests on the interplay of: (1) Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets. (2) Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims. (3) Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that are previously impossible, with the aura of truth, objectivity, and accuracy.

In the meanwhile, there are also Big Data definitions come from some of the institutions who won high reputations: Ganter still uses the definition of Big Data aligned with the 3Vs, where "Big data is high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.", while a new "V" is added by some organizations, such as IBM, where the veracity refers to the truth in the information (Morgan, 2012). In the Wikipedia, Big Data is defined as "a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications." According to Mckinsey, Big Data is "data sets, whose size is beyond the ability of typical database software tools to store, manage and analyze" (Manyika et al., 2011). In addition to those definitions which focus on the solution of Big Data, the NESSI (Networked European Software and Service Initiative) gives us a definition which also includes the technologies have been used with Big Data, where "Big Data" is a term encompassing the use of techniques to capture, process, analyze and visualize potentially large data sets in a reasonable time frame not accessible to standard IT technologies. By extension, the platform, tools and software used for this purpose are collectively called "Big Data technologies".

This research adopts the latest definition of the term "Big Data" combining with business context, which refers to a cultural and technological phenomenon that rests on the interplay of "Big Data technologies" in order to generate business value out of the large data sets. The technologies in this research include specific systems, platforms and software which have been adopted by ING.

3.1.2 ING Description

The research by Morgan (2012) shows that, in the financial industry, R&D department is most likely to be the one that sponsors Big Data initiatives and IT analysts is the most preferred group to have direct access to Big Data projects. ING Group is not an exception.

As a financial institution, ING Group has been through its reorganization for a few years where IT plays an increasingly more important role in shaping the future of the organization. ING Group has already invested billions of Euros in building data centers. In the Netherlands only, there are as many as 16 data centers and each of them contains more than 4000 systems. Part of ING Group's reorganization is about integrating data centers and reducing IT cost. The most important task is about to better use the data and drive value out of it. Big Data have shown at the right time, which offers ING Group a new possible approach to know its businesses and customers better.

This radical innovation firstly started from ING Group's intranet social media platform "Buzz", where "Big Data Community" is a community that employees from different departments who share the same passion for Big Data can discuss and share knowledge there. Before the implementation of "Buzz" a year ago, "PeopleFinder" was the system that had been used for a few years and the records stored in it were transferred into "Buzz" eventually. During the 20 months' discussion about Big Data relevant topics in "Big Data Community", more than 40 conversations were generated where people shared knowledge and opinions about Big Data. Until the time of this research, there are 363 employees who had already joined in this community and the amount is still increasing over time (see Figure 8). Therefore, the 363 members of this community are the objective group of this research.

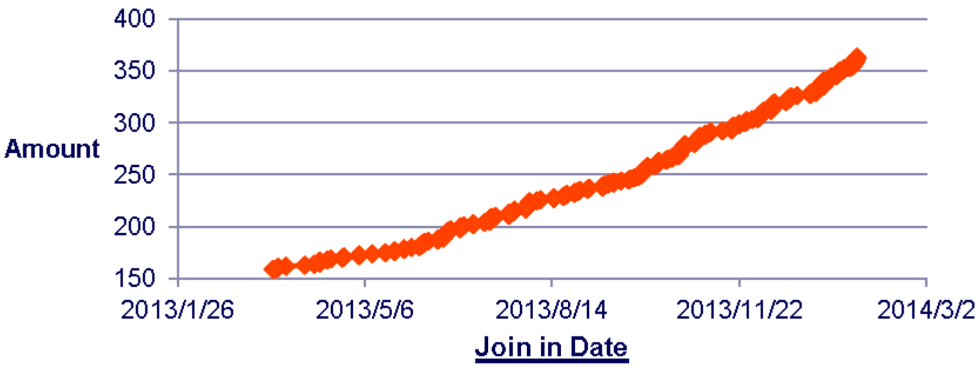

Figure 8. Membership amount of the Big Data community over time.
(Note: The diagram initiates with the amount of 150 and the date of"2013-03-06". Membership amount data before 2013-03-06 cannot be observed in this figure, due to the incomplete data transfer during the system change.)

3.2 Research Design

To understand the role of coalitions as a mode of social influence during technology acceptance in organizations, this research studies the adoption of Big Data in ING Group. This empirical setting is highly appealing, given that the organization has recently embarked upon introducing Big Data into their operations and has undertaken initiatives to create visibility of this strategic decision. The "Big Data Community" in the organizational intranet social media platform has garnered 363 employees to voluntarily join since its inception in June 2012, of which 66 individuals actively participated in the discussion and 258 meaningful comments has been generated during the 20 months by the time of investigation. The discussion forum affords fruitful grounds to study the employees' shared opinions about an emergent technological issue (i.e. Big Data), the emergence of networks or latent coalitions about this issue, and the influence of the forming coalition upon the attitude of individuals who participate in the discussion forum.

Given that prior research has already verified the correlation between "intention to use" (intention of acceptance) and "actual use" of technologies in organizational contexts, this research focuses on investigating the former construct. In other words, this research aims to understand the role of coalitions as a social influence upon intention to use. Intention to use is denoted through the proxy of sentiment, such that, the positive sentiment signals intention of use, while negative sentiment indicates reluctance to use a technology. Using the results of prior scholarly work, it is subsequently believed that the uncovered intention to use will translate into actual use.

In this study, sentiment analysis reveals the attitude of individuals who are opinionated towards a given technology. The historical development of TAM has embedded "attitude" as a concept into the models over time. In the most recent models, namely, TAM2 and UTAUT, the concept of attitude change' has been integrated into the social influence externalities. By analyzing the changes in sentiment (i.e. attitude change), this research therefore aligns with these models to understand the effect of social influence on intention to use.

3.2.1 Data Collecting Approach

Quantitative historical data is gathered from the company's intranet social media platform.

Data Collection Timeline

Dec. 2013: A notification about requesting the permission of using the discussion data was posted one month before the data collection time. The validation period of the notification is one month (see Appendix II: Data Collection Notification).

Jan. 2014: Empirical data from the organization's intranet discussion forum were collected and used to verify the empirical framework.

Data Collection Process

Quantitative data from the company's intranet social media platform "Buzz" – "Big Data Community" are collected manually, which is within the period from 2012-06-01 to 2014-01-24, since there is no method available from the company to extract the information from the file systems automatically. Two types of data are collected manually: discussion text data (later "comments") and network interaction data. All members' names and their time of joining the community are stored, and a unique ID is assigned to each community member in the form of a running number, correlating with the sequence of their membership.

All comments made on the forum since its inception is collected and then screened through a preliminary filter with respect to four conditions. Firstly, an individual who initiates or replies to a comment must be a community member. That is to say, comments from members outside of "Big Data Community" are excluded. Secondly, comments include: posts (from individual who initiates a dialog) and replies (from individual who replies to the initiator). Thirdly, comments must be written in English[5]. And finally, the temporal range of the dataset in this research is limited to a period stretching from June 1, 2012, until 24 January, 2014.

