Doctoral Thesis

Leveraging Digital Content into Knowledge Assets - the Role of Business Information Systems

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Leveraging Digital Content into Knowledge Assets: The Role of Business Information Systems

A thesis submitted to attain the degree of
Doctor of Sciences of ETH Zurich
(Dr. sc. ETH Zurich)

presented by
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2014
ABSTRACT

The massive proliferation of digital content has lead to its widespread use in today's rapidly changing business environment. Although turning digital content into actionable knowledge is of increasing strategic importance for business leaders, organizations continue to encounter difficulties in applying knowledge to gain economic benefits. It is essential for both academics as well as practitioners to update their understanding of the modern opportunities and challenges in fostering knowledge processes. This cumulative dissertation seeks to develop novel theoretical and practical insights for understanding the current developments in the knowledge management practice and enrich the conventional knowledge management paradigms. The studies presented in this dissertation make significant contributions to understanding knowledge processes in both (1) online communities and (2) companies. The most important findings are: (1) the success of knowledge creation and reuse in online communities largely depends on the ability to organize and intrinsically motivate peer contributions, and (2) long-term successful knowledge application in companies is a matter of avoiding technology workarounds and synchronizing the spectrum of knowledge practices into a company-wide practice benefiting from a single pool of knowledge.
ZUSAMMENFASSUNG

ACADEMIC NOTE: CUMULATIVE DISSERTATION

This is a cumulative dissertation, namely a collection of scientific scripts that altogether form a unified representation of my research work and its results. The main scope of this dissertation is to present a unitary view of my doctoral research, along with a discussion of each of its individual elements. The list of publications, as well as the original texts corresponding to each publication are available in the end of this document.
ACKNOWLEDGEMENTS

I would like to express my highest regards to Prof. Juliana Sutanto for her continuous guidance throughout my doctoral work. She has always been available and supportive. Her excellent advice and comments had an extremely positive impact on my work.

At the same time, I want to thank Prof. Christoph Rosenkranz for his tremendous support. His excellent guidance and advice during our many-hour working meetings were essential in inspiring this work, as well as in helping me gain a comprehensive perspective on research.

A great thank you goes to Bernadetta Tarigan for her inspiration not only as an outstanding colleague, but also as a human being.

I would also like to thank Prof. Chris Dellarocas and Prof. Roland Holten for our productive collaborations.


I would like to take this chance to express my deepest gratitude to my family and my girlfriend for their unquestioning support when I needed it most.

Mihai Grigore
ETH Zurich
October 2014
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INTRODUCTION

Motivation

The last two decades have brought a substantial shift in the digital media (Manyika et al., 2011). Empowered with information technologies, both organizations and end users have reached unprecedented levels of connectivity and access to resources - even beyond organizational boundaries. This shift has lead to a gradual increase in the amount of digital content - in form of data, information, and knowledge - being created and consumed with the help of information technologies. In 2013, the total size of digital content was estimated to be about 4.4 trillion gigabytes and is expected to grow 10 times by 2020 (IDC, 2014).

This massive proliferation of digital content raises several policy, economic, and strategic issues (Brynjolfsson, 2011). The importance of digital content for businesses is growing steadily — and with it, both opportunities and challenges are arising (Westerman et al., 2014). Indeed, organizations often see opportunities to gain actionable knowledge from digital content and aim to remain competitive (Saleh et al., 2013). In this sense, digital content that is produced online has been used to support decision-making and analysis in business settings such as healthcare (Agarwal et al., 2010), e-commerce (Zwass, 2010) and trading (Wang et al., 2013). Despite its pervasiveness, digital content raises potential challenges. First, organizations willing to exploit the potential of digital content need to systematically collect and evaluate a multitude of digital content, hoping to obtain actionable knowledge out of it. However, while organizations spend billions on infrastructure1 to support data collection and knowledge discovery, knowledge remains in many cases an intangible asset unless organizations are able to strategically apply that knowledge to gain economic benefits (Datta, 2010). Indeed, recent research indicates a pattern occurring in the majority of cases: major investments in novel technologies are not necessarily followed by significant business improvements (Fitzgerald et al., 2014). Second, it is remarkable that organizations were estimated to hold responsibility for nearly 85% of the total amount of digital content in 2013 (IDC, 2014); among others, this translates into potential exposure to risks such as cyber attacks (Shackelford, 2012). Even further, by opening the production of digital content to end users, it has become increasingly challenging for organizations to systematically monitor, evaluate or control the quality of digital content (Lukyenko et al., 2014). In this light, for organizations to achieve the right balance between reducing possible risk exposures and harnessing actionable knowledge from digital content, investments in data analytics services2 are an imperative (McAfee and Brynjolfsson, 2008).

Given the increasing strategic importance of actionable knowledge in today's rapidly changing business environment (Manyika et al., 2011), it is essential for both academics as well as practitioners to update their understanding of the modern opportunities and challenges in fostering knowledge processes. There is a need to develop novel theoretical approaches that can provide support for understanding the current developments in the

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2 Approx. $30 billion (est. 2014) in hardware, software, and professional services related to big data analytics, see http://www.researchandmarkets.com/research/s2t239/the_big_data
knowledge management practice and enrich conventional knowledge management paradigms. Thus this dissertation poses the following research question:

*How can organizations improve their knowledge management processes with the help of information technologies?*

To attempt to answer this important research question, this dissertation adopts the framework of Alavi and Leidner (2001) to analyze the role of information systems on organizational knowledge management. According to Alavi and Leidner, the aim of knowledge management systems is to facilitate a collection of four intertwined knowledge processes: (1) creation, (2) retrieval and storage, (3) transfer, and (4) application (Holzner and Marx, 1979; Massa and Testa, 2009; Pentland, 1995). First, knowledge *creation* represents the development of new knowledge or replacement of existing knowledge with new knowledge from either internal or external sources (Pentland, 1995). Second, knowledge *retrieval* and *storage* refer to the processes of making knowledge more structured and accessible (Stein and Zwass, 1995). Third, knowledge *transfer* can generally be subdivided into knowledge *sharing*, i.e., the process by which knowledge is acquired and made available to those who need it (Appleyard, 1996; Majchrzak et al., 2004) and knowledge *reuse*, i.e., the process by which shared knowledge is being enriched or used further to create new knowledge (Argote and Ingram, 2000). Fourth and last, knowledge *application* is the process of applying existing knowledge to solve specific problems and deriving value from it; that is, incorporating knowledge into an organization’s products, processes or services (Massa and Testa, 2009). These four processes are essential to achieve effective organizational knowledge management with the help of information systems (Alavi and Leidner, 2001). In the following, this dissertation takes the lens of the above framework to systematically identify and analyze research gaps corresponding to each of the four knowledge processes.

**Scope**

Research on IT-enabled knowledge management in traditional organizations has increasingly been employed for several decades. A well established body of literature consistently analyzed the role of information systems as effective means to (1) create, (2) store, and (3) transfer knowledge in traditional organizations (Arling and Chun; Benbya, 2011; Leidner et al., 2012; Romano et al., 2001; Sarin and McDermott, 2003); (4) knowledge application in traditional organizations has arguably remained the most understudied process in the knowledge management literature (Datta, 2010). However, the recent widespread adoption of Internet technologies has facilitated an increased access to peers, resources, information and knowledge - even outside the boundaries of traditional organizations. In this sense, new forms of organizing have emerged and have opened substantial opportunities to research knowledge processes at unparalleled scales (Puranam et al., 2013). Among the most prominent examples of these new forms of organizing are online communities that support knowledge creation, such as Linux and Wikipedia (Faraj et al., 2011; Puranam et al., 2013; von Hippel and von Krogh, 2003). Following the framework of Alavi and Leidner (2001), for each of the four knowledge processes, the main research issues that continue to be under-addressed in the recent literature - on both traditional organizations and online communities - are identified and analyzed as follows.
To start with, knowledge creation (1) in online communities has attracted significant attention from both researchers and practitioners in recent years (Von Hippel, 2009). Indeed, the development of a theoretical model of knowledge creation in online communities (Lee and Cole, 2003) opened the ground for substantial research efforts in this direction (von Krogh and Geilinger, 2014). Despite these research efforts, recent investigations on knowledge creation in online communities have called for in-depth analysis of membership retention as catalyst for the success of knowledge creation (Faraj et al., 2011; Ransbotham and Kane, 2011). This aspect is addressed in Study 1 of this dissertation.

Relative to knowledge retrieval and storage (2), research on information systems and knowledge has been abundant in proposing various models for explaining knowledge management success (Kulkarni et al., 2007), building on previous models on technology acceptance and use (Davis, 1993; Davis and Venkatesh, 1996; Venkatesh et al., 2003), and information systems success (DeLone, 2003; DeLone and McLean, 1992). Since this research venue is well theorized and has received extensive research attention in the fields of information systems and knowledge management, it is not included in this dissertation.

With respect to knowledge transfer (3), information technologies have been subject to extensive research for their role to facilitate sharing and reuse of knowledge (Majchrzak et al., 2004; Nonaka and Takeuchi, 1995). On the one hand, Majchrzak et al. (2013a) provided comprehensive theorizing of how peers engage in knowledge sharing via online knowledge conversations. On the other hand, while knowledge reuse in traditional organizations has been relatively well researched (Majchrzak et al., 2013b; Markus, 2001), knowledge reuse in online communities continues to be under-researched (Haefliger et al., 2008; Von Krogh et al., 2012). This represents the focus of Study 2 of this dissertation.

Finally, knowledge application (4) in traditional organizations is arguably the most understudied process in the knowledge management literature on traditional organizations (Alavi and Tiwana, 2002). In theory, information technologies offer potential benefits in terms of facilitating effective knowledge application and boosting organizational performance (Alavi and Leidner, 2001; Mills and Smith, 2011). Organizations that excel at knowledge application with the help of information technologies are inherently better at continuously translating their knowledge assets distributed throughout the organization into innovative products and services (Alavi and Tiwana, 2002). However, in the absence of its effective application, knowledge represents a sunk cost rather than an opportunity cost for organizations. Indeed, in practice, organizations continue to encounter issues in knowledge application, mainly because leveraging knowledge through information technology is often not easy to achieve (Benbya and Van Alstyne, 2011; Walsham, 2001). In this sense, organizations that do not realize the full value of their knowledge assets reportedly experience difficulties in effectively using knowledge to gain systematic business benefits (Benbya et al., 2004; Fitzgerald et al., 2014). Yet, systematic research on knowledge application in organizations is largely missing in the literature and practice of knowledge management (Datta, 2010; Massa and Testa, 2009). Study 3 in this dissertation investigates knowledge application in a large international technology provider.

