COALITION FORMATION DURING TECHNOLOGY ADOPTION

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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 considered the contribution of referent individuals to technology acceptance (i.e. social influence), this paper introduces the notion of the ‘coalition’ as a social group that influences the opinion of other, non-coalitional members of an organization. We employ this framework in an empirical study centering on an organization – 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, we demonstrate the emergence of a central coalition on the Big Data issue, and the dynamics of influence of this coalition upon the attitude (i.e. intention to use) of individuals who participated in the discussion forum. Our paper contributes to existing TAM frameworks by elaborating the social influence variable and providing a dynamic lens to the technology acceptance process, while offering a methodological tool that can be utilized by organizations to understand social dynamics that form about a newly introduced technology and accelerate its acceptance by employees.

Keywords: technology acceptance, TAM, coalitions, coalition formation

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 a supply chain software. One of the underlying reasons for this failure was, a well reported and studied phenomenon, namely, 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. A framework known as the ‘Technology Acceptance Model’
(TAM) has been offered by scholars to explain 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 claimed 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), draw 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 [moving] 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 and the dynamics of opinion generation subject to group influence. 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. In response to this much needed elaboration, this paper 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 & March, 1963; Gamson, 1961; March & Simon, 1958).

In this paper, we subsequently develop a theoretical framework that brings together TAM and coalition theory, 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 a referent collective for other individuals that are not coalitional members. Furthermore, rather than focusing on traditionally studied, simple, individually used technologies, we purposefully selected a large, encompassing technological issue that influences usage by multiple individuals directly and indirectly, thereby addressing the hitherto limitations noted by prominent TAM scholars. Hence, we illustrate the applicability of our framework in an empirical study centering on an organization – a global financial group – which has decided to introduce Big Data (platforms, tools and software to enhance the use of a large volume, variety and velocity of data for the creation of business value) into the organization’s formal operations at the beginning of 2014. Our assumption is that Big Data represents an emergent and important technological issue within the organization that will motivate individuals to derive a positive or negative opinion, potentially creating coalitions as individuals converge on similar opinions.

Empirically, our work departs substantially from earlier studies that have traditionally utilized qualitative methods such as interviews, surveys, and questionnaires. Instead, we
undertake 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 are actively participated in the community and have contributed to the opinion sharing, 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, we focus our investigation on the former. We denote intention to use through the proxy of sentiment, such that, positive sentiment signals intention of acceptance, while negative sentiment would indicate reluctance to use. We conducted the sentiment analysis of the online forum comments by using the IBM SPSS Text Analytics for Surveys 4.0.1 software, which is built upon a class of natural language processing algorithms. The resulting sentiment data allowed 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 participated in the discussion forum.

Theoretical Background

IT acceptance in organizations

The literature studying 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 this literature highlights a number of models that have been developed by scholars to understand individual users’ IT adoption intention, including, the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model, the Theory of Planned Behavior (TPB), the Combined TAM and TPB model, the Model of PC Utilization, Innovation Diffusion Theory, and Social Cognitive Theory.

As one of the pioneers in this endeavor, Davis (1989) introduced the concept of “user’s acceptance of IT”, identifying two measurements – perceived usefulness, and perceived ease of use – to build the TAM model. Essentially, Davis constructed the model upon the TRA model (see Figure 1) through which the correlation between the intention of use and actual acceptance of the technology had been demonstrated in prior literature.

![Diagram of TRA model](image)

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

The TRA model suggests that the subjective norm of an individual results from the multiplication of normative beliefs (i.e. perceived expectation of specific referent individuals or groups), and his or her own motivation to comply with these expectations. Therefore, the
model expects subjective norm to influence intention to use (behavior intention), which leads to actual use behavior. However, little explication of the referent, either as individuals or as groups, have been provided. In fact, Fishbein and Ajzen (1975) have suggested that this is one of the least understood aspects of TRA in their seminal work.

Over the two decades following Davis’ contribution, TAM (see Figure 2) has been extended several times with the introduction of specific factors to more accurately predict users’ technology acceptance behavior. 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; Venkatesh and Davis, 2000).