Network interaction data refer to the relationships between individuals. (A, B) is defined as either A responses B's comment or A clicks "like" button for B's comment. Data are collected manually and checked for accuracy by an employee from the company, and any apparent errors (accuracy rate of 98%) were in turn corrected to attain a reliable dataset.

3.2.2 Research Protocols

The participants in the company's intranet social media platform are not notified with the subject of this present research. Community members are notified that data collected during the study will be kept securely and in confidence. Moreover, all the data used in this research remain anonymous (see Appendix II: Data Collection Notification).

3.2.3 Research Settings

This objective organization does not prohibit discussions and interactions among employees during the introduction of Big Data.

[5] This filter was necessary owing to the fact that the organization is multinational company.

3.3 Research Method

3.3.1 Text Analysis Method

IBM SPSS Text Analytics for Surveys 4.0.1 (refer as "software") is used as a tool to conduct a quantitative analysis of the comments acquired from the online forum for two purposes: thematic analysis and sentiment analysis. The software is a linguistics-based solution, which is built upon a class of Natural Language Processing (NLP) algorithms. These algorithms consider both the grammatical structure and meaning of the language of a text, therefore, enables the software to analyze the ambiguities inherent in verbal communications and capture synonymous words by understanding the language. Since reliability and repeatability are the most central issues when conducting such text analysis, the software allowed us to deliver higher speed with reduced inaccuracies (typically born from individual interpretations inherent to manual analysis[6]).

3.3.2 Preliminary Screening of the Data

Based on observation, there exist comments that do not contain information related to "Big Data", such as, an individual only wrote @ [Strategy and Business Change (S&BC)] (which is the name of another community), or some comments lack of substantial meaning, such as, individuals only shared a link or a picture as a comment. Following the preliminary screening of the discussion forum data, a secondary filtering procedure to establish a dataset that is relevant for this study is implemented. Specifically, this preliminary screening aimed to reduce the noise in the raw data by removing the comments that do not relate to Big Data issues or lack substantial meaning.

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[6] The information is from IBM® SPSS® Text Analytics for Surveys, Analyzing survey text: a brief overview.

To this end, the build-in NLP algorithms of IBM SPSS Text Analysis for Surveys 4.0.1 is used to segment the sentences in the posted text and abstract meaningful concepts. In total, 2263 concepts are initially generated by the software, indiscriminately. From this collective, 162 concepts are identified containing the word "data" (e.g., "raw data", "data analysis", and "unstructured data") and deemed to be highly relevant for the purposes of this research. Following the analytical procedure of Nokelainen and Dedehayir (2012), additional concepts are identified from the text and classified these into three generic categories:

(i) Big Data systems and vendors
(e.g., the concepts containing "vendor", "hadoop", "hortonworks")
(ii) Big Data relevant issues
(e.g., the concepts containing "privacy", "security", "hype")
(iii) Big Data technical characteristics
(e.g., the concepts containing "predictive", "cluster", "analytics")

All together, 226 concepts are established that are meaningful and relevant to Big Data. To delimit the dataset, in turn, the comments that do not contain any of these 226 concepts were selected out, assuming that the comments would be out of the scope of big data related discussion. Subsequently, 258 comments are left that formed the final dataset. These 226 lexicons are presented in Appendix III. Since the data are collected from the organizational social media platform without any intervention by the author, the lexicon table is assumed suitable to be used as a preliminary screening tool to reduce data noise for future research with similar research context.

Chapter 4

EMPIRICAL RESULTS

4.1 Text Mining

After ensuring the quality of the comments, a thematic analysis is conducted in order to get an overview of the comments' content. A similar method as the preliminary screening at above is used. Firstly, all the substantial concepts from the whole body of text are extracted. Concepts are automatically generated by using the software's predefined templates, libraries and compiled resources. Lexical concepts that are not included, such as, prepositions and articles, carry insubstantial importance from a quantitative semantic analysis point of view.

In order to identify the topics that are the most frequently discussed, which are assumed to be more prominent issues, concepts which appear at least five times in the whole body of the text are selected. However, certain terms such as "large", "no", "good", "more" that have high frequency, but are non-thematic concepts are excluded, since they can appear in almost any context. Moreover, this thematic analysis aims to identify "Big Data" related topics, therefore, "big" "large", "data", and "big data" as the "Big Data" topic itself are excluded as well.

The extracted frequently used and thematically meaningful concepts were further classified into categories which are defined according to the similarity.

4.1.1 Thematic Analysis Results

258 valid comments are used to identify meaningful topics among the discussion. Company specific concepts such as, the name of other communities, the name of the company are excluded, which may be frequently used but difficult to generalize to

other studies. At the same time, non-thematic concepts such as, “bad”, ”good”, “big”, are virtually in any context of discussion, thereby, are excluded as well.

All the concepts that are selected have a frequency of more than 5 times. In total, 72 most talked sub topics are identified and grouped into the following three categories:

Category 1: Company Level Topics

The concepts in this category are at the company-level: such as, “customer”, “customer centricity”, and “service” are more focused on external customers; “business”, “bank”, “product”, “research”, and “projects”, are related to the company’s internal operation. There are some concepts about the long-term development of the company. For instance, “strategy”, “goal”, “investment” and “vision”. Moreover, other words, such as, “advantage”, “opportunity”, and “competitive”, describe “Big Data” technology from the company’s point of view.

Category 2: Knowledge Sharing Method

The concepts in this category are related to the methods used in this community to share knowledge, where “link”, “documents”, and “articles” are the most frequently used methods. In the meanwhile, “social media”, “website” and “video” as new channels of knowledge sharing also play an increasingly important role in the organization nowadays.

Category 3: Technology Related Topics

The concepts in this category are related to the technology itself, the vendors, and issues. For instance, “information”, “solution”, “development” are people’s general talks about the technology; systems and vendors, such as “hadoop”, “ibm”, “hortonworks”, and “sas”, are more technical discussions. In the meanwhile, some “Big Data” related issues, such as, “legal”, “privacy”, and “hype” are also frequently discussed by the members.

The full version of the topics is seen in the Table 2 below.

Table 2. Big Data related concepts extracted from text data.

Company	Knowledge Sharing Method	Technology
Customer	link	information
business	documents	solution
bank	article	development
service	pdf	technology
value	file	hadoop
people	social media	analytics
products	discussion	support
strategy	colleague	bi
cost	reports	vendors
research	website	tool
department	bookmark	insights
projects	video	ibm
benefit	knowledge	hardware
marketing	data community	communication
investment		capabilities
goal		unstructured data
case		performance
vision		reliable
advantage		infrastructure
customer centricity		hortonworks
governance		creative
opportunities		legal
competitive		datamining
		impact
		architecture
		experience
		partners
		sas
		potential
		model
		database
		privacy
		storage
		hype
		google

Secondly, sentiment analysis is conducted by using the secondary analyzer in the software. This algorithm determines the importance of the sentimental words and their positions in the sentences. That is to say, on one hand, the software uses a representative sentiment process, which means only the more representative opinions or emotions expressed in each sentence are extracted. On the other hand, if two sentiment keywords with the same importance are found, the latter one will be selected as the sentimental keyword. A type is a semantic grouping of terms. The software has predefined sentiment types, such as, general positive and general negative.