Altogether, consistent with the identified research gaps, and using as a reference point the framework of Alavi and Leidner (2001), this thesis analyzes knowledge creation and reuse in a
prominent online community (Studies 1 and 2), and knowledge application in an international technology provider (Study 3). An overview of these studies is presented in Table X below.

<table>
<thead>
<tr>
<th>Study Nr.</th>
<th>Article Title</th>
<th>KM Process</th>
<th>Research Setting</th>
<th>Research Method</th>
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<tr>
<td>1</td>
<td>Whose Activity and Membership Retention Matter in Rapidly Changing Environments? Analysis of Knowledge Creation in Wikipedia</td>
<td>Knowledge Creation</td>
<td>Online community</td>
<td>Longitudinal study: regression analysis</td>
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**Structure of this Dissertation**

This cumulative dissertation is organized as follows. After this introduction, the three studies are presented in distinct sections covering the processes of knowledge creation, knowledge reuse, and knowledge application. Each section presents a summary containing the motivation, research gap, research methodology, and contributions of the respective study. The presentation of the studies is followed by a discussion featuring the overall contributions of the thesis, its limitations, and further work. Last, as part of this cumulative thesis, an overview of contributed research publications is presented at the end of this document, followed by the publications in their original forms.
COMMUNITY-BASED KNOWLEDGE CREATION

Motivation

The first main goal of this thesis is to provide a sound understanding of the key factors that determine the success of knowledge creation in online communities. This understanding is important, since online communities have become an increasingly viable and popular way to create knowledge goods that are often of relatively high quality (Erden et al., 2012; Ren et al., 2007). Wikipedia, the online encyclopedia “that anyone can edit”, is a prominent online community that has become one of the world’s most popular sources of knowledge, with more than 4.5 million articles in its English version. The quality of knowledge on Wikipedia articles has repeatedly been found to be on par to traditionally organized processes, carried out by professional editors over several years, such as the Encyclopedia Britannica (Giles, 2005; Tapscott and Williams, 2006).

With respect to knowledge creation, Wikipedia fundamentally differs from traditional network organizations in terms of its model of governance, membership characteristics and restrictions, intellectual property ownership, and control of production (Lee and Cole, 2003). Wikipedia is not based on monetary rewards in exchange of editing work, but on voluntary contributions. In contrast to traditional network organizations, membership in Wikipedia is open: Wikipedia peers self-select articles, spend as much time on articles as they like, and collaborate with whom they prefer, without economic benefits (Dahlander and O’Mahony, 2011). To support collaborative knowledge creation by its own community of readers, Wikipedia provides a Wiki technology. This Wiki technology acts as a knowledge management tool, by supporting the constant refinement of article knowledge through collaboration, which is considered as the main added value of Wikipedia.

There are three specific reasons for considering Wikipedia as a suitable resource for examining the success of knowledge creation in a Wiki-based online community. First, the underlying Wiki technology records the full editing and interaction activity for each article. Second, Wikipedia’s articles can only be edited using the Wikipedia platform, allowing researchers to have a complete editing and social interaction history of each article. Third, any Internet user can contribute knowledge to the articles, allowing researchers to examine group interactions in an uncontrolled setting. The first study of this dissertation analyzes the factors that lead to the success of knowledge creation in Wikipedia in terms of article quality.

Study 1: Knowledge Creation in Online Communities

Research Gap:
What underlying factors in Wikipedia are necessary to facilitate the creation of high quality knowledge? In Wikipedia, the composition and contributions of editors may drastically vary over time, with some editors moving from peripheral roles towards central roles (Bryant et al., 2005), while others abandoning article editing (Brandes and Lerner, 2009; Halfaker et al., 2011). In lieu of this rapidly changing environment, Ransbotham and Kane (2011) notably found that membership retention does not exhibit a strictly positive effect on the success of knowledge creation in Wikipedia in terms of article quality. Some membership retention is
necessary in order to retain the knowledge created by the community, but moderate turnover is also desirable in order to introduce new knowledge to the community (Ransbotham and Kane, 2011). This finding is particularly interesting, as it contradicts most of the previous work that established that membership retention is a positive condition for collaboration success in online communities (e.g., Arguello et al., 2006; Ma and Agarwal, 2007). One possible explanation is to analyze the social structure of Wikipedia contributors. In this sense, Wikipedia community resembles a social structure with a minority of peers that ensures the coherence of an article (Sundin, 2011), and a majority of peers holding peripheral roles with a more narrow focus (Wang et al., 2009). The resulting social structure is arguably consisted of a densely connected core exerting a central role in the community, i.e. elite group, and a loosely attached majority of peers having peripheral roles, i.e., non-elite group (Zhu et al. 2011). In light of the surprising finding of Ransbotham and Kane (2011), it is unclear whether moderate turnover is beneficial at peripheral roles or rather at central roles in the creation of knowledge on Wikipedia articles.

Study 1 addresses this research gap by analyzing whether and how membership retention and contributions of editors having central (i.e., elite editors) and peripheral roles (i.e., non-elite editors) impact the success of knowledge creation in Wikipedia in terms of article quality.

**Research Methodology:**
Study 1 conducts a longitudinal analysis in a similar manner to Kittur et al. (2008), i.e., for each quality assessment of an article, the period between the previous and the current change in quality is considered. This allows capturing what contributes to a quality assessment.

**Contributions:**
The findings of Study 1 reflect that elite and non-elite editors exhibit different patterns of membership retention and edit contributions in terms of knowledge quality in Wikipedia. Interestingly, high membership retention at elite level appears to be detrimental in terms of article quality, whereas high membership retention at non-elite level is desirable. Study 1 suggests that membership retention at non-elite level is necessary in order to retain the information and knowledge generated by the community, but some turnover at elite level is desirable to introduce new knowledge to the community. This research thus confirms and nuances the result of Ransbotham and Kane (2011); at the same time, this research contradicts most of the previous work that established that membership retention is a positive condition for success of knowledge creation in online communities (e.g., Arguello et al. 2006; Butler 2001; Lazar and Preece 2002; Ma and Agarwal 2007). With regard to edit activity, contrary to the current findings in the literature (e.g., articles of Kittur and Kraut, 2008; Wilkinson, 2008)), inequality of edits at elite level appears to be detrimental to article quality, whereas inequality of edits at non-elite level is desirable. This may be explained by the fact that elites form a small world, whereas non-elites contribute as part of a large community.

Altogether, Study 1 contributes in two main areas. First, this study complements the extant literature on online social production in general and Wikipedia in particular, by focusing on the contrast between central (elite) and peripheral (non-elite) roles, rather than following the
common approach of looking at the entire Wikipedia community, such in Ransbotham and Kane (2011) and Kittur and Kraut (2008). Study 1 unveils that membership retention and edit contributions at central and peripheral roles impact the likelihood of knowledge quality improvement in different manners. Second, this study offers insights for organizations on how to achieve high quality outcomes in such online distributed labor networks. This is important, given the growing tendency of organizations to outsource complex tasks to large masses of workers via distributed labor networks using limited or no monetary incentives (Downs et al., 2010; Kittur et al., 2008; Ross et al., 2010).

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<tbody>
<tr>
<td>Authors</td>
<td>Mihai Grigore, ETH Zurich, Switzerland Bernadetta Tarigan, ETH Zurich, Switzerland Juliana Sutanto, ETH Zurich, Switzerland Chris Dellarocas, Boston University, USA</td>
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<tr>
<td>Abstract</td>
<td>With the rise of knowledge creation in Wikipedia, significant research efforts have been put on explaining why some articles receive more attention and are more developed than others. Although studies have been discussing the core/periphery structure in online communities, there is still limited knowledge about central and peripheral roles when analyzing the quality of knowledge in Wikipedia. This research explains that both central and peripheral roles are important for knowledge creation in Wikipedia, but they exhibit different effects. Precisely, through a longitudinal analysis, the study unveils that membership retention and edit contributions at central and peripheral roles impact the likelihood of improvement in article quality in different manners. Interestingly, high membership retention at central roles appears to be detrimental to the success of knowledge creation in terms of article quality, whereas high membership retention at peripheral roles is desirable. With regard to edit activity, contrary to the current findings in the literature inequality at central roles appears to be detrimental to article quality, whereas inequality at peripheral roles is desirable. These surprising results enrich recent important investigations on online peer production in general and Wikipedia in particular, by focusing on the contrast between central and peripheral roles, rather than following the common approach of looking at the entire Wikipedia community.</td>
</tr>
<tr>
<td>Keywords</td>
<td>Knowledge creation, membership retention, edit activity, online peer production, online community, central versus peripheral roles, elites versus non-elites.</td>
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<tr>
<td>Research Methodology</td>
<td>Longitudinal study: regression analysis</td>
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COMMUNITY-BASED KNOWLEDGE REUSE

Motivation

The second main purpose of this cumulative dissertation is to study knowledge reuse in online communities. Research on knowledge reuse is important, since knowledge reuse has been shown to enhance efficient and effective problem solving in organizations (Gray, 2001). Efficient knowledge reuse may prevent organizations from spending time and resources on redeveloping already existing solutions (Carlile, 2002). Previous research systematically reported that traditional organizational repositories are not suitable to efficiently and effectively leverage the knowledge within organizations (Rafaeli and Ariel, 2008; Yates et al., 2010). However, in a recent attempt to explain knowledge reuse in communities of practice within traditional organizations, Majchrzak et al. (2013b) focused on the unique affordance of Wiki technologies to foster online knowledge integration for knowledge reuse. Contributing knowledge to a Wiki may involve not only contributing the content of one’s domain expertise but also integrating knowledge already contributed to the Wiki in order to make it more logically organized. In a Wiki-based knowledge-sharing context, knowledge reuse can often be visibly observed and tracked (Chi et al., 2008; Grudin and Poole, 2010). Understanding what drives knowledge reuse using Wiki technologies is thus important for organizations in order to more efficiently incorporate their knowledge into products, processes, or services (Massa and Testa, 2009). Online communities provide several examples, such as Linux and Wikipedia, that have been able to leverage the benefits of efficient knowledge reuse in order to produce knowledge goods of relatively high quality. To study knowledge reuse in online communities, Wikipedia is a suitable research venue: the underlying Wiki technology records the full editing and interaction activity for each article; thus Wikipedia enables its users to integrate others’ knowledge for efficient knowledge reuse (Grant, 1996).