![Figure 2: Validated TAM Model (Davis et al, 1989).](image)

One of the key factors that determined the trajectory of theoretical development was identified by Hartwick and Barki (1994) as the ‘mandatory setting’, which moderated the significance of subjective norm in technology acceptance. The authors concluded that subjective norm had a significant direct effect on intention to use in mandatory settings but not in voluntary settings. Incorporating Hartwick and Barki’s results, Venkatesh and Davis (2000) subsequently proposed TAM2 (see Figure 3), an extension of the original TAM. The model focuses on the exploration of externalities of the main construct of TAM and reflecting the impacts of two social forces: subjective norm, and image, and two moderators: voluntariness, and experience.

![Figure 3: Social Influence aspect of TAM2 (Venkatesh and Davis, 2000).](image)

(Note: This model is without other externalities: Job Relevance, Output Quality, and Result Demonstrability).
In the TAM2 model, subjective norm is seen to be synonymous with ‘social norm’ (Fishbein and Ajzen, 1975), while 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 by comparing technology acceptance in two sites where the system use was mandatory with two sites where the system use was voluntary. 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 findings. 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. 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 be 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), TAM 3 (Venkatesh et al, 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.

The UTAUT model incorporates eight models in the IT acceptance research, where 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 usage, compared with the previous models’ 40% (Davis et al, 1989; Venhatesh and Davis 2000; Venhatesh et al, 2003).

*Overview of social influence in TAM*

While the underlying mechanisms used to explain the social influence factor in recent models (subjective norm, social factors, and image) have been inherited from the TAM2 model, these remain without further elaboration. The TAM2 model integrates Kelman’s (1958) three ways of attitude change, namely, ‘compliance’, ‘internalization’, and ‘identification’, which explain the social influence factor. The premise of Kelman’s argument rests on differences in the nature or level of attitude changes that take place, corresponding to
differences in the process through which the individual accepts influence. In other words, even though the resulting overt behavior may appear the same (such as the individual having intention to use a given technology), the underlying processes through which the individual engages when adopting 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. Much of the IT acceptance research has incorporated this process under the label of subjective norm for predicting individuals’ intention to use IT. In turn, ‘identification’ occurs when an individual accepts influence because he or she wants to establish or maintain a satisfying self-defining relationship with another person or a group. By performing behaviors that are consistent with group norms, an individual achieves membership and the social support that such membership affords as well as possible goal attainment (Pfeffer, 1982). And finally, ‘internalization’ takes place when an individual accepts influence because he or she is content that the induced behavior – and the ideas and actions of which it is composed – is intrinsically rewarding for him or her. The behavior adopted in this fashion tends to be congruent and integrated with the individual’s existing values, with satisfaction derived from this induced behavior.

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 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. And finally, image fits with the identification process, whereby the user makes a reasoned decision under group influence because he or she expects greater payoff, even though it is not demanded by others.

To gain a more comprehensive picture of the employment of social influence factors in technology acceptance, especially in more recent scholarly work, we conducted a systematic literature review using the Web of Science database1, which identified five articles that had specifically conducted empirical research on this topic within the organizational context2. 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 relationship between perceived usefulness and attitude, attitude and behavior intention, and belief and usage. In the development of a

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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).
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.

Our 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, we aim to introduce a coalitional view, which may bolster the explanatory power of social factors in the TAM model.

**Coalitions in organizational settings**

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, view the organization as a coalition of individuals, some of them organized into sub-coalitions. The coalition members can therefore include managers, workers, stockholders, suppliers, customers, lawyers, tax collectors, and regulatory agencies. Nevertheless, this definition still remains broad. A more refined view of coalitions is provided by Stevenson et al. (1985), who have conducted a comprehensive review of the literature studying intra-organizational coalitions, clarifying the differences between coalitions in an organizational context and others. The authors present eight characteristics that define 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.

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 & 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, the conflict of goals generates opposing coalitions in the organization, which compete and bargain for payoffs. Traditional research has subsequently implied ‘game theory’ to predict potential coalitions by calculating the maximum possible payoff (e.g., Gamson, 1961; Caplow, 1956).