However, there are two limitations when applying this method to the present research: Firstly, the results generated by basic sentiment analysis algorithms are polarized, in which the outcome is either "Positive" or "Negative"; Secondly, although these algorithms can process responses that are several hundred words in length, they have a higher accuracy rate in predicting small comments, such as, a phrase, sentence or short paragraph. In this research, the forum is within the organization and used primarily for knowledge sharing. The comments from the "Big Data Community" tend to be longer and more informative on average than the tweeter messages (on average, about 70 words for each comment). Therefore, individuals are more likely to express both positive and negative opinions within one comment. The commonness that both positive and negative opinions are expressed within the same comment results in a large amount of neutral comments and makes it difficult to analyze the differences among individuals' opinions. As a result, an improved algorithm is proposed in this research, which aims to gain a more refined understanding of the sentiments expressed in a comment.

To this end, the notion of a "type" is introduced, which refers to a semantic grouping of terms. The software has predefined sentiment types, which are not limited to the basic distinction between positive and negative, but, rather, include more specific varieties of sentiments. In this manner, six aspects from both positive and negative sentiments can be identified by using the software: "general", "functioning", "budget", "competence", "feeling", and "attitude". All in all, 12 types of sentiment can be captured by the software's built-in analyzer, which are listed in Table 3 along with illustrative sentences extracted from the analyzed posts.

Table 3. The 12 aspects of sentiment studied.

Sentiment	Aspect	Example
positive	general	"good to see that Hortonworks is also in the picture .. soon we gonna install HW for the Big Data team."
	functioning	"Something like hadoop in itself is easy, you could build a fully functioning (highly scalable, fault tolerant) hadoop cluster in under a day on commodity hardware."
	budget	"The problem of Big Data is not storing it as storage has become very cheap but making it accessible, manageable and performing all kinds off analytics on them even (near) real-time."
	competence	"It will help us understand the social cultural context of our customer."
	feeling	"Most articles are about storage of, or uses for big data. This one is about managing the life cycle of big data. Refreshing."
	attitude	"The specialists using the data and making reports should still add qualitative comments to make sure the right answers (read steering) will be given by responsible management."
negative	general	"Maybe from a legal perspective it is allowed, but from a moral perspective it remains plain wrong."
	functioning	"This thread again proves to me that Big Data is an overhyped, inflated and badly defined term."
	budget	"If left unmanaged, the sheer volume of unstructured data that's generated each year within an enterprise can be costly in terms of storage."
	competence	"If they are not informed or have to trust on the media, they will not perceive us as being trustworthy."
	feeling	"This thread again proves to me that Big Data is an overhyped, inflated and badly defined term."
	attitude	"('the black swan', 'anti-fragility') who bluntly states that Big Data is a lie."

The underlying assumption of this proposed approach is that the more of the six aspects of a sentiment (positive or negative) that appears in a comment, the more likely the comment represents that sentiment. For instance, if there are two positive sentiment aspects and one negative sentiment aspect shown in a comment, the comment is considered to be overall positive.

To assist the evaluation, "PositiveScore" is defined as the summation of the number of positive aspects (general, functioning, budget, competence, feeling, and attitude), and similarly, "NegativeScore" as the summation of these aspects that are negative (also see the formulas below). The tweleve of sentiment aspecs are kept as binary number in the evaluation. Any aspect that appears in a comment will be counted as 1, otherwise will be kept as 0.

PositiveScore = General Positive + Functioning Positive + Budget Positive + Competence Positive + Feeling Positive + Attitude Positive

NegativeScore = General Negative + Functioning Negative + Budget Negative + Competence Negative + Feeling Negative + Attitude Negative

If the PositiveScore is higher in a comment than the NegativeScore, that comment will be positive overall, and vice versa. Moreover, the greater the difference between the PositiveScore and NegativeScore, the more pronounced is the sentiment. For instance, a comment that has positive functioning, positve feeling and negative budget will be kept as positive (0,1,0,0,1,0) and negative (0,0,1,0,0,0). Therefore, the PositiveScore of this comment equals 2 and NegativeScore is 1. The overall sentiment in this comment is 1, thereby, labeled as P.

4.1.2 Sentiment Analysis Results

Applied the proposed method to the textual dataset for Big Data, the results are presented in Figure 9. In the figure, the increasing degrees of positivity embedded in the comments are indicated by P, P+, and P++, respectively. Similarly, N and N- denote the increasing degree of negativity in the comments posted on the community forum.

Comments comprising no positive or negative concepts (i.e. no sentiment expressed in the comment at all) are labeled as "Non".

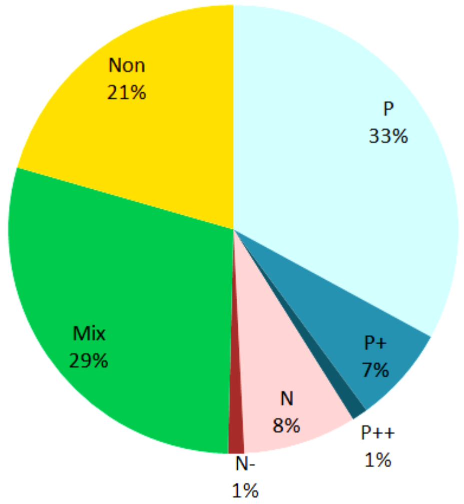

Figure 9. Distribution of sentiments[7].

(Note: The colors represent the sentiment categories, where blue, red, green and yellow stand for positive, negative, neutral, and no sentiment, respectively. The increase of the color depth shows the increasing degree in that sentiment category.)

The pie chart above provides an overview of the sentiment distribution of the 258 comments that formed the dataset. It is observed that 50% of the comments posted on the forum had neutral or no sentiment. There are a couple of reasons for this observation. Firstly, comments on the intranet social media platform tend to be long, thus making it possible that the comments contain the same level of positive and negative sentiment, resulting in a "mix" outcome. Secondly, as the comments are from the intra-organizational social media platform, this professional working environment may prohibit some employees to freely express their opinions, and their neutrality translates into a "Non" outcome. Of the remaining comments that do present a sentiment, however, roughly 80% are attributed to some level of positivity, indicating that there is a notable inclination towards the intention to use of Big Data in the organization.

Figure 9 presents a static picture of the sentiment distribution at the time of the data assessment. To understand how the intensities of different sentiments have been changing over time, which may, for instance, indicate convergence upon a particular

[7] No comment has been rated N- -, therefore, N- -is not displayed in figure 5 and figure 6.

sentiment (i.e. positive or negative), this research presents the evolution of sentiment distribution in Figure 10. Each blue diamond represents a positive comment, red ones are for negative comments, and the green diamond stands for the neutral comments from the “Mix” and “Non” categories.

Figure 10. Distribution of sentiments over time.

(Note: In this graph, each diamond is a comment and the color represents the sentiment of this comment, however, there are diamonds that are covered due to overlapping.)