Study 2: Knowledge Reuse in Online Communities

Research Gap:
The extant literature on motivation to contribute with knowledge to online communities established that peers follow diverse motivational drives (e.g., the pleasure involved in completing a task) and social signals (e.g., community belonging and social recognition) (Benkler, 2006). Previous research on factors that motivate contribution of knowledge in communities of practice has focused mostly on factors explaining why peers contribute their personal knowledge (Carlile, 2004; Carlile and Rebentisch, 2003), with little research on why peers reuse the knowledge contributed by others in online communities (Yates et al., 2010). Evidence that intrinsic motivation positively influences knowledge reuse with the help of electronic repositories has been found through a field survey on customer service (Kankanhalli et al., 2011). A recent study in the context of organizational Intranets supported by Wikis showed that knowledge shaping promotes knowledge reuse through improved integration of knowledge (Majchrzak et al., 2013b). The research objective of Study 2 is to provide an explanation of the motivational factors that lead to the success story of knowledge reuse in Wikipedia, an exemplar of online social production. Thus Study 2 aims to provide answer to the following research question: “How and why do Wiki editors reuse knowledge?”
Study 2 builds on the work of Markus (2001) on knowledge reuse. Specifically, one of the aspects stressed by Markus (2001) is that successful knowledge reuse is in part a matter of how to provide incentives for contributions. In line with this research, Study 2 aims to contribute to the extant literature by providing the first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse in online communities.

**Research Methodology:**
This study conducts a longitudinal analysis of peers’ editing and interaction activity in Wikipedia. The study integrates the analysis of specific peer content collaboration - the editing process of Wikipedia articles - with the analysis of informal discourse - the level of sentiments in discussions between Wikipedia editors. Regression analysis is used to test whether sentiment-driven feedback (Te’eni, 2001; Zhang, 2013) among Wikipedia editors motivates collaborative working behavior, using knowledge reuse as a proxy for collaboration.

**Contributions:**
The findings of Study 2 suggest that peer content collaboration in Wikipedia - in terms of higher levels of knowledge reuse - appears to be influenced by peer feedback in form of sentiment-driven inter-editor discussions. Study 2 further confirms a significant difference in the degree of knowledge reuse between editors who share mainly positive or mainly negative sentiments. Indeed, displaying mainly positive affect corresponds to a superior level of knowledge reuse than displaying mainly negative affect. Study 2 contributes to the extant literature of online social production communities in general, and Wikipedia in specific, by providing the first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse.

From a theoretical perspective, the collective ethic of online social production appears to be in conflict with traditional policies, perceptions, and theories of organizational work (Arvidsson, 2008; Banks and Deuze, 2009; Sanger, 2009). Indeed, social production systems raise a series of challenges for traditional organization, as it so far has been shown that peers do not necessarily follow the normal signals generated by firms or markets, either as employees in the firms following managerial directions, or as individuals in the markets following price signals (Benkler and Nissenbaum, 2006; Tapscott and Williams, 2006). In this sense, a micro-foundation of peer production is important to develop up-to-date theoretical concepts for management and organizational sciences. In order to design efficient policies that boost an innovative, networked economy, a systematic empirical analysis and an empirically grounded theoretical understanding of the processes involved in peer production is needed. As an exploratory research, Study 2 helps to discover strategies to encourage collaboration in online communities and make the crowd sustainable without relying either on markets or hierarchies (Metiu and Kogut, 2001; Stephen and Suzanne, 2006). The results of Study 2 open a link to further controlled studies such as experiments observing the affective implication of individuals who reuse content. Researchers may transfer and test our findings from Wikipedia to more general scenarios involving peer collaboration. An immediate point of interest would be to investigate collaboration in communities of open source software development (e.g., Linux, Apache, GitHub, or SourceForge).
From a managerial perspective, organizations increasingly consider the outsourcing of knowledge tasks to large masses of workers via distributed labor networks using limited or no monetary incentives; this is possible, in part, due to the fact that the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of collaboration. While open collaborative innovation can potentially displace producer innovation at many parts of the economy (Baldwin and von Hippel, 2011; Maiolini and Naggi, 2011), the fluid generativity of distributed innovation suggests that knowledge resources will be increasingly heterogeneous and often only temporarily integrated (Yoo et al., 2012). Reflecting from the Wikipedia case, having insights about practical mechanisms to motivate the refinement of collectively created knowledge resources is important for organizations who would like to outsource knowledge tasks to large masses of online distributed workers.

<table>
<thead>
<tr>
<th>Title</th>
<th>The Impact of Sentiment-Driven Feedback on Knowledge Reuse in Online Communities</th>
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</table>
| Authors | Mihai Grigore, ETH Zurich, Switzerland  
Christoph Rosenkranz, University of Cologne, Germany  
Juliana Sutanto, ETH Zurich, Switzerland |
| Abstract | Knowledge reuse is of increasing importance for organizations. Despite the extant research, the ways peers are motivated to reuse knowledge with the help of Wiki technologies are still not well understood. The purpose of this work is to study the motivation for knowledge reuse in a prominent instance of online social production, Wikipedia. The study of knowledge reuse in Wikipedia is important, since Wikipedia has been able to leverage the benefits of efficient knowledge reuse in order to produce knowledge goods of relatively high quality. This research explores: (1) how Wikipedia editors communicate their feedback towards each other’s work in peer conversations, and (2) to what extent sentiment-driven feedback impacts the level of knowledge reuse in Wikipedia. The results show that displaying sentiment-driven feedback positively influences the level of knowledge reuse. Our study further shows a significant difference in the level of knowledge reuse between editors who share mainly positive or mainly negative sentiments. Specifically, displaying mainly positive feedback corresponds to a superior level of knowledge reuse than displaying mainly negative feedback. We contribute to the extant literature of online social production communities in general, and Wikipedia in specific, by providing a first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse. Implications for theory and practice are discussed. |
| Keywords | Knowledge reuse, sentiment-driven feedback, affective communication, affect in information systems, online collaboration |
| Research Methodology | Longitudinal study: regression analysis |
KNOWLEDGE APPLICATION: ENTERPRISE KNOWLEDGE

Motivation

The third main goal of the thesis is to analyze practical ways to improve knowledge application in large companies. Among the four knowledge processes in the framework of Alavi and Leidner (2001), knowledge application in traditional organizations appears to be the most understudied process in the knowledge management literature (Alavi and Tiwana, 2002). The study of knowledge application is important, given that organizations that excel at knowledge application have been recognized to be inherently better at continuously translating their intellectual capital into innovative products and services (Alavi and Tiwana, 2002).

Although information systems offer potential benefits in terms of facilitating more effective knowledge application (Mills and Smith, 2011), in practice, companies continue to encounter issues in knowledge application; one of the main reasons is that leveraging knowledge through information technology is often not easy to achieve (Benbya et al., 2004; Benbya and Van Alstyne, 2011; Walsham, 2001). In this sense, companies that do not realize the full value of their knowledge assets reportedly experience most of the difficulties in effectively using knowledge to support their business processes (Benbya et al., 2004). Study 3 in this dissertation analyzes what determined the success of knowledge application in a large international technology provider.

Study 3: Knowledge Application in Enterprises

Research Gap:

Knowledge is a key asset for organizations to remain competitive and create value in today’s constantly changing business environment (Foss and Pedersen, 2002; Saleh et al., 2013). To effectively and efficiently leverage their knowledge assets, many enterprises implement knowledge management systems (KMS). KMS are a class of information systems (IS) designed to facilitate the management of organizational knowledge (Alavi and Leidner, 2001). More precisely, theoretically, KMS are information systems developed to support and enhance the organizational processes of knowledge creation, retrieval, storage, transfer, and application (Alavi and Leidner, 2001; Romano et al., 2001). However, in practice, organizations continue to encounter issues with respect to their knowledge creation, retrieval, storage, transfer, and application through their KMS. In response to these challenges, IS researchers investigated how organizations could achieve efficient and effective knowledge management processes through KMS. Among the essential processes, knowledge application is arguably the most valuable process as it is the process of applying existing knowledge to solve specific problems and deriving business value from it (Lee and Sukoco, 2007). Yet knowledge application has been recognized as being the most understudied process in the knowledge management literature (Alavi and Tiwana, 2002; Datta, 2010).

Knowledge remains in many cases an intangible asset unless organizations are able to strategically apply that knowledge to gain economic benefits (Benbya et al., 2004; Fitzgerald et
al., 2014). Yet, systematic research on knowledge application in terms of work performance in organizations is largely missing from the body of literature on knowledge management. Despite the extant literature on IS-enabled knowledge management processes (Massa and Testa, 2009), little research has empirically examined the effect of knowledge application on work performance in organizations (Zheng et al., 2010). Indeed, IS-enabled knowledge management plays an essential role in the ability of enterprises to apply existing knowledge effectively and to create new knowledge (Alavi and Leidner, 2001). However, successful KMS adoption and use do not guarantee that the systems will efficiently support knowledge application. In this sense, it is necessary to understand whether and how the adopted KMS are able to enhance work performance throughout the organization (Ahearne et al., 2008).

Although successful IS adoption and its efficient use are prerequisites for KMS success, post-adoption patterns of KMS use reportedly reveal that IS is often used differently than the intended use case design (Azad and King, 2008). Where mismatches occur between the expectations of IS use and the actual work practice, users may implement workarounds in order to handle recurring “exceptions to workflow” (Ferneley and Sobreprezer, 2006). The practice of workarounds usually consists of deviating from the initially designed use cases, or even bypassing the use of the system entirely (Koopman and Hoffman, 2003). Although workarounds are widespread IS post-adoption phenomena in organizations, the current literature does not provide a consistent view towards the impact of workarounds in knowledge application on work performance. Instead, the current body of literature suggests that workarounds may have an ambivalent character, i.e. may exert positive or negative effects on performance, depending on the context of the research (Mainemelis, 2010).

Our motivation in this research is to contribute to an improved theoretical and empirical understanding of the effect of workarounds on knowledge application success by means of superior work performance in a time-critical environment. Our study addresses important but still unanswered questions: Do workarounds undermine the performance of knowledge workers in time-critical tasks? Or is it rather the case that workarounds represent a viable alternative to the use of existing KMS in time-critical tasks?

**Research Methodology:**
Study 3 analyzes the impact of workarounds on the success of knowledge application by means of a case study; the study contrast the employment of workarounds with the use of existing knowledge management systems in terms of organizational performance using interviews and a survey of 158 knowledge workers.