Since the 1980s, there has been growing interest in the development of intra-organizational coalitions. For instance, 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.” Models, such as those based on game theory, have been mostly premised on the assumption that organizational members are rational players and will do their strategic best to acquire payoffs. However this assumption is not always accurate. In real organizational settings,
individuals cannot always form the optimal coalition, due, for example, to the lack of information.

Three schools have tried to map out the coalition formation process, albeit from different vantage points. Stevenson et al. (1985) firstly propose an empirical model – “The Process of Coalition Development” – which focuses on the macro-level sequences of causal relationships between different stages. These authors suggest that in the organizational context, antecedent conditions can facilitate the formation of coalitions through a series of stages. 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 settings. 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.

Narayanan and Fahey (1982) have, in turn, employed a decision making approach in identifying the micro-political dynamics of each stage in coalition formation. The authors divide the coalition formation process into two meta-level phases, namely, ‘gestation’ and ‘resolution’. Gestation is also called “problem formulation”, while resolution accordingly is also 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. This phase is further divided into three steps: activation, mobilization, and coalescence. Activation provides a clear understanding of the issue to individuals, mobilization builds up political commitment and a network of interrelationships among individuals, and coalescence aims to achieve the integration of efforts. Similarly, the resolution phase has two steps: encounter and decision. Actions are expected to be taken in the first step, such as, negotiation with external individuals, groups, or organizations in order to sponsor the coalition’s preferred alternatives, while decision is an end when agreements and disagreements are achieved and cleared out.

And thirdly, 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, and gradually subsumes other individuals into the negotiation. It is assumed a similar process exists 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 that 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. As the amount of nodes and links grow, some of the characteristics of the network start to become obvious. Clusters are formed since some individuals have more mutual interactions as a group compared with individuals outside of that cluster. Furthermore, individuals with the most links are likely be in the center of the network and are known as ‘focal nodes’, while those with fewest ties are usually located at the edge of the network.
Coalitions as social influence in TAM

In this section we focus on the technology acceptance process by taking a coalitional view of the social influence highlighted by Venkatesh et al. (2003). While TAM forms one of the fundamental models in the Technology and Innovation Management (TIM) literature, we aim to firstly understand the extent of use of the coalition theory in the same field of inquiry. Furthermore, we aim to gain an overview of the prior use of a coalitional approach to study social influence in technology acceptance. To these ends, we undertook a structured review of the literature 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 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 did not link the coalitional view of social influence with TAM, therefore giving some level of confidence that our research may fill a gap in the literature, by contributing a new perspective of technology acceptance within organizations.

Our 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, we aim 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, we suggest that a coalitional view provides greater accuracy in reflecting such 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) suggest 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, the referent group has the power to affect an individual’s attitudes with respect to a technology which will lead to his or her intention of using this technology. In fact, the literature shows that 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”, prove that people tend to comply with a prominent referent.

We further elaborate 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 championship in the process of innovation adoption in the organization. Two behavioral characteristics identified in this study that positively affect innovation success are adopted in our own 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


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.
important to note that, for intra-organizational coalitions around technological issues, the ‘core’ (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, we tentatively anticipate internalization and identification to be more powerful explanations of the social influence factor than compliance, which also echoes with Venhatesh et al (2000), Venhatesh et al (2003).

Methodology

Empirical context

To understand the role of coalitions as a mode of social influence in technology acceptance, we studied the adoption of Big Data in a single organization (a global financial group). This empirical setting was highly appealing, given that the organization had recently embarked upon introducing Big Data into their operations and had undertaken initiatives to create visibility of this strategic decision. Most importantly for our research, the organization had established a discussion forum centering on this technology on the company’s intranet social media platform. This “Big Data Community” had garnered 363 employees to voluntarily join since its inception in June 2012, of which 66 individuals actively participated in the discussion with 258 meaningful comments during a 20-month period (i.e. by the time of our investigation). The discussion forum afforded us 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 participated 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, we focused our investigation on the former construct. In other words, we aimed to understand the role of coalitions as a social influence upon intention of use. We denote intention of use through the proxy of sentiment, such that, positive sentiment signals intention of use, while negative sentiment indicates reluctance to use a technology. Using the results of prior scholarly work, we subsequently believe that uncovered intention of use will translate into actual use.