This figure reveals a growing density in the quantity of communication among forum members across the 20 months period of investigation. While the graph does not indicate the interchange among particular individuals, the growing density provides preliminary support for the anticipation of the coalescing of individuals about a common issue, in this instance of Big Data. Interestingly, the first few months of discussions signal positive attitude towards Big Data. In turn, the early period of 2013 is marked by the dense exchange of opinions, which is accompanied by increasing skepticism toward Big Data. However, the more recent timeframe appears to be dominated by burgeoning positive sentiment and hence a more pronounced intention to use of the technology.

Another interesting discovery is that positive and neutral comments spread relatively evenly over time, while the negative attitude seems to appear as clusters at certain points in time, for instance, at the beginning of 2013 and then later at the end of that year. To better understand this phenomenon, this research looks into the content of the comments. During early 2013, it appears that an intensive discussion took place, amounting to more than 50 comments. Strong arguments arise as to why and how to use Big Data within the industry. Positive arguments are built on the Big Data's integration of information and creation of insights, which are seen helpful in building the competitive advantage of the organization. Negative comments, in opposition, claimed that Big Data is overhyped and that the organization needed to establish a purpose of technology usage. And later in 2013, the members discussed how to deal with data privacy and security issues and how organizations could build customer centricity without violating these issues.

As noted above, while the data inform of the evolution of the positive and negative sentiments, they do not provide information concerning the individuals behind these sentiments. As a preliminary step towards this end, the community members are classified with respect to four groups according to their sentiments expressed during the timeframe of the investigation of this research.

An individual who has been commenting positively, continuously, is placed into the "PositivePerson" group, while an individual with purely negative comments is allotted to the "NegativePerson" group. Individuals who show mixed sentiments expressed in either a single comment or over multiple comments are placed into the "NeutralPerson" group. All remaining individuals who have displayed no sentiment or have not provided any commentary are subsequently placed into the "NoEmotionPerson" group. The graph below visualizes the classifications of individuals, with the assistance of formulas.

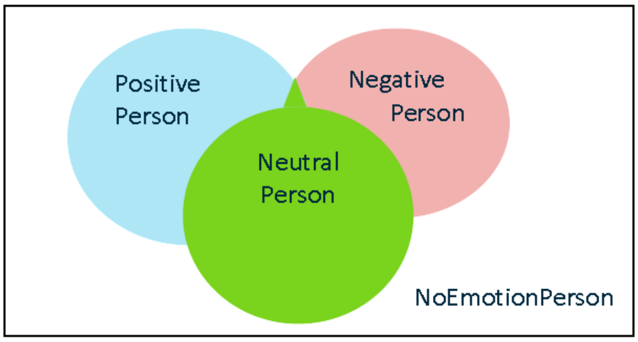

Figure 11. Four classifications of individuals.

(Note: Colors of blue, red and green present comments hold the positive, negative and mix sentiment, respectively. Comments contain no sentiment are put into the blank area.)

$$NeutralPerson = Mix\ (individual) \cup [Positive\ (individual) \cap Negative\ (individual)]$$

$$PositivePerson = Positive\ (individual) - NeutralPerson$$

$$NegativePerson = Negative\ (individual) - NeutralPerson$$

$$NoEmotionPerson = \Omega - PositivePerson - NegativePerson - NeutralPerson$$

Of the 66 individuals who actively participate in the forum, the NeutralPerson group has amassed the largest membership with 30, followed closely by the PositivePerson group with 23 members (i.e. individuals displaying intention to use). The NegativePerson group has a membership of only 5 individuals. The remaining 8 individuals are classified into the NoEmotionPerson group. These results align with the earlier findings and indicate a highly positive overall attitude towards Big Data in the community at large. At the same time, they may provide some evidence of coalitions that have formed about attitudes towards big data.

4.2 Dynamic Network Analysis

Using these classifications, the social network is mapped with Gephi, an open-source software for network visualization and analysis, which has been successfully used for the Internet link and semantic network case studies, as well as for social network analysis (SNA) in prior scholarly work (Bastian et al., 2009). For this purpose the “reply” and “like” as two types of interaction relationship data are stored, using the format (A, B), where A and B denote individuals in dialogue on the community forum. With respect to the network of interconnections, A is the source node, B represents a target node, and (A, B) is a link between the source node A and the target node B[8]. To capture the dynamic behavior, Gephi's degree algorithm is to calculate the in-degree and out-degree of each node by taking the direction of the interaction into account. Furthermore, Force Atlas is utilized, a force-directed algorithm built into Gephi, to identify the centrality of the network and simulate the formation of coalitions in this research.

4.2.1 Coalition Evolution

Overall, the social network that formed around Big Data was identified, which contains 95 connected nodes and 206 links with varying degrees of weight. Figure 12 presents the overview of this network and the center of gravity (i.e. focal node).

Four colors are used for differentiating the nodes. Blue color represents "PositivePerson", red color means "NegativePerson", green ones stand for "NeutralPerson", and white nodes are "NoEmotionPerson". "Degree", as a parameter, is used to filter out the nodes that have not linked to others, due to the reason of not participating in the discussion.

[8] Gephi employs the 'PageRank' algorithm used by Google to rank the importance of web pages, to study networks and identify the position of the nodes in this network. The PageRank algorithm works on the basis of interpreting a link as "A votes for B", and, in turn, establishing the more important nodes as those that receive more votes.

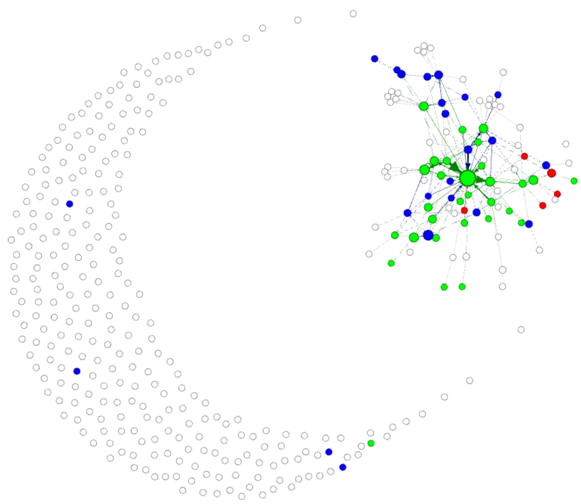

Figure 12. The holistic Big Data community network and center of gravity.

Figure 12 illustrates that the NoEmotionPerson group (white nodes) dominates the network in terms of membership. In the network, a node is disconnected either because this individual has not participated in the discussion, or because comments from this node do not receive any reply from other nodes. It is importantly observed that a cluster of interconnected nodes that represents the interactions of the Big Data Community, shown in greater detail in Figure 13. The NeutralPerson group members (green nodes) appear to form the center of this cluster of communicating individuals, with the PositivePerson group (blue nodes), in other words, individuals with intention to use the technology are also active in correspondence. A few members of the NegativePerson group (red nodes) are positioned somewhat on the periphery of this cluster[9]. Furthermore, contrary to the NeutralPerson and PositivePerson groups, which display dense interactions (both within and among groups), it is interesting to note that the NegativePerson group demonstrates no interactions within the group. Therefore, this finding seems to suggest that a coalition has not formed among the individuals that carry negative sentiment.