**Contributions:**
The results of Study 3 suggest that, in order to achieve superior performance, knowledge workers should focus their activities on improving the functionalities of the existing knowledge management systems, instead of dedicating their time on creating workarounds. By examining the workaround practices in knowledge application in a time-critical environment, this study has important implications for both knowledge management as well as information systems literature. Relative to the knowledge management literature, this is one of the few studies to analyze the direct link between knowledge application and work performance. This was possible due to the setting of the study; that is, in a time-intensive environment, such is the case of this study, there is very little time between using the KMS
and closing a customer case. Notably, most of the knowledge management studies in conventional settings (i.e., time non-critical work environments) that analyze system use do not go further into assessing work performance, as the theoretical link is not very direct such as in the case of time-critical contexts. Thus, in our study, we are able to capture the direct effect of knowledge application on work performance with little or no noise. With respect to the contribution to the information systems literature, this is research is one of the first studies to look at computer workarounds in knowledge application. The study thus constitutes a response to recent calls to produce more consistent IS research into post-adoption behaviors, see (Lapointe and Rivard, 2007). Additionally, the study extends recent post-adoption research on motivation for differences in technology use in an enterprise context (Li et al., 2013). By studying workarounds, our study regards the whole spectrum of technologies used by the customer service department, instead of focusing on the use of a particular technology.

<table>
<thead>
<tr>
<th>Table 4: Knowledge Application in Enterprises (Study 3)</th>
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<td><strong>Title</strong></td>
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| **Authors** | Mihai Grigore, ETH Zurich, Switzerland  
Juliana Sutanto, ETH Zurich, Switzerland |
| **Abstract** | Business decision makers have spent and continue to spend a great deal of resources to invest in information systems to support knowledge application. Yet, companies continue to encounter issues with knowledge application, mostly because of knowledge workers’ recurring difficulties in using the knowledge management systems (KMS). In response to the recurring difficulties with the existing KMS, knowledge workers often employ workarounds. The aim of this study is to enrich the current literature on knowledge application by analyzing the impact of workarounds on knowledge work performance in a time-critical environment. Through survey of 158 knowledge workers in a time-critical environment, we find that employing workarounds does not bring performance gains. In order to achieve superior work performance, such knowledge workers should continuously use and attempt to improve the existing KMS, instead of finding workarounds that may only bring temporary solutions. Contributions to the body of literature on knowledge management and information systems are outlined. |
| **Keywords** | Workarounds in time-critical tasks, knowledge application, improvisation, knowledge management systems, knowledge work |
| **Research Methodology** | Case study: interviews and survey |
DISCUSSION AND CONCLUSION

In order to better understand knowledge management practices in today’s business environment, this cumulative dissertation takes the perspective of Alavi and Leidner (2001) on the role of information systems on organizational knowledge management. This dissertation consists of a cumulative set of research studies that investigate knowledge *creation* and *reuse* in a prominent online community (Studies 1 and 2), and knowledge *application* in a worldwide technology provider (Study 3). Below we discuss the contributions of each study, together with their limitations and suitable venues for further work.

Contributions to Theory and Practice

This cumulative dissertation contributes to the current developments of knowledge management in the academic literature as well as in practice.

From a *theoretical* standpoint, Studies 1 and 2 contribute to the growing body of knowledge management in online communities. Knowledge creation and knowledge reuse in online communities represent important knowledge processes that need in-depth research attention and careful theorizing. Study 1 complements the extant literature on online social production in general and Wikipedia in particular, by focusing on the contrast between central and peripheral roles, rather than following the common approach of looking at the entire Wikipedia community. To our knowledge, this is the first large scale study to show that membership retention in central roles may be detrimental in terms of group outcomes. While much of the research on online communities has emphasized the importance of membership retention for collaboration success, recent investigations in Wikipedia suggest that retention may exhibit detrimental effects at different stages of the knowledge creation process (Kane et al., 2014; Ransbotham and Kane, 2011). Study 1 thus enriches this research by showing that membership retention at elite level appears to be detrimental in terms of article quality, whereas high membership retention at non-elite level is desirable. Study 2 contributes to the extant literature on knowledge reuse by providing the first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse. Although recent studies provided comprehensive theorizing of how peers engage in knowledge sharing via online knowledge conversations (Majchrzak et al., 2013a), a theoretical understanding of technology-enabled knowledge reuse in online communities is still lacking. Study 2 helps to discover strategies to encourage collaboration and foster knowledge reuse in online communities and make the crowd sustainable without relying either on markets or hierarchies. By examining the workaround practices in knowledge application in a time-critical environment, Study 3 has important implications for both knowledge management as well as information systems literature. Relative to the knowledge management literature, this is one of the few studies to analyze the direct link between knowledge application and work performance. This was possible due to the setting of the study; that is, in a time-intensive environment, such is the case of this study, there is very little time between using the KMS and closing a customer case. Notably, most of the knowledge management studies in conventional settings (i.e., time non-critical work environments) that analyze system use do not go further into assessing work performance, as the theoretical link is not very direct such as in the case of time-critical contexts. Thus, Study 3 captures the direct effect of knowledge application on work performance with little or no noise. With respect to the contribution to the information
systems literature, this research is one of the first studies to look at computer workarounds in knowledge application. Study 3 constitutes a response to recent calls to produce more consistent IS research into post-adoption behaviors. Additionally, Study 3 extends recent post-adoption research on motivation for differences in technology use in an enterprise context. By studying workarounds, Study 3 regards the whole spectrum of technologies used by the customer service department, instead of focusing on the use of a particular technology. Altogether, the three studies form a unitary theoretical contribution to the framework of Alavi and Leidner (2001) to analyze the role of information systems on organizational knowledge management.

From a practical perspective, the results presented in Studies 1 and 2 are important, since organizations increasingly consider the outsourcing of knowledge tasks to large masses of workers via distributed labor networks using limited or no monetary incentives; this is possible, in part, due to the fact that the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of collaboration. While open collaborative innovation can potentially displace producer innovation at many parts of the economy (Baldwin and von Hippel, 2011; Maiolini and Naggi, 2011), the fluid generativity of distributed innovation suggests that digital content will be increasingly heterogeneous and often only temporarily integrated into knowledge (Yoo et al., 2012). Reflecting from the Wikipedia case, having insights about practical mechanisms to motivate and organize the refinement of the collectively created knowledge resources is important for organizations who would like to outsource knowledge tasks to large masses of online distributed workers. Moreover, companies could benefit from the success recipe of Wikipedia to build effective ways to harness digital content with the help of the Wiki technology. In practice, by opening the production of digital content to end users, companies increasingly face challenges to systematically monitor, evaluate or control the quality of digital content (Lukyanenko et al., 2014). The example of Wikipedia could be a source of inspiration for these companies in their attempt to ensure high quality of digital content and presumably extract actionable knowledge out of it. Of course, the underlying conditions in Wikipedia are fundamentally different than in today’s traditional organizations; however, with the increasing prevalence of communities of practice inside companies, conditions that are closer to (open) online communities could be imitated. Another salient contribution of this thesis is the analysis of knowledge application in organizations. Study 3 shows that computer workarounds should not substitute the use of traditional content management systems in companies. Instead, knowledge workers should focus their efforts in improving the capabilities and the content stored in the existing systems, instead of thinking how to find suitable workarounds that would suit immediate purposes. In this sense, successful knowledge application in companies is a matter of avoiding technology workarounds and synchronizing the spectrum of knowledge practices into a company-wide practice benefiting from a single pool of knowledge.

As the importance of knowledge for businesses is growing steadily in today’s rapidly changing business environment, it is essential for both academics as well as practitioners to update their understanding of the modern opportunities and challenges in fostering knowledge processes. Through three distinct studies, this cumulative dissertation offers up-to-date theoretical and practical approaches to advance the current understanding of knowledge management and enrich conventional knowledge management paradigms. Using a mixture of both quantitative research methods (surveys and secondary data), as well as qualitative research methods
(observations and interviews), an unitary view is provided throughout these studies by following the framework of Alavi and Leidner (2001) on the role of information systems on knowledge management processes.

**Limitations**

Notwithstanding the contributions of this cumulative dissertation, each of the three studies is subject to limitations. The findings of Study 1 and Study 2 are based on observational secondary data and could be improved by triangulation. In this context, interviews or surveys with Wikipedia peers could provide substantial insights on the knowledge creation practices in Wikipedia. This would further help towards establishing causal claims. At the same time, making use of the full data set provided by the Wikimedia foundation would confirm the results obtained at a smaller scale in Studies 1 and 2. With regard to generalizability and endogeneity, we acknowledge that several areas dealing with the dynamics of social interaction in online collaboration were not examined in this study, such as the issues of social power or culture. Pragmatically, one can take several other perspectives for examining peer interactions in online social production communities. Conditions other group activities and characteristics – such as users’ capabilities and goals, their interpretations of technology, and institutional contexts, power, or culture – may play key roles in causal explanations. Due to the possibility of omitted variable bias, simultaneous causality bias, and errors-in-variable bias, future research should examine our identified relationships using more controlled settings or methods such as instrumental variables regression. Extending the investigations to other forms of online communities that do not necessarily focus on collaborative knowledge creation may yield further contrasting results. Additionally, Study 2 is bound by the use of proxies to measure knowledge reuse and sentiment-driven feedback in Wikipedia. Both computations use innovative methods from the field of natural language processing and require further empirical testing and theoretical validation. Study 3 is limited by the research setting, since the study is employed in one large traditional organization. We acknowledge that this may generate a bias in our results. Indeed, it would be worthwhile to complement the results of this study with insights on workaround practices from other companies, and, if possible, from other industries. Of particular interest would be to compare our results with the potential effect of workarounds on work performance in time non-critical work environments. A further limitation of this study is the lack of objective data, which is due to the fact that objective data on work performance is difficult to obtain because of confidentiality issues. Indeed, for this investigation, we have primarily used self-reported data from surveys and interviews. We acknowledge that this study could be complemented with the analysis of more objective data. Given the difficulty to obtain performance data, we have devoted special attention to ensure content validity and avoid potential biases.

**Further Work**

Promising avenues of future research for Studies 1 and 2 include investigating the content of conversations between peers who engage in both knowledge creation and knowledge reuse. Of particular interest would be the use of machine learning techniques to automatically recognize conflict in conversations. This could further confirm at a larger scale the recent theoretical findings on how peers engage in knowledge sharing via online knowledge conversations. To gain additional insight on the peers’ motivations and work practices, qualitative investigations would greatly strengthen the results of our large scale analyses;
interviews would presumably open the ground for studying subsequent phenomena that are hard to be spotted from observational data. A tremendous further study to unify Studies 1 and 2 would be to analyze knowledge creation and knowledge reuse as different stages of knowledge management using the same underlying data set in one study. Relative to Study 3, further work could involve analysis of user log data on how knowledge workers use the existing systems and comparing these with self-reported figures. Relative to the setting of the study, it would be worthwhile to redo this investigation in conventional settings (i.e., time non-critical work environments), where knowledge workers may have sufficient time to maintain a healthy knowledge management practices. Results may show in this case that workarounds stimulate the innovativeness of knowledge workers to find alternative solutions to improve the existing practice. Analyzing workaround practices in other companies, and, preferably, in other industries may as well lead to surprising results.
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LIST OF PUBLICATIONS

The list consists of selected publications from the three main parts of the dissertation, namely: knowledge creation (Table 5), knowledge reuse (Table 6), and knowledge application (Table 7).