In our 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 factor. By analyzing the changes in sentiment (i.e. attitude change), we therefore align with these models to understand the effect of social influence on intention to use.
**Big Data**

The concept of “Big Data” appeared several decades ago when the first attempt was made to quantify the growth rate in the volume of data, which is known as the “information explosion”. Over these years, the data counted was initially acquired from printed sources such as papers and articles, and later, with increasing volume, from digital sources ranging from telecommunication data to mass media. The key milestone of drawing attention to Big Data in purely academic circles came with the article of Michael Cox and David Ellsworth (1997), who 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”. In turn, the generally-accepted “3Vs” (volume, velocity and variety) dimensions of describing Big Data were defined a decade ago by Laney (2001). And most recently, Boyd and Crawford (2012) have defined 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 were previously impossible, with the aura of truth, objectivity, and accuracy.”

We align our research with a generic definition provided by Manyika et al. (2011), who refers to Big Data as "data sets, whose size is beyond the ability of typical database software tools to store, manage and analyze". In addition to this view, which focuses on the characteristics of Big Data, we adopt the definition given by the NESSI (Networked European Software and Service Initiative) that encompasses the use of techniques that capture, process, analyze and visualize potentially large data sets in a reasonable timeframe not accessible to standard IT technologies. Hence, the platform, tools and software used for this purpose are collectively called “Big Data Technologies”.

**Empirical data**

To illustrate the applicability of our developed framework we gathered and analyzed data comprising discussion text from a forum dedicated to Big Data (i.e. the Big Data Community) on the focal company’s intranet social media platform. We commenced by requesting permission from the online community to use the posted text in our study, one month before the data collection date, guaranteeing that the data would be kept anonymous. No objection was received in this validation period, thus allowing us to gather the data from the forum.

All member names and the time of their joining the community were stored, and a unique ID was 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 were collected and then screened through a preliminary filter with respect to four conditions. Firstly, we included only comments in the form of a ‘post’ (e.g., by individuals who initiated a dialogue) or a ‘reply’ (e.g., by individuals who replied to the dialogue’s initiator). Secondly, we only retained the comments initiated or replied to by a community member, thereby precluding the comments made by members outside of the “Big Data Community”. Thirdly, we preserved the comments that were written only in the English language⁴. And finally, we

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⁴ This filter was necessary owing to the fact that the organization is multinational company.
limited the temporal range of our dataset to a period stretching from June 1, 2012, until 24 January, 2013. Data was 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.

Text analysis

We used IBM SPSS Text Analytics for Surveys 4.0.1 (referred to as ‘software’) as a tool to conduct a quantitative sentiment analysis of the comments acquired from the online forum. This 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, enabling the software to analyze the ambiguities inherent in verbal communications. 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).

Following the preliminary screening of the discussion forum data, we implemented a secondary filtering procedure to establish a dataset that was relevant for our study. Specifically, we aimed to reduce the noise in the raw data by removing text that did not relate to Big Data issues or lacked substantial meaning. To this end we employed the built-in NLP algorithms of the software to segment sentences in the posted text and abstract meaningful concepts. In total, 2263 concepts were initially generated by the software, indiscriminately. From this collective, we identified 162 concepts containing the word “data” (e.g., “raw data”, “data analysis”, and “unstructured data”) and deemed these to be highly relevant for our purposes. Following the analytical procedure of Nokelainen and Dedehayir (2012), we identified additional concepts 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, we established a list of 226 concepts that were meaningful and relevant to Big Data. To delimit our dataset, in turn, we selected out the comments that did not contain any of these 226 concepts, assuming that the comments would be out of the scope of big data related discussion. We were subsequently left with 258 comments that formed our final dataset.