[9] In these figures, the size of the node represents the amount of interaction of that node, and the arrow direction designates the source and target nodes in this interaction.

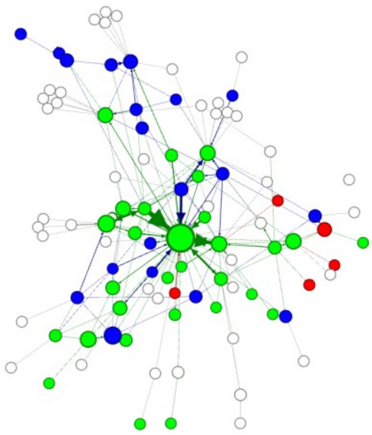

Figure 13. Network of interactions within the Big Data Community.
(Note: the size of the node represents its degree, the thickness of the link represents its weight, and the arrow of a link represents the direction of communication between two nodes.)

The aim of this study is to shed light on the role of a coalition that imparts social influence on individuals concerning the acceptance of a technology. However, it is difficult to discern a clear coalition of members with similar ideologies (Axelrod, 1970; Rosenthal, 1970) in the above figures. The centrality of mixed sentiment possessing individuals in the network indicates that distinct coalitions (positive or negative), comprising multiple nodes, have not emerged by the time of the analysis. However, there appear to be individuals who hold a large share of the interaction on the network. In order to identify the most prominent individuals, the Big Data community as a network of individuals is displayed with at least 5 degrees of interaction in Figure 14, and at least 10 degrees in Figure 14.

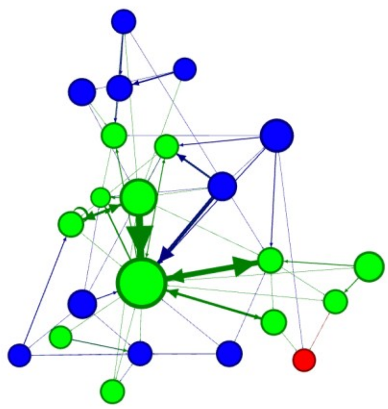

Figure 14. Network of interactions with nodes' degree no less than 5.

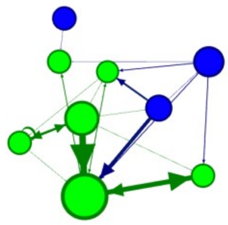

Figure 15. Network of interactions with nodes' degree no less than 10.

The figures above confirm there to be a distinct focal node (the largest green node) in the Big Data community, which has a substantially higher degree of interaction than any other node in the network. Related to the empirical framework in the previous chapter, this individual is a potential champion, which intends to assume a central role in the network by interacting with other nodes. Champions are important for the successful adoption of the technology within the organization, bestowed by their power as referents to affect others' opinions. In this empirical investigation, this focal node is subsequently treated as a "one-person coalition", which has the power to influence the opinions of others and trigger the formation of a larger coalition with increasing dyadic connections over time. In this manner, the focal node acts as a "referent", a "core", or a champion.

4.2.2 Social Influence of the Referent

Figure 16 shows the interactions of the referent with other members of the Big Data community via "reply" the comments.

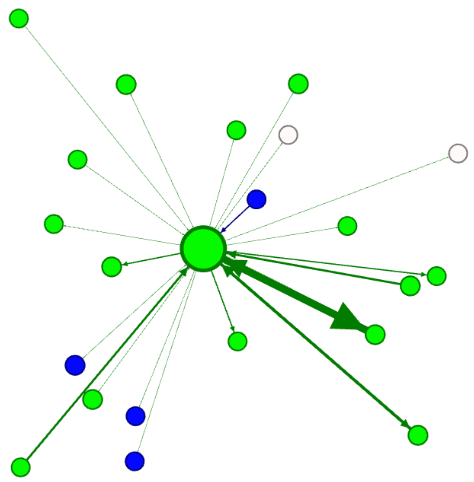

Figure 16. Network of the Big Data community focal node.
(Note: This network only displays the interactions via "reply")

As shown in the above figure, 21 nodes (holding positive, neutral, or mixed opinions towards Big Data) actively interact with the focal node. The direction and weight of the arrows indicate the flow of this communication. However, this is a static figure. To understand the dynamics of social influence of the one-person coalition upon the intention of use (i.e. positive sentiment) of the other individuals, the sentiment change (i.e., attitude change) of the focal node is plotted and compared with the sentiments of the individuals who interact with the focal node, over time, in Figure 17.

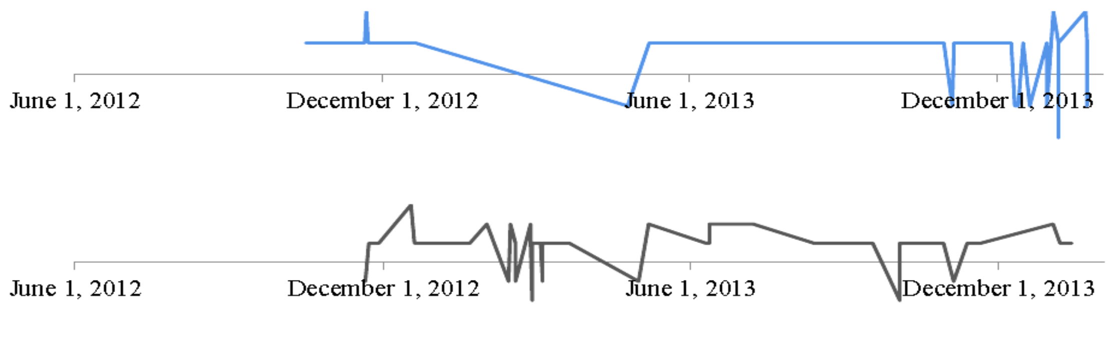

Figure 17. Sentiment evolution of the focal node and its network.

During the 20 months of interaction, both the focal node and interacting 21 nodes show sentimental fluctuation. However, it is not hard to notice that these two groups' behavioral patterns are somehow correlated. The positivity of the focal node at the beginning of the timeframe is followed, with a short delay, by positive reactions from the 21 nodes, including the peak of positivity around December 2012. In turn, close to June 2013, the focal node's negative sentiment is matched immediately by the group of interconnected individuals. From this point on, the general sentiments expressed by both the focal node and the 21 nodes' group remain largely positive, except for two intensive vibrations in the graph above (during early and late 2013), which were triggered by two issues divulged at the beginning of this section.

Figure 18 shows the interactions of the Big Data community via "like" a comment. In total, 22 nodes involve in this type of interaction with a degree of at least 5. It is notable that this network is covered by individuals only from "PositivePerson" and "NeutralPerson" groups, which indicate that individuals are more likely to converge on similar opinions (Axelrod, 1970; Rosenthal, 1970).