### Table 5: Publications on Knowledge Creation

<table>
<thead>
<tr>
<th>Title</th>
<th>Publication</th>
<th>Appendix</th>
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<tbody>
<tr>
<td>Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia</td>
<td>INFORMS CIST 2013: Conference Paper</td>
<td>Appendix II</td>
</tr>
<tr>
<td>Effects of Stick-Togetherness on the Emergence of Collective Intelligence: A Longitudinal Analysis</td>
<td>SCECR 2013: Conference Paper</td>
<td>Appendix III</td>
</tr>
<tr>
<td>Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia</td>
<td>CI 2014: Conference Paper</td>
<td>Appendix IV</td>
</tr>
<tr>
<td>The Impact of Elite vs. Non-Elite Contributor Groups in Online Social Production Communities: The Case of Wikipedia</td>
<td>SCECR 2014: Conference Paper</td>
<td>Appendix V</td>
</tr>
<tr>
<td>Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia</td>
<td>WCBI 2014: Conference Paper</td>
<td>Appendix VI</td>
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### Table 6: Publications on Knowledge Reuse

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<th>Title</th>
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<td>The Impact of Sentiment-Driven Feedback on Knowledge Reuse in Online Communities</td>
<td>AIS THCI: Journal Paper (under last round of review: conditionally accepted)</td>
<td>Appendix VII</td>
</tr>
<tr>
<td>Increasing the Willingness to Collaborate Online: Analysis of Sentiment-Driven Interactions in Peer Content Production</td>
<td>AIS ICIS 2011: Conference Paper</td>
<td>Appendix VIII</td>
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### Table 7: Publications on Knowledge Application

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<td>Is Improvising Worth Your Time? Challenges in Fostering Knowledge Application in Time-Critical Work Environments</td>
<td>Ready for Submission as Journal Paper to JMIS</td>
<td>Appendix IX</td>
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APPENDIX

List of Publications


Appendix II: Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

Appendix III: Knowledge Creation: Effects of Stick-Togetherness on the Emergence of Collective Intelligence: A Longitudinal Analysis

Appendix IV: Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

Appendix V: Knowledge Creation: The Impact of Elite vs. Non-Elite Contributor Groups in Online Social Production Communities: The Case of Wikipedia

Appendix VI: Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

Appendix VII: Knowledge Reuse: The Impact of Sentiment-Driven Feedback on Knowledge Reuse in Online Communities

Appendix VIII: Knowledge Reuse: Increasing the Willingness to Collaborate Online: Analysis of Sentiment-Driven Interactions in Peer Content Production

Appendix IX: Knowledge Application: Is Improvising Worth Your Time? Challenges in Fostering Knowledge Application in Time-Critical Work Environments
Appendix I

WHOSE ACTIVITY AND MEMBERSHIP RETENTION MATTER IN RAPIDLY CHANGING ENVIRONMENTS? ANALYSIS OF KNOWLEDGE CREATION IN WIKIPEDIA

ABSTRACT

With the rise of knowledge creation in Wikipedia, significant research efforts have been put on explaining why some articles receive more attention and are more developed than others. Although studies have been discussing the core/periphery structure in online communities, there is still limited understanding about central and peripheral roles when analyzing the quality of knowledge in Wikipedia. This research explains that both central and peripheral roles are important for knowledge creation in Wikipedia, but they exhibit different effects. Precisely, through a longitudinal analysis, this study unveils that membership retention and edit contributions at central and peripheral roles impact the likelihood of improvement in article quality in different manners. Interestingly, high membership retention at central roles (or the elite group) appears to be detrimental to the success of knowledge creation in terms of article quality, whereas high membership retention at peripheral roles (or the non-elite group) is desirable. With regard to edit activity, contrary to the current findings in the literature, inequality at central roles appears to be detrimental to article quality; whereas inequality at peripheral roles is desirable. These surprising results enrich recent important investigations on online peer production in general and Wikipedia in particular, by focusing on the contrast between central and peripheral roles, rather than following the common approach of looking at the entire Wikipedia community.

KEYWORDS

Knowledge creation, membership retention, edit activity, online peer production, central versus peripheral roles, elites versus non-elites.
1. INTRODUCTION

Wikipedia is a prominent instance of network organization that aggregates the contributions of individuals who parse their resources and capabilities in the creation of knowledge across encyclopedic articles. The success of knowledge creation in Wikipedia depends on how peers self-organize and coordinate their work, e.g. by directly communicating with each other and by concentrating most of the editing among a subset of the editors (Arazy and Nov, 2010). In Wikipedia, the composition and contributions of editors may drastically vary over time, with some editors moving from peripheral roles towards central roles (Bryant et al., 2005), while others abandoning the article (Brandes and Lerner, 2009; Halfaker et al., 2011).

In lieu of this rapidly changing environment, through a large scale, longitudinal investigation, Ransbotham and Kane (2011) notably found that membership retention does not exhibit a strictly positive effect on the success of knowledge creation in Wikipedia. Membership retention is indeed necessary in order to retain the knowledge generated by the community, but some turnover may also be desirable in order to introduce new knowledge to the community (Ransbotham and Kane, 2011). This finding is particularly interesting, as it contradicts most of the previous results that established that membership retention is a positive condition for collaboration success in online communities (e.g., Arguello et al., 2006; Ma and Agarwal, 2007). However, in light of this finding, it is unclear whether turnover is beneficial at the peripheral or central roles or both in the process of knowledge creation on Wikipedia articles.

Our study addresses this research gap by showing at a large scale how membership retention and contributions of editors having central or peripheral roles impact the success of knowledge creation in Wikipedia in terms of article quality. The results show that these two groups of editors exhibit different patterns of membership retention and edit contributions in terms of the success of knowledge creation in Wikipedia. Interestingly, high membership retention at the central roles appears to be detrimental to the success of knowledge creation in
terms of article quality, whereas high membership retention at the peripheral roles is desirable. With regard to edit activity, contrary to the current findings in the literature (e.g., Kittur and Kraut, 2008; Wilkinson, 2008), we find that inequality at the central roles appears to be detrimental to the success of knowledge creation, whereas inequality at peripheral roles is desirable.

This research contributes in two main areas. First, this study complements the extant literature on online peer production communities in general and Wikipedia in particular, by focusing on the contrast between central and peripheral roles, rather than following the common approach of looking at the entire Wikipedia community (e.g., Ransbotham and Kane, 2011; Kittur and Kraut 2008). We unveil that membership retention and edit contributions at central and peripheral roles impact the likelihood of improvement in article quality in different manners. Second, as organizations exhibit a growing tendency to outsource complex tasks to large masses of workers via distributed labor networks using limited or no monetary incentives (Downs et al., 2010; Kittur et al., 2008; Ross et al., 2010), this study offers insights for organizations on how to achieve high quality outcomes in such online distributed labor networks.

2. ELITE VERSUS NON-ELITE ROLES IN KNOWLEDGE CREATION

Knowledge creation in online peer production communities has two defining characteristics: 1) it is based on the online collaboration of volunteers who carry out productive activities primarily for social and psychological purposes rather than for financial remuneration (Benkler, 2006; Shirky, 2010), and 2) knowledge creation happens in the absence of governance mechanisms based on price mechanisms or managerial structures (Aaltonen and Lanzara, 2011; Benkler, 2006). The first characteristic has motivated a bulk of studies in online peer production communities to examine the motivational drives of the participating individuals (e.g., (Benkler,
Cumulatively, these studies suggest that the motivational drives of the participating individuals may range from altruism and enjoyment to solving challenging problems, to social recognition and future employment benefit. The second characteristic of online peer production communities has motivated research on the governance mechanisms (e.g., Feller et al., 2008; Mehra, 2012; Singh, 2010). Such communities are typically governed by self-organization (Crowston et al., 2007), a usually slow and difficult process to ensure global coordination out of local interactions between people. This is made possible by the Internet technologies that keep a detailed trace of the community members’ interactions while they are interacting in real-time (Lanubile et al., 2010). The ability of Internet technologies to maintain a detailed trace of community members’ interactions enables researchers to explore how exactly people interact with one another in the production of common goods. Most of the studies either construct the social network of interactions and analyze the social network properties on the quality of group outcomes (Arazy et al., 2011; Conaldi and Lomi, 2013; Singh, 2010; Zhang and Wang, 2012), or analyze how the way peers interact with one another affects the resultant outcome (Collier and Kraut, 2012; Kittur et al., 2009; Wilkinson, 2008; Wilkinson and Huberman, 2007; Zhu et al., 2012).

Wikipedia is an excellent resource to examine knowledge creation in online peer production communities. There are four specific reasons for this. First, the underlying Wiki technology records the full editing activity and all editors’ social interactions for each article. Second, Wikipedia’s articles can only be edited using the Wikipedia platform, allowing researchers to have a complete editing and social interaction history of each article. Third, any Internet user can contribute content to the articles, allowing researchers to examine group interactions in an uncontrolled setting. Fourth, there are formal guidelines and mechanisms for
assessing and evaluating quality ratings of Wikipedia’s articles, allowing researchers to have a somewhat objective measurement of group performance outcomes.

It is common knowledge that only a few users account for the vast majority of contributions in the process of knowledge creation in Wikipedia (Collier and Kraut, 2012; Zhu et al., 2012). Concentrating edit contributions in relatively small groups of highly active editors has been found to enable more efficient harnessing of the wisdom of the crowds via episodic edits (Arazy and Nov, 2010; Kittur et al., 2009; Laniado and Tasso, 2011). In this sense, “the top 10% of editors by number of edits contributed 86% of the PWVs (persistent word views), and top 0.1% contributed 44% - nearly half!” (Priedhorsky et al., 2007). However, it is not clear whether these highly active volunteers indeed act as catalysts in the creation of high quality knowledge in Wikipedia. Surprisingly, Wikipedia editors who hold privileges (i.e., administrators) are not among the most active contributors to the articles (Ortega and Gonzalez Barahona, 2007). Moreover, the percentage of knowledge contributions coming from administrators has been shown to decrease over time (Kittur et al., 2007; Ortega et al., 2008). In addition to this, Okoli and Oh (2007) showed that Wikipedia editors who usually span their activities across various articles (i.e., members of Wikiprojects1) are more likely to gain administrative rights than those Wikipedia editors who rather focus their contributions only on a few articles. This observation may be explained by the edit practice of Wikiproject members, complemented by admins, who typically organize and keep Wikipedia articles stable, and intervene when others’ edits become a threat for the quality of the articles (Sundin, 2011). In this sense, research of Bryant et al. (2005) and Zhu et al. (2011) proposed that participation in a Wikiproject can be used to distinguish more central roles in the Wikipedia community from peripheral ones.