Results and Discussion

The information is from IBM® SPSS® Text Analytics for Surveys, Analyzing survey text: a brief overview.
We firstly conducted a sentiment analysis by using the built-in algorithm of the software that determines the importance of the sentimental word and its position in the sentence. On the one hand, the software uses a representative sentiment process to extract only the more representative opinions or emotions expressed in each sentence. On the other hand, if two sentiment keywords with the same importance are found, the latter one will be selected as the sentimental keyword. Results generated by the basic sentiment analysis algorithms are polarized, in which the outcome is either ‘positive’ or ‘negative’. However, in our research, the social media platform within the organization is used primarily for knowledge sharing and the comments we collected tend to be longer and informative (on average, about 70 words for each comment). It is common that both positive and negative opinions are expressed within the same comment, which results in a large amount of neutral comments and makes it difficult to analyze the differences among individuals’ opinions. As a result, we propose an improved algorithm, which aims to gain a more refined understanding of the sentiments expressed in a comment.

To this end we introduce the notion of a ‘type’, 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 we list in Table 1 along with illustrative sentences extracted from the analyzed posts.

Table 1: The 12 types of sentiment studied.
The underlying assumption of our proposed approach is that the more of the six aspects of a sentiment (positive or negative) that appears in a comment, the more likely that the comment represents that sentiment. To assist our evaluation, we define ‘positive score’ as the summation of the number of general, functioning, budget, competence, feeling, and attitude concepts that are positive, and similarly, ‘negative score’ as the summation of these concepts that are negative. If the positive score is higher in a comment than the negative score, that comment will be positive overall, and vice versa. Moreover, the greater the difference between the positive and negative scores, the more pronounced is the sentiment.

We applied our method to the textual dataset for Big Data and present the results in Figure 5. In the figure, we indicate the increasing degree of positivity embedded in the comments with P, P+, and P++, respectively. Similarly, N and N- denote the increasing degree of negativity in the comments posted on the community forum. Comments with equal positive and negative scores are categorized as ‘mix’, while comments comprising no positive or negative concepts (i.e. no sentiment expressed in the comment at all) are grouped as ‘non’.

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6 “P” represents “positive”, and N means “Negative”. The sentiment degree of a comment is indicated in the following manner from the most positive to the most negative: P++, P+, P, 0, N, N-, and N- -. No comment has been rated N- -, therefore, N- -is not displayed in figure 5 and figure 6.
The pie chart in the above figure provides an overview of the sentiment distribution of the 258 comments that formed our dataset. We observe 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 comments contain the same level of positive and negative sentiment, resulting in a ‘mix’ outcome. And 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 did present a sentiment, however, roughly 80% are attributed to some level of positivity, indicating that there is a notable inclination towards intention of use of Big Data technology in the organization.

Figure 5 presents a static picture of the sentiment distribution at the time of our data assessment. To understand how the intensities of different sentiments have been changing over time, which may, for instance, indicate convergence upon a particular sentiment (i.e. positive or negative), we present the evolution of sentiment distribution in Figure 6.

The above figure reveals a growing density in the quantity of communication among forum members across the 20 month period of our investigation. While the graph does not indicate the interchange among particular individuals, the growing density provides
preliminary support for our anticipation of the coalescing of individuals about a common
issue, in this instance, the Big Data technology. Interestingly, the first few months of
discussion signal positive attitude towards Big Data. In turn, the early period of 2013 is
marked by 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 of use of the
technology.

Another interesting finding 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, we looked 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 arose as to why and how to use Big Data within the industry. Positive arguments
were built on Big Data’s integration of information and creation of insights, which were seen
to build competitive advantage. Negative comments, in opposition, claimed that Big Data
was 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 informs of the evolution of the positive and negative
sentiments, we do not have information concerning the individuals behind these sentiments.
As a preliminary step towards this end we classified the community members with respect to
four groups according to their sentiments expressed during the timeframe of our
investigation. An individual who had been commenting positively, continuously, was placed
into the “PositivePerson” group, while an individual with purely negative comments was
allotted to the “NegativePerson” group. Individuals who showed mixed sentiments expressed
in either a single comment or over multiple comments were placed into the “NeutralPerson”
group. All remaining individuals who had displayed no sentiment or did not provide any
commentary were subsequently placed into the “NoEmotionPerson” group. Of the 66
individuals who actively participated in the forum, the NeutralPerson group had amassed
the largest membership with 30, followed closely by the PositivePerson group with 23 members
(i.e. individuals displaying intention of use). The NegativePerson group had a membership of
only 5 individuals. The remaining 8 individuals are classified into the NoEmotionPerson
group. These results align with our 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.