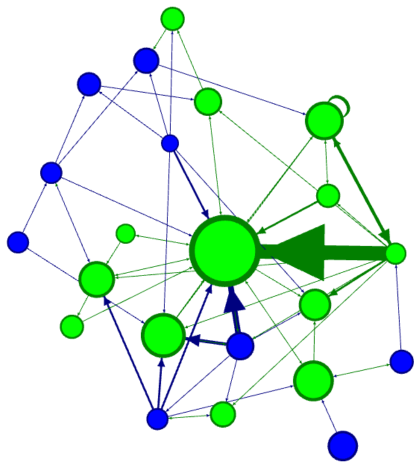

Figure 18. Network of interactions via "like" with nodes' degree no less than 5.
(Note: The sizes of the nodes are ranked by their in-degrees.)

The communications in this network converge to the focal node, which can be observed from the direction of the links in the graph. Also the focal node attracts the largest amount of "like" from a group of individuals, in which the green node on the left side and the blue node below the focal node contribute the most. These results prove the statement in the empirical framework that people tend to comply with a prominent referent.

In summary, Figure 17 seems to indicate that the sentiments of individuals that actively interact with the coalition (in this case a one-person coalition or referent) centering on Big Data are influenced by the latter. Figure 18 additionally reveals individuals' tending to comply with the referent. This suggests that coalitions forming about technological issues in organizations are important social influence factors that have the power to affect the other individuals' intention to use the technology.

Chapter 5

CONCLUSIONS

The study of IT adoption in organizations is a prominent topic for both academia and industry. One of the main motivations behind this is the improvement of the employees' productivity by using new technological innovations, which can improve the competitive position of that organization. Experience indicates that the individual employee, as the end user of the technology, acts as a gate-keeper of the successful adoption of the innovation into the organization's ranks, subsequently assuming a position through which they can influence the competitiveness of the organization. However, the adoption of the technology by employees in the organization is not always a success, due to the barriers in using the technology (i.e., lack of training, complicated system design, etc.), which challenges scholars and practitioners alike to gain better understanding of the technology acceptance behavior of employees in organizations.

Prior research has contributed various models to this end, among which TAM (Technology Acceptance Model) has emerged as the most popular in the academic community. Despite the widespread use of the TAM framework to predict users' acceptance of a variety of technologies, social influence has remained a difficult factor to understand. Studies in the literature have typically focused more on individual-oriented and simple technologies, therefore, paying little attention to the elaboration of the influence of a referent, especially from a group perspective. However, when a complex technology, such as that which has been studied in this research, is introduced in an organization, it is likely to be accompanied by widespread awareness and resulting discussions among a large group of employees. Therefore, individual's perception about this complex technology is more likely to rely on others' perception of it. In order to adapt the TAM model to predict individual's acceptance of complex technologies, this research uses the notion of "coalition" in the organization research as a complementary to better understand the social dynamics around the technological issues.

To answer the questions of what are the social dynamics around a technological issue and their influence on individuals, an empirical case study was conducted in the ING Group – a global financial group – which has decided to introduce Big Data into the organization. Since June 2012, Big Data has emerged as a prominent technological issue, which has attracted the attention of 363 employees to voluntarily join the "Big Data community" and share opinions in Big Data related discussions. Departing from prior research endeavors, such as interviews and surveys, this research followed a novel approach to predict individuals' potential acceptance of a technology by investigating a referent group, which is referred to as the coalition.

The discussion content in the community was analyzed by using the text mining software, IBM SPSS Text Analytics for Surveys 4.0.1. The sentiments distributed in the comments were investigated, which were assumed to be representative of the individuals' attitudes toward Big Data, thereby showing their intentions to use this technology. Overall, positive opinions overrated negative opinions, a pattern that was continuously observed over a 20 months of observation period, which indicates a general positive attitude about Big Data among employees. It was also identified that, negative opinions cluster upon certain issues. The two obvious clusters of negative comments appeared in the discussions are about the technology's usability within the organization and the Big Data relevant ethical issues, for instance, data privacy and data security.

With the results of the sentiments distribution, this research studied the emerging coalition that formed around Big Data. The focal node in the network of interactions contributed the most to the discussion context and generated the largest amount of interactions with other members of the community, and was subsequently referred to as the "one-person" coalition. Individuals who were neutral or positive about Big Data were seen to coalesce and constitute the centrality of the network, while the coalition formation of individuals who held negative opinions upon Big Data could not be observed from the network.

It was also notable that this one-person coalition received the largest amount of “like” responses from other community members. Among them, there exist members who do not share much of personal opinions but always tend to comply with the opinions of this focal node, which gives evidence that this one-person coalition is a referent in this community.

Related to the theory, that is to say, this one-person coalition acts as a core of the network and is able to have the referent power upon other individuals’ intention to use Big Data. To this end, this research also observed the 20 months’ attitude changes of this coalition and individuals from its network. The same patterns of attitude change were identified, which in turn could be translated as the coalition positively influencing other individuals’ intention to use Big Data in this community. Due to the overall sentiment of this one-person coalition being positive, therefore, it influences other individuals to have an overall positive attitude toward Big Data, which in turn signals an overall intention to use Big Data.

As studied in the literature, an intra-organizational coalition is defined based on eight characteristics. In this empirical case, the organization’s intranet social media platform served as a desirable location for forming coalitions, due to this virtual environment being positioned away from the organization’s direct, formal structure, thereby, presenting no strict formal structure of the membership. Individuals could voluntarily join and share knowledge on this technology-specific forum. However, in order to form a coalition, concerted member action was required. Besides the focal node that is identified as the one-person coalition, the concerted membership action between this one-person coalition and individuals from its network can be obviously detected. Therefore, it is predicted that this one-person coalition and individuals from its network constitute a latent “multiple-person” coalition, which is able to influence a larger scope of individuals in the network.

However, the amount of data gathered does not allow this research to conclude about the formation of the multiple-person coalition. Therefore, it is proposed that the one-person coalition and individuals from its network form a latent coalition. When the interactions around Big Data issues accumulated to a certain amount or when Big Data issues become so urgent that require the joint action of the members, it is likely that this latent coalition will transform into a real coalition which has impact on a larger amount of individuals. Therefore, the influence of the coalition is like a wave that initiates from the center and expands further.

5.1 Contributions

Research in this filed aims to predict individual user's acceptance of a technology, where the most used research methods are self-reported questionnaires and interviews. Innovatively, this research provided a succinct and affordable methodology for both practitioners and scholars to forecast the potential acceptance of a given technology. It was essentially demonstrated that posted comments on a technology-specific forum allow investigators to undertake a quick test to understand opinions and sentiments among the forum members, which can be used to predict their intentions to use of this technology.

In academia, prior research has demonstrated the relationship between social influence and intention to use a technology, while this research looks into the social influence factor and explores the dynamic behaviors centering on the technology-specific issues. The referent is studied from a group perspective in this research, which is assumed to play an important role in studying the acceptance of a complex technology, a point that has been overlooked by prior research. This research adopts the theory of coalitions to explain the behavior of the referent, and therefore, strategically fills the research gap.

Moreover, during this research, a structured literature review was conducted to identify the publications of coalition in the field of TIM (Technology Innovation Management). Only two articles were found relevant to this study, which are in the context of organizations. No literature has directly connected the technology acceptance model with coalition theory. Therefore, this research sheds new light on elaborating the social dynamics during technology adoption through a unique approach.