1 A Wikiproject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women’s history) or a specific kind of task (for example, checking newly created pages). Joining a Wikiproject can be considered as a proxy of an editor’s interest for or familiarity with a specific sub-domain, as well as of the willingness to contribute to the Wikipedia content in that specific sub-domain (Chen et al. 2010). The English Wikipedia currently has about 2,000 Wikiprojects: http://en.wikipedia.org/wiki/WikiProject
Although studies have been discussing the core/periphery structure in online communities (Garton et al., 1997), there is still limited knowledge about central and peripheral roles when analyzing the quality of Wikipedia articles (Ransbotham and Kane, 2011). Instead, literature on Wikipedia claims that the success of peer production in Wikipedia depends on the ways in which peers self-organize and coordinate their work, e.g. by directly communicating with each other and by concentrating most of the editing among a subset of editors (Arazy and Nov, 2010). Besides interaction patterns, group composition dynamics, e.g. membership retention has been shown to affect the success of knowledge creation in Wikipedia in terms of article quality (Liu and Ram, 2011; Ransbotham and Kane, 2011). The central roles in Wikipedia provide a basis of interpersonal salience and visibility (Friedkin, 1993; Gulati, 1998), as the work done by central actors, such as Wikiproject members and admins, is likely to gain faster recognition and acceptance by the Wikipedia community. This, in turn, may enable the particular Wikiproject to attract more resources from the network, i.e. both central and peripheral contributions, to continue with renewal and innovation. Zhu et al. (2011) further proposed two main development paths for Wikipedia users from peripheral roles towards more central ones, namely: from non-administrators to administrators and from non-Wikiproject members to Wikiproject members. In alignment with these two development paths, in this paper we distinguish between an *elite group* (formed by admins and Wikiproject members) that has central roles, from a *non-elite group* (formed by Wikipedia users who are not Wikiproject members or admins) that has peripheral roles. In the following, we hypothesize how elite and non-elite editors may affect the quality of knowledge on Wikipedia articles in different ways.

3. **HYPOTHESES DEVELOPMENT**

Current literature views network organizations as entities that promote innovation in a dynamically uncertain and competitive environment (Grant, 1996). Network organizations have
the ability to avoid inefficiencies in knowledge transfer and integration (Liebeskind et al., 1996). These organizations gain access to a wide set of knowledge in the network and counter the difficulty in determining valuable knowledge for innovation in competitive environments (Tracey and Clark, 2003).

Wikipedia fundamentally differs from traditional network organizations in terms of its model of governance, membership characteristics and restrictions, intellectual property ownership, and control of production (Lee and Cole, 2003). Wikipedia is not based on monetary rewards in exchange of editing work, but on voluntary contributions. In contrast to traditional network organizations, membership is open: Wikipedia editors self-select articles, spend as much time on articles as they like, and collaborate with whom they prefer, without economic sanctions (Dahlander and O'Mahony, 2011). Wikipedia community resembles a social structure with a minority of contributors holding central roles in ensuring the coherence of articles (Sundin, 2011), and a majority of contributors holding peripheral roles with a more narrow focus and poorly connected (Wang et al., 2009). This is supported by previous literature on peer production acknowledging the importance of a social structure in knowledge creation. According to this literature, early contributors take central roles in the knowledge creation process; later on, they eventually reduce their editing activities and focus on directing and regulating the contributions from peers having peripheral roles (Kane et al., 2014; Lee and Cole, 2003; Preece and Shneiderman, 2009; Shaw and Hill, 2014). In Wikipedia, the resulting social structure is arguably consisted of a densely connected core exerting a central role in the community, i.e. elite group, and a loosely attached majority of contributors having peripheral roles, i.e., non-elite group (Zhu et al. 2011). While previous studies pointed to the long tail distribution of knowledge contributions on Wikipedia articles (Kittur and Kraut, 2008; Wilkinson, 2008), it is unclear from the extant literature if this inequality of knowledge contributions holds at both levels of elite and non-elite editors.
On the one hand, given that elite editors form smaller, densely connected groups, it is likely that they develop shared mental models (Gasson, 1999; Rouse et al., 1992). Sharing the same mindset may allow them to efficiently coordinate their efforts to maintain a common view of the content and structure of an article. The attempt to establish a grounded content as result of collaborative work (Convertino et al., 2009) may further motivate and engage elites to contribute, as part of the group, more actively to the article. That is, content coordination may require mutually exchanging and reviewing content, while the elites being relatively equally involved in the editing process of an article. Thus we expect uniformly distributed contributions from the elite editors to have a positive influence on the article quality.

On the other hand, non-elite editors are weakly connected and find themselves in larger groups. With respect to large groups, previous research showed that as the number of contributors grows, articles in which edits are concentrated among only a relatively small fraction of contributors are more likely to increase in quality than articles in which edits are evenly distributed among contributors (Kittur and Kraut, 2008). Although larger groups of contributors appear to be more likely to represent a higher diversity of knowledge bases and points of view (Cummings, 2004), Linus’ law that “many eyes make all bugs shallow” has been repeatedly questioned by findings that show that, in reality, only few volunteers significantly contribute to common goods (Raymond, 1999). In Wikipedia, these large groups of non-elites more likely do not share a common view of the article content and structure, as opposed to the relatively small elites group. In this context, contribution among non-elites appears to bring in different points of view related to the topic of the article (Arazy and Nov, 2010); thus, contribution inequality may act as a catalyst for knowledge creation and minimize the overhead that would be required if a large group of non-elites was highly involved in contradictory edits (Kittur and Kraut, 2008). Thus we expect unequally distributed contributions of non-elites to be beneficial in terms of article quality improvement. We hypothesize:
H1a: Equality of distribution of edits of elite editors increases the likelihood of article promotion.

H1b: Equality of distribution of edits of non-elites decreases the likelihood of article promotion.

Organizational theorists have become intrigued by how innovation in online communities works and how it can be harnessed (O’Mahony and Bechky, 2008). However, the explanations have been rather disconnected from the social structures in the communities where users are embedded to. Previous literature acknowledges that, when group members stay and work together over a period of time, they are able to develop a common ground, unspoken expectations and shared mental models of the task to be accomplished (Aral et al., 2008; Chen et al., 2010). Indeed, research on online communities established that membership retention is a positive condition for effective collaboration in online communities (e.g., Ma and Agarwal, 2007). The ability to attract and retain members frequently serves as a key metric for success in online communities (e.g., Arguello et al., 2006; Ma and Agarwal, 2007). A stable group of peers can develop experience working together effectively, develop shared rules and norms, and agree on a common vision for the community (Ren et al., 2007). This shared experience might allow the community to work steadily toward a goal, whereas the loss of participants would mean that useful components of these shared norms and visions were no longer available to the community (Lazar and Preece, 2002).

Although membership retention is necessary to retain the knowledge generated by the community, in Wikipedia, it appears that moderate turnover is also desirable to introduce new knowledge to the community of editors (Ransbotham and Kane 2011). Elite editors may have better opportunities for innovation in comparison to non-elite editors because of their superior access to information flows. Nevertheless, elite editors can become too entrenched in the conventions of Wikipedia and thus be averse to discard existing knowledge and practices (Kane et al., 2014). Therefore those elite editors may tend to ignore the potential contributions of new ideas from the outside. In this sense, it may be necessary for some elite editors to
eventually leave an article, which would then allow other non-elite peers to introduce new resources to meet the changing collaborative needs of the community.

In the case of non-elite editors, Bryant et al. (2005) refer to the theory of legitimate peripheral participation, developed by Lave and Wenger (1991), to understand how users’ “perceptions of their roles in Wikipedia change as they become more engaged in the community” (p. 2). Forte and Bruckman (2008) found that Wikipedia governance tends to decentralize: “As the community grows, it has become necessary for governance mechanisms to shift outward into the community. This decentralization was not entirely accidental; self-organization was dependent in part on the design of the technology and embedded in the philosophy of the community’s founder and early participants” (p. 10). Forte et al. (2009) further demonstrated how this governance may be explained by “theories of commons-based governance developed in offline contexts” (p.49). More specifically, they showed that such governance “relies heavily on community-generated social norms” (p.70).

Indeed, organization processes in online communities are often regulated by norms and rules for effective collaboration (Butler et al., 2008), which are often developed by the contributors as they work together (Hinds and Mortensen, 2005). The emergence of a social system of such norms, values, and rules (Hargadon, 2006; Hargadon and Bechky, 2006) help streamline the collaboration process (Arazy et al., 2011) and may allow the community to work steadily toward a goal (Lazar and Preece 2002), which, in Wikipedia, is article knowledge creation and development. We argue that, in Wikipedia, where group size fluctuates dynamically as members come and leave at their own will (Brandes and Lerner, 2009; Bryant et al., 2005; Halfaker et al., 2011; Ransbotham and Kane, 2011), it is important that non-elite groups are stable to achieve a community that abides the community norm, which in turn is beneficial for producing better quality articles.
The above arguments about membership retention of elite and non-elite editors make an interesting contrast with regard to the functions or purposes of membership retention in these two groups of editors. Elite editors, who are usually committed into the article development process, do not necessarily need their activity to be regulated by community-generated social norms. In fact, when the elite editors are highly stable, they can become too entrenched and may tend to ignore the potential contributions of new ideas (Kane et al., 2014). Hence, less stable groups of elite editors may be needed to allow new members to introduce new knowledge and ideas, which in turn is beneficial for producing better quality articles. In contrast, non-elites need community-generated social norms to work steadily during article development. Hence, membership retention of non-elites is important to achieve a community that abides the community norm while working towards improving the article quality. We therefore hypothesize:

H2a: The higher the degree of elite retention, the lower the likelihood of an article to be promoted.

H2b: The higher the degree of non-elite retention, the higher the likelihood of an article to be promoted.

4. RESEARCH METHODOLOGY

To test the above hypotheses, we conduct a longitudinal analysis in a similar manner to Kittur et al. (2008), i.e., for each quality assessment of an article, we consider the period between the previous and the current change in quality. A graphical representation of the considered time span of analysis is presented in Figure 1. Note that our analysis takes into account only those articles that receive at least two quality assignments during their lifespan. The instantiations of all the subsequent constructs in our model are computed relative to this time span.