Using these classifications, we next mapped the social network 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 we stored the ‘reply’ as
interaction relationship data, 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’. To capture the dynamics behavior, we also made use of Gephi’s degree

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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 n“A votes for B”, and, in turn, establishing the more important nodes as those that receive
more votes.
algorithm, which calculates the in-degree and out-degree of each node by taking the direction of the interaction into account. Furthermore, we utilized Force Atlas, a force-directed algorithm built into Gephi, to identify the centrality of the network and simulate the formation of coalitions in our research.

Overall, we identified the social network that formed around Big Data, which contains 50 connected nodes and 82 links with varying degrees of weight. Figure 7 presents the overview of this network and the center of gravity (i.e. focal node).

Figure 7 shows that the NoEmotionPerson group (white nodes) dominates the network in terms of membership. In the network, a node is disconnected either because this individual did not participate in the discussion, or because comments from this node did not receive any reply from other nodes. We importantly observe a cluster of interconnected nodes that represents the interactions of the Big Data Community, shown in greater detail in Figure 8. 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 likely intention to use the technology, also active in correspondence. A few members of the NegativePerson group (red nodes) are positioned somewhat on the periphery of this cluster. Furthermore, contrary to the NeutralPerson and PositivePerson groups, which display dense interactions (both within and between groups), it is interesting to note that the NegativePerson group demonstrates no interactions within the group. We interpret this finding to suggest that a coalition has not formed among the individuals that carry negative sentiment.

The aim of our 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 indicate to us that distinct coalitions (positive or negative), comprising multiple nodes, have not emerged by the time of our analysis. However, there appear to be individuals who hold a

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8 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.
large share of the interaction in the network. In order to identify the most prominent individuals, we display the Big Data community as a network of individuals with at least 5 degrees of interaction in Figure 9.

The figure above confirms 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. 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 our empirical investigation, we subsequently treat this focal node as a ‘one-person coalition’, which has 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. Figure 10 shows the interactions of the referent with other members of the Big Data community.

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, we plot the sentiment change (i.e., attitude change) of the focal node, and compare this plot with the sentiments of the individuals who interact with the focal node, over time, in Figure 11.

![Figure 11. Sentiment evolution of the focal node (above) and the 21 nodes of its network (below).](image)

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 sentiment expressed by both the focal node and the 21 node group remains 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. In summary, Figure 11 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. This suggests that coalitions forming about technological issues in organizations are important social influence factors that have the power to affect other individuals’ intention to use the technology.

**Conclusions**

Despite the widespread use of the TAM framework to predict users’ acceptance of a variety of technologies, social influence remains a difficult factor to understand. Addressing this gap, this study aimed to interpret social influence of technology acceptance issues within the organization through a coalitional view. To this end, departing from prior research endeavors, we followed a novel approach to predict individuals’ potential acceptance of a technology by investigating a referent group, which we refer to as the coalition. The empirical results showed us that the coalition positively promotes the individual’s intention to use a technology as part of the overall technology acceptance process. However, the timespan of our study did not allow us to observe the full implementation of the Big Data technology within the organization, which rendered it difficult to test the relationship between the referent group and individual’s actual usage of a technology. We therefore advocate future
studies to look at the coalition’s effect on individuals’ actual usage behavior of a technology, concurrently extending our present work that has centered on the intention to use.

Our work has important practical and theoretical implications. Firstly, knowing the social aspect, especially the formation of referent networks, in the technology adoption process has great impact on the organization’s implementation success of the technology. In this sense, managers can utilize their knowledge of the core individuals or the central coalition can enable them to approach them strategically to catalyze the transition of other employees’ to actual use behavior. Secondly, our work provides a succinct and affordable methodology for both practitioners and scholars to forecast the potential acceptance of a given technology. We have essentially demonstrated that posted comments on a technology specific forum allow investigators to undertake a quick test to understand opinions and sentiments, which translate to intention of use.

References


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