The development of the TAM model over the three decades has prominent growth, which results in a steeply increasing collection of predictors from various theories. However, the lacking of elaboration of the externalities contributes its overall weakness of providing practitioners actionable guidance (Lee et al. 2003). Rather than the traditional static research approach that validates the relationship between the social influence determinant and intention to use of a technology, this dynamic approach zooms in this social influence factor and gives readers more in-depth knowledge of the referent. Following this approach and understanding the dynamic behaviors of the participants provide practitioners with concrete references in facilitating the acceptance of a complex technology in organizations.

As concluded in this research, the coalition impacts individual employees' adoption of a technology, by serving as a referent or a referent group. In this sense, managers can utilize their knowledge of the coalition to facilitate the adoption of the technology. For instance, during the introduction of a new technology in organizations, not every employee has the knowledge to form their opinions upon it. Therefore, a coalition as the referent is the information sources for these individuals who seek information. By generating a larger awareness of the technology, and diffusing the knowledge of the technology in the organization, the coalition can help employees to form their perception of the technology. At times, the central coalition can enable managers to approach them strategically to catalyze the transition of other employees' to actual usage behavior. For instance, as studied in the coalition literature, the champion is individual who is keen on building network to get his or her idea approved by others, therefore, it is by nature that the champion will accelerate the adoption of the technology, as long as he or she is in favor of this technology.

Furthermore, by analyzing the posted comments on a technology-specific forum, the results gave a summary of the discussion content and provided an overview of the forum members' attitude towards the specific technology, at the same time, providing managers the transparency of employees' technology acceptance intentions in the forum. Positivity can guarantee a higher chance of success in adopting the technology. However, by knowing the negative comments, managers can easily spot employees' concerns, and therefore, take in time actions to remove the bias before the implementation of the technology. At times, these concerns expressed by employees are able to affect the policy makers' decision about the adoption of the technology. For instance, strong negative feedback from employees or unsolvable issues (i.e., data privacy and security issues about Big Data) may force the policy makers in the organization to critically reevaluate the applicability of implementing the technology.

Last but not the least, nowadays organizations are stepping away from enterprise 1.0 into enterprise 2.0 systems. Within the organization, this transition is characterized by the emerging usage of the social media software platforms that help employees share, organize and collaborate information. In response to one of the two weaknesses of the TAM pointed by Venkatesh et al (2003), which is mentioned at the beginning of this research that organizations are undergoing a development from hierarchy towards networked collaboration, this research of using intra-organizational social media platform to monitor employees' behaviors becomes a high potential approach. Besides, as the trend of "go virtual" and "work at home" continues, this channel of communication is assumed to be even more highly valued as time goes by.

5.2 Limitations

Nevertheless, there are a few limitations in this research.

Firstly, the time span of this study does not allow the observation of the full implementation of Big Data within the organization, which rendered it difficult to test the relationship between the referent group and individual's actual usage of a technology. Therefore, future studies are advocated to look at the coalition's effect on individuals' actual usage behavior of a technology, concurrently extending this present work that has centered on the intention to use of a technology.

Secondly, the IBM SPSS Text Analytics for Surveys 4.0.1 is used as the sentiment analysis tool in this research for two reasons. Firstly, this commercial software can be easily installed and practiced in any organization, requiring not much training on using the software. Secondly, IBM has fame in research on artificial intelligence and this specific software has been used in various prior academic studies. For instance, the study of Ice (2012) used the software to analyze individual students' sentiments in the comments about education. With a pilot test of 100 records, the author concluded an accuracy of 80% between the software and qualitative coding methods, which assures that the software is of significant interrater reliability. Therefore, this research adopts this software and conducts a quick way to evaluate the results.

However, the scale of the research and the limited amount of data do not support the test of accuracy rate in this research. Future research is encouraged to use multiple software and algorithms to compare the accuracy of the results, and adopt the most robust solution. Also, future research can collect data from other resources (e.g., Email and Message data), if applicable, to enrich the dataset.

Additionally, a bias might exist in this current empirical case study that people who register the "Big Data Community" tend to be those who already have interest in Big Data, and therefore, might partly contribute the overall positive attitude about Big Data in this community. Moreover, this empirical study only investigated Big Data as the technology in a single organization – ING Group. Therefore, the research results might have limited generalizability out the scope of the current research context. However, discussions among employees in the organizations' social media platform during the introduction of a new technology is assumed to be a common phenomenon, therefore, future studies can conduct multiple case studies by using the research approach proposed in this thesis to verify the results of this current study.

Notwithstanding this inherent limitation imposed by potential selection bias, the study method presents the advantage of monitoring user behavior with minimum research involvement, which has been a limitation of other empirical approaches such as surveys and interviews.

GLOSSARY

C-TAM-TPB. Combined TAM and TPB

IDT. Innovation Diffusion Theory

IT. Information Technology

MM. Motivation Model

MPCU. Model of PC Utilization

NESSI. Networked European Software and Service Initiative

NLP. Natural Language Processing

SCT. Social Cognitive Theory

SN. Subjective Norm

SNA. Social Network Analysis

TAM. Technology Acceptance Model

TAM2. Technology Acceptance Model 2

TAM3. Technology Acceptance Model 3

TIM. Technology Innovation Management

TPB. Theory of Planned Behavior

TRA. Theory of Reasoned Action

UTAUT. Unified Theory of Acceptance and Use of Technology

UTAUT2. Unified Theory of Acceptance and Use of Technology 2

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Appendix I: TAM Model Utilization by Academic Community

The following two figures (see Figure 19 and Figure 20) give an overview the utilization of the TAM model in scholarly work, in particular for the TIM field of inquiry. Web of Science has been utilized to scour the database of publications for the search term "technology acceptance model" in the title, abstract, and keyword (on 28 March, 2014).

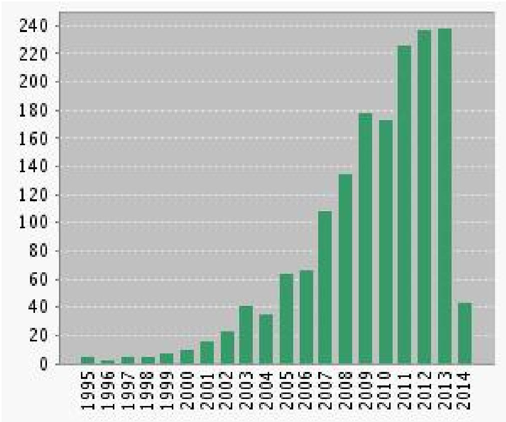

Figure 19. TAM published items in each year.

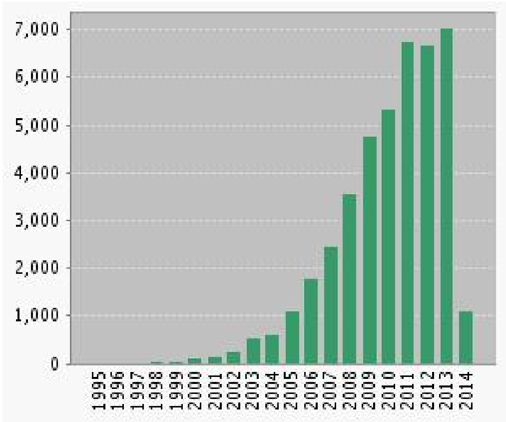

Figure 20. TAM citations in each year.