[Insert Figure 1 here]
4.1. Dependent Variable

**Change in Quality.** As previously mentioned, the Wikipedia community has developed formal guidelines and mechanisms for evaluating quality ratings of its articles. The ratings vary from a very low quality to the highest quality and are termed (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good articles’, ‘A-class’, and ‘Featured articles’ (Table 1). For our dependent variable, we indicate whether, following a quality assessment, an article was promoted (to a superior quality class) or demoted (to a lower quality class). Of the seven quality classes listed in Table 1, we restrict our focus to articles rated as ‘C-class’, ‘B-class’, ‘Good articles’, and ‘Featured articles.’ These four classes represent well-distinguished and non-transitional quality classes (Nemoto et al., 2011). Similar to Liu and Ram (2011), we excluded articles rated as ‘Stub’ or ‘Start’ since it is not meaningful to analyze collaboration patterns of articles that are stubs or that have just been created. We also excluded ‘A-class’ articles for two reasons. First, ‘A-class’ represents a transitional status between ‘Good’ articles and ‘Featured’ articles. As such, there is an underrepresentation of ‘A-class’ in Wikipedia; such articles are mostly concentrated in a few domains, such as military history. Second, in contrast to other quality assessments, ‘A-class’ quality assessments are not made by external panels. An article is promoted to a higher rating or demoted to a lower rating only after an official assessment of peer reviewers. In order to maintain objectivity and neutrality, the assessments of ‘Good’ and ‘Featured’ articles are made by Wikipedians who did not participate in heavy or repeated edits of the article proposed for assessments (Liu and Ram, 2011). A summary of the reasons to consider featured, good, B-class, and C-class articles is presented in Table 1.

[Insert Table 1 here]

4.2. Dataset

The dataset we use in this study is extracted from the June 2011 dump of English Wikipedia. The dataset includes full texts of Wikipedia pages and their complete edit history from the...
Since our intention is to examine the influential factors of Wikipedia article quality, we selected an equal proportion of articles of different Wikipedia-designated quality levels as follows. Altogether, we randomly sampled 60% of the 3.6 million articles. We chose random sampling against purposive sampling (e.g. snowball sampling), because, for example, selecting articles that are more popular and attract more editors would not create a representative subset population. Random sampling ensures that each article has identical probability to be chosen independently of other articles it is connected to. As explained above, and similar to Liu and Ram (2011), we only consider articles labeled as ‘Featured’ (fa), ‘Good’ (ga), ‘B-class’ (b), and ‘C-class’ (c), totaling a number of 84,915 articles. As we are interested in quantifying the likelihood for an article to be promoted versus demoted, we further choose only those articles that are at a stage where they can be promoted or demoted. In our dataset we observe that there is no ‘c’ class article being demoted to ‘stub’ or ‘start.’ Furthermore, ‘fa’ articles have reached the highest possible article quality level (so they cannot be promoted any further). For that reason we removed ‘c’ and ‘fa’ class articles from the dataset and kept only those articles that have initial quality ‘b’ or ‘ga’. Finally, we identified all the changes in article quality during an article’s lifespan, ranging from 2-level demotion (ga→c) to 2-level promotion (b→fa). The resulting dataset contains in total 10,954 changes in article quality, on which we base our analysis. Table 2 gives an overview of the counts.

4.3. Independent Variables

Equality of Edits. We operationalize the edit equality in the same manner as Woolley et al. (2010). For each article, we count the number of times each elite and non-elite contributed an edit on the article. The distribution of these counts represents the distribution of turn-taking among elites and non-elites who worked on the article (TTi, 1≤i≤N with N is the number of
elites or non-elites). We then computed the coefficient of variation of turn-taking (CV$_{TT}$) as the ratio between the standard deviation and the mean of the turn-taking scores ($\mu_{TT}$):

$$CV_{TT} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^{N} (TT_i - \mu_{TT})^2}}{\mu_{TT}}.$$

For example, if there are 16 edits of 4 elites who each edited the article 4 times, then $CV_{TT}$=0 (that means there is an equality in the edits turn-taking of the elites). The smaller the value of $CV_{TT}$, the more equal the distribution of edits turn-taking of elites or non-elites. Since this appears to be counterintuitive when interpreting equality, we compute equality as follows:

$$Equality = \frac{1}{1 + CV_{TT}}.$$

Equality takes a value between 0 and 1; larger values indicate higher degrees of equality.

**Membership Retention.** Membership retention refers to groups members who are willing to stay with the group and to engage in group’s activities over time (Dyaram and Kamalanabhan, 2005). Retention is achieved, for instance, when the members of the group are committed to work together to accomplish a collective task (Guzzo et al., 1995; Hsu et al., 2011; Kidwell et al., 1997). In online groups, the retention of members represents the bonds of unity that hold group members together to achieve their common goals (Ren et al., 2012). We operationalize membership retention relative to the knowledge creation process in Wikipedia as the proportion of elites and non-elites respectively who previously contributed to the article development, and stayed in the team during the most recent interval of quality change (Chansler et al., 2003; Dyaram and Kamalanabhan, 2005). Larger values indicate increased membership retention.

**4.4. Control Variables**

To account for exogenous variables, relative to each Wikipedia article, we consider the following variables that may influence the article quality: previous article quality, article age,
article popularity, number of article edits, and number of article talks. To further quantify differences between the activities of elites and non-elites, we computed the percentage of edits, and the percentage of talks done by elites. Moreover, to have a correspondent for equality of edits that refers to talk activity, we computed equality of talks, using the same formula. We considered including the number of editors and the diversity of editors as control variables, but it was not possible because they both highly correlate with the number of edits. An overview of variables and their operational definitions are presented in Table 3.

[Insert Table 3 here]

5. DATA ANALYSIS AND DISCUSSION OF THE FINDINGS

A summary of the unstandardized dataset is presented in Table 4, whereas Table 5 shows the cross-correlations between the standardized variables. Descriptive statistics and correlations were computed for all variables relative to the time span described in Figure 1.

[Insert Tables 4 and 5 here]

We employ a regression analysis using the standardized variables (Harrell, 2001, p. 97) in three steps. We first consider a baseline model (referred in Table 6 as Model 1) that consists only of control variables referring to article characteristics: previous quality, article age, article popularity, as well as the total number of edits and the total number of talks for each article. In Model 2, we introduce variables that quantify the activity of both elites and non-elites, in terms of edits and talks. More precisely, we include the equality of edit and talk distribution, as well as the relative proportions of edits and talks done by elites versus non-elites. Model 3 adds the retention of group membership, at both elite and non-elite members. For each of these models, we compute the AIC value together with a summary measure for the goodness of fit: the Nagelkerke’s R-squared (also known as Cragg and Uhler’s R-squared) (Archer et al., 2007; Lemeshow and Hosmer, 1982). A summary of the results of the logistic regressions is presented in Table 6. Following a robustness check with respect to the number of edits and
talks, the effect size and significance levels for each main predictor (equality of edits and membership retention) remain unchanged. Details are presented in Table 7.

[Insert Tables 6 and 7 here]

Table 8 presents an overview of the results. Our findings are able to shed a light on the results of Ransbotham and Kane (2011) and Kane et al. (2014), who suggested that membership retention does not exhibit a strictly positive effect on the success of knowledge collaboration in Wikipedia, but that some turnover in key roles may be beneficial. Interestingly, high membership retention among the elite group appears to be detrimental in terms of article quality, whereas high membership retention among the non-elite group is desirable (H2a and H2b are supported). We are thus able to confirm the results of Ransbotham and Kane (2011) and Kane et al. (2014), and at the same time, disagree with most of the previous work that established that membership retention is a positive condition for effective collaboration in online communities (e.g., Arguello et al. 2006; Lazar and Preece 2002; Ma and Agarwal 2007). With regard to edit activity, contrary to the current findings in the literature (e.g., Kittur and Kraut, 2008; Wilkinson, 2008; Wilkinson, 2008), inequality at the elite group appears to be detrimental to the success of knowledge creation, whereas inequality at non-elite group is desirable (H1a and H1b are supported). This may be explained by the fact that elites form a small world, whereas non-elites contribute as part of a large community.

[Insert Table 8 here]

With respect to the control variables, we interestingly found non-significant effects of the equality of talks on the likelihood for an article to be promoted. Moreover, both percentages of edits and talks by elites have a positive effect on promotion likelihood. Interestingly, while the overall number of edits is beneficial, the number of talks appears to be detrimental. This suggests that, since peers have only limited time and attention span, large amounts of talking would likely to reduce the time allocated for edits, and may thus negatively influence the
likelihood for an article to be promoted. For a more comprehensive understanding, for both edits and talks we computed weekly time series data, starting 10 weeks before and ending 10 weeks after the event of either promotion or demotion (see Figure 2). The visual inspection of the time series data reveals several interesting patterns before and after the event of promotion or demotion. First, there is a peak in the proportion of edits and talks of elites before the moment of promotion/demotion. However, the peak in the case of promotion is much more prominent than in the case of demotion. Second, it seems that at the peak of the editing activity, the elite members contribute almost 40% of the edits which means the non-elite members contribute approximately 60% of the edits (Figure 2a); whereas at the peak of the talking activity, the elite members contribute almost 30% of the talks which means the non-elite members contribute approximately 70% of the talks (Figure 2b). Altogether, it appears that in the case of promotion, relative to the overall editing and talking, the elite members focus their efforts slightly more on editing the article than talking; whereas the non-elite members spend slightly more time editing the article than talking. This additional insight lends support to the argument that given that elite editors form smaller and densely connected groups, it is likely that they develop shared mental models (Gasson, 1999; Rouse et al., 1992) that may further motivate and engage the elite editors to equally contribute more actively to the editing of the article; instead of spending time discussing what the potential edits could be. In contrast, as non-elite editors are weakly connected and find themselves in larger groups, they are more likely to represent a higher diversity of knowledge bases and points of view, and may not share a common view of the article content and structure, as opposed to the relatively small elites group. In this context, besides inequality in editing activities to avoid contradictory edits (Kittur and Kraut, 2008), spending more time discussing about their points of view may act as a catalyst for knowledge creation. However, as shown in Table 7, when the non-elites talk too much, it is detrimental to article promotion.
Finally, article age appears to have a negative effect, i.e., articles that are left longer in an underdeveloped stage are less likely to receive the attention of the community and so, less likely to be promoted.

6. CONTRIBUTIONS TO RESEARCH AND PRACTICE

Although online peer production has attracted significant attention in the research community in recent years, our understanding of the factors that affect the quality of peer production outcomes is still limited. This research complements the extant literature on online peer production in general and Wikipedia in particular, by focusing on the contrast between central and peripheral roles, i.e., how peers who hold central (peripheral) roles in the production of the common goods, i.e., the elite (non-elite) editors, affect the quality outcomes. Through longitudinal analysis of Wikipedia articles’ quality promotions and demotions, we unveil that membership retention and edit contributions at central and peripheral roles impact the likelihood of the article’s quality improvement in different manners.