The most prominent areas are: computer science, information science, and management, with roughly equal percentage of publications. In the field of management, which is the focal area of investigation in this research, a steep growth is observe for most of the years in both publications and citations (see Figure 21 and Figure 22).

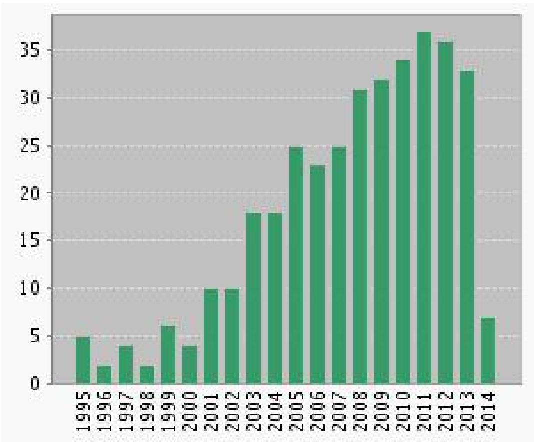

Figure 21. TAM published items in each year (management).

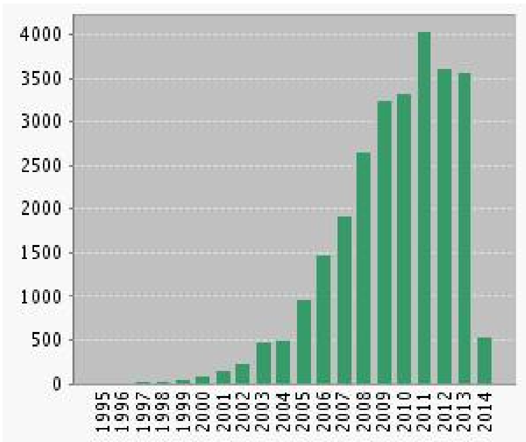

Figure 22. TAM citations in each year (management).

Appendix II: Data Collection Notification

Hi everybody, I am a research intern from the transaction services lab and currently I am working on my master thesis that will investigate the introduction of a new technology into an organization. I have selected Big Data as the technology that is being introduced into ING as my case and would like to use the text in this discussion forum to obtain quantitative data which will help me analyze the use of Big Data in our company.

Before I go ahead with this, it is important that I receive your approval for letting me use the discussions on the Big Data community in Buzz. The quantitative nature of my study means that I will not be making an in-depth qualitative assessment of the messages. Rather, my study will focus on the number of users of the discussion forum, general opinions shared with respect to the technology, and any emergent topics of discussion that relate to the technology.

I would like to ensure you that individual users of the Big Data forum will remain anonymous and any information related to individual users will not be used in my quantitative data analysis whatsoever. However, if there are any objections or concerns, please let me know before January 12.

If you would like to know more about my research, I am more than happy to let you know at your request. Thanks a lot!

Appendix III: Lexicon for Big Data Text Mining

Table 4. 162 concepts which contain "data" (part 1).

Concepts contain the word of "data"		
data analysis	petabytes data	spaghetti pile of automated data
relational database	raw data	data community
customer data	use data	bigdata usage
unstructured data	data v1.0	run hadoop
data project	external data	data set
data infrastructre	instructured data	sharing data
data solutions	data technologies	master medium data
data organization	oracle data integrator	pos data from shops
database	data	data challenge
bigdata vendors	exabytes of data	bigdata solution
data to deliver	reservoir of data	data strategy
cloudera plans data hub	datamanagement	internal data
bigdata domains	data landscape	data recovery
speed of data	splunk data insight	database cluster
data question	data lakes	80% of an organization's data
data volume	data analysis contact	end of data
data insights	data team	datamining
regular data warehouses	stakeholders in data	sql database
data business case	data scientist	bigdata challenges
data geen wetenschap	structured data	bigdata customers
data era	parts of bigdata	introduction to data science
business data	data vendors	poc bigdata
caption to bigdata diner	example of bigdata	bigdata projects
quantitative data analysis	data power	trx data
amount of data	data analytics	machine data
real-time access to data	range of data	data for cost
bigdata technology	exadata	data storage

Table 5. 162 concepts which contain "data" (part 2).

Concepts contain the word of "data"		
proposal for bigdata development	representative sample of data	data application
discussion data equity	data concepts	data compression method
datascience	data changes	data vendor marketing
png in bigdata	parallel data warehouse	use data mining algorithms
interpretation of data	bigdata development	referencearchitecture to manage data
datastax	database sources	unstructured and semi-structured data
morgage data	bigdata analytics	development of bigdata solutions
income data	bigdata discussions	datastax enterprise edition
process data	data to trade	data to find virtual wallet
data database	datacentre	center of their data centers
bonuscard data	side of the data center	bigdata component
banking data of our customers	data risk control	data architecture
data presentation	data points	forrester's data management reference
raw enterprise data	datamining bi developments	bigdata course of abis
data pool	data visualization	internal and external data to prevent cybercrime
example of the future of bigdata	meta data	bigdata analytics banks capture
data sources	purchasing data	idataagent to provide integration
data c0.92	masterdatamanagement	context of individual data
example of a bigdata development	data nodes	data management company
structured data analysis	bigdata functionalities	sheer volume of unstructured data
quantitative data	data to create a path	transformation from data to information
data preparation	lean data mgt	data capabilities
bigdata in marketing	data search	data forum
exploratory work on data logistics	place data	data model
data to retailers	current structured data	bigdata
data grid	vortex data warehouse	data community privides
techniques of bigdata	scope of data	www.economistinsights.com/technology-innovation/opinion/big-data-no-teenage-dream

Table 6. 64 other Big Data relevant concepts.

Big Data systems and vendors				
hadoop	hadoop adoption	hadoop cluster	built-in hadoop	apache's hadoop upgrade
co-creator of the hadoop	bookmark hadoop	hadoop distributions	mobile hadoop cluster	vendors
releases of apache hadoop	vendor lock	hadoop2.0	hadoop technology	overview of vendors
use hadoop	net sdk for hadoop	hadoop2.0 hadoop creator	management of your hadoop cluster	shift to hadoop
watson story	hortonworks sandbox	hortonworks	development of mapreduce hadoop	external vendors
management components of hadoop's mapreduce	releases of apache hadoop	hortonworks data platform	watson apps	hortonworks co-founder
twitter	partners	google	test drive coursera	start to follow the coursera course
cloudera poc				
Big Data technical characteristics				
predictive capabilities	predictive analysis	predictive analytics technology	predictive analytics	predictive bank of the future
realtime analytics	realtime analysis	analytics	techie	cluster of machines
predictions	capabilities	power of predictive and prescriptive analytics	social network	social media
social cultural context	technology	capacity		
Big Data relevant relevant issues				
privacy topic	sense privacy	security	privacy	privacy aspect
speakers comments privacy	hyper'marketing tool	not hype	goldmine	cost