To our knowledge, this is the first large-scale study to show that, against the common belief, membership retention in central roles may be detrimental in terms of group outcomes. While much of the research on online communities has emphasized the importance of membership retention for collaboration success (Ma and Agarwal, 2007), recent investigations in Wikipedia suggest that retention may exhibit detrimental effects at different stages of the knowledge creation process (Kane et al., 2014; Ransbotham and Kane, 2011). Our study complements this research by showing that elites’ membership retention is detrimental to knowledge creation, whereas non-elites’ membership retention is desirable. Notwithstanding the values of the previous studies, we also find a contrasting finding, with regard to edit activity, to the current findings in the literature (e.g., Kittur and Kraut, 2008; Wilkinson, 2008; Wilkinson,
2008). Specifically, it is desirable to have edits equality at the elite group and edits inequality at non-elite group.

The findings of this study have to be viewed in light of its limitations. We acknowledge that several areas dealing with the dynamics of social interaction in online collaboration were not examined in this study, such as the issues of social power or culture (Baym, 2006; Jiang et al., 2011). Pragmatically, other group activities and characteristics – such as users’ capabilities and goals, their interpretations of technology, and institutional contexts, power, or culture – may also play key roles in online collaboration. Moreover, extending this work to other forms of online communities that do not necessarily focus on collaborative knowledge creation may yield further contrasting results. Nonetheless the findings of this study have important implications for practitioners.

From a managerial perspective, organizations increasingly consider the outsourcing of knowledge tasks to large masses of workers via distributed labor networks using limited or no monetary incentives; this is possible, in part, due to the fact that the virtual workplace constantly evolves towards more spontaneous and decentralized forms of collaboration. While open collaborative innovation can potentially displace producer innovation at many parts of the economy (Baldwin and Von Hippel, 2011), knowledge resources may increasingly become heterogeneous and often only temporarily integrated (Yoo et al., 2012). Reflecting from the Wikipedia case, having elites (who could be individuals employed by the organization) tasked with constantly organizing and refining the collectively produced knowledge resources is important for organizations that outsource knowledge tasks to large masses of online distributed workers. This study provides insights on the most effective patterns of elites’ activity and membership retention. While the focal organization may not be able to control the way elites interact with one another, it should be able to define and alter their membership over time. Findings in this study can guide the organization in doing so.
Figure 1: Analysis window
Figure 2. Comparison of percentage of (a) edits and (b) talks done by elites (versus non-elites) in terms of promotion and demotion.
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<th>Quality Class</th>
<th>Description</th>
<th>Include or Exclude</th>
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| Featured (fa) | “Professional, outstanding, and thorough; a definitive source for encyclopedic information.” Additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is necessary, “unless new information becomes available.” Information, additionally, no other information is 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Table 2: Total counts of quality changes (lines represent the starting quality, whereas columns represent the ending quality). The previous quality is on the top left and the promoted quality in the top right.

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<thead>
<tr>
<th>Previous Quality</th>
<th>De-promoted</th>
<th>Promoted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>8556</td>
<td>1544</td>
<td></td>
<td></td>
</tr>
<tr>
<td>569</td>
<td>285</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>9125</strong></td>
<td><strong>1829</strong></td>
<td><strong>10954</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Previous Quality</th>
<th>De-promoted</th>
<th>Promoted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>9125</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>285</td>
<td>569</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>9125</strong></td>
<td><strong>1829</strong></td>
<td><strong>10954</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Previous Quality</th>
<th>De-promoted</th>
<th>Promoted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>854</td>
<td>695</td>
<td></td>
<td></td>
</tr>
<tr>
<td>285</td>
<td>569</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>9125</strong></td>
<td><strong>1829</strong></td>
<td><strong>10954</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Previous Quality</th>
<th>De-promoted</th>
<th>Promoted</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>854</td>
<td>695</td>
<td></td>
<td></td>
</tr>
<tr>
<td>285</td>
<td>569</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>9125</strong></td>
<td><strong>1829</strong></td>
<td><strong>10954</strong></td>
</tr>
</tbody>
</table>

Table 2: Total counts of quality changes (lines represent the starting quality, whereas columns represent the ending quality). The previous quality is on the top left and the promoted quality in the top right.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Effects</td>
<td>Membership retention: The proportion of editors (either elites or non-elites) who previously contributed to the article development, and stayed in the team during the most recent interval of quality change (Chansler et al., 2003; Dyaram &amp; Kamalanabhan, 2005). Higher values indicate more retention.</td>
</tr>
<tr>
<td></td>
<td>Edit equality: The inverse of the coefficient of variation of article edits. Higher values indicate more equality.</td>
</tr>
<tr>
<td></td>
<td>Talk equality: The inverse of the coefficient of variation of article talks. Higher values indicate more equality.</td>
</tr>
<tr>
<td>Controls</td>
<td>Initial Quality: Quality label of an article at the beginning of the time span of the analysis.</td>
</tr>
<tr>
<td></td>
<td>Article Age: Duration from the creation of an article until the current change in quality.</td>
</tr>
<tr>
<td></td>
<td>Article Popularity: Number of web search hits.</td>
</tr>
<tr>
<td></td>
<td>Number of edits: Total number of edits on the article page.</td>
</tr>
<tr>
<td></td>
<td>Percentage of edits done by elites: Percentage of edits done by elites relative to the total number of edits.</td>
</tr>
<tr>
<td></td>
<td>Percentage of edits done by non-elites: Percentage of edits done by non-elites relative to the total number of edits.</td>
</tr>
<tr>
<td></td>
<td>Total number of edits on the article talk page.</td>
</tr>
<tr>
<td></td>
<td>Total number of talks on the article talk page.</td>
</tr>
<tr>
<td></td>
<td>Talk equality: The inverse of the coefficient of variation of article talks. Higher values indicate more equality.</td>
</tr>
<tr>
<td></td>
<td>Dependent Variable: Change in Quality: Binary variable measuring whether an article was promoted (+1, i.e. to a superior quality standard) or demoted (-1, i.e. to an inferior quality standard).</td>
</tr>
<tr>
<td></td>
<td>Membership retention: The proportion of editors (either elites or non-elites) who previously contributed to the article development and stayed in the team during the most recent interval of quality change (Chansler et al., 2003; Dyaram &amp; Kamalanabhan, 2005). Higher values indicate more retention.</td>
</tr>
</tbody>
</table>

Table 3: Overview of variables and their operational definitions
<table>
<thead>
<tr>
<th></th>
<th>min</th>
<th>max</th>
<th>mean</th>
<th>std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>1.00</td>
<td>43.00</td>
<td>7.20</td>
<td>2.00</td>
</tr>
<tr>
<td>Popularity</td>
<td>0.69</td>
<td>0.79</td>
<td>0.72</td>
<td>0.16</td>
</tr>
<tr>
<td>#Edits</td>
<td>2.00</td>
<td>7300.00</td>
<td>270.00</td>
<td>440.00</td>
</tr>
<tr>
<td>%Edits(Elites)</td>
<td>0.00</td>
<td>0.99</td>
<td>0.21</td>
<td>0.18</td>
</tr>
<tr>
<td>#Talks</td>
<td>2.00</td>
<td>7700.00</td>
<td>57.00</td>
<td>190.00</td>
</tr>
<tr>
<td>%Talks(Elites)</td>
<td>0.00</td>
<td>0.98</td>
<td>0.30</td>
<td>0.20</td>
</tr>
<tr>
<td>Retention(Elites)</td>
<td>0.00</td>
<td>1.00</td>
<td>0.20</td>
<td>0.14</td>
</tr>
<tr>
<td>Retention(Non-Elites)</td>
<td>0.00</td>
<td>1.00</td>
<td>0.10</td>
<td>0.14</td>
</tr>
<tr>
<td>Edit equality(Elites)</td>
<td>0.12</td>
<td>1.00</td>
<td>0.59</td>
<td>0.22</td>
</tr>
<tr>
<td>Edit equality(Non-Elites)</td>
<td>0.08</td>
<td>1.00</td>
<td>0.50</td>
<td>0.18</td>
</tr>
<tr>
<td>Talk equality(Elites)</td>
<td>0.16</td>
<td>1.00</td>
<td>0.79</td>
<td>0.22</td>
</tr>
<tr>
<td>Talk equality(Non-Elites)</td>
<td>0.16</td>
<td>1.00</td>
<td>0.69</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Table 4: Descriptive statistics
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Age</td>
<td>0.01</td>
<td>0.03</td>
<td>0.23</td>
<td>0.27</td>
<td>0.14</td>
<td>0.31</td>
<td>0.49</td>
<td>0.49</td>
<td>0.38</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>2</td>
<td>Popularity</td>
<td>0.04</td>
<td>0.09</td>
<td>0.05</td>
<td>0.34</td>
<td>0.13</td>
<td>0.19</td>
<td>0.47</td>
<td>0.27</td>
<td>0.19</td>
<td>0.33</td>
<td>0.25</td>
</tr>
<tr>
<td>3</td>
<td>#Edits</td>
<td>0.26</td>
<td>0.26</td>
<td>0.23</td>
<td>0.44</td>
<td>0.11</td>
<td>0.24</td>
<td>0.19</td>
<td>0.33</td>
<td>0.35</td>
<td>0.12</td>
<td>0.40</td>
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<tr>
<td>4</td>
<td>%Edits(Elites)</td>
<td>-0.30</td>
<td>-0.17</td>
<td>-0.16</td>
<td>-0.19</td>
<td>-0.30</td>
<td>-0.30</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.19</td>
<td>-0.19</td>
</tr>
<tr>
<td>5</td>
<td>#Talks</td>
<td>0.08</td>
<td>0.18</td>
<td>0.09</td>
<td>0.44</td>
<td>0.04</td>
<td>0.24</td>
<td>0.19</td>
<td>0.33</td>
<td>0.21</td>
<td>0.23</td>
<td>0.24</td>
</tr>
<tr>
<td>6</td>
<td>%Talks(Elites)</td>
<td>-0.25</td>
<td>-0.24</td>
<td>-0.33</td>
<td>-0.30</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
</tr>
<tr>
<td>7</td>
<td>Retention(Elites)</td>
<td>-0.38</td>
<td>-0.15</td>
<td>-0.17</td>
<td>-0.44</td>
<td>-0.21</td>
<td>-0.04</td>
<td>0.11</td>
<td>0.21</td>
<td>0.11</td>
<td>0.21</td>
<td>0.11</td>
</tr>
<tr>
<td>8</td>
<td>Retention(Non-Elites)</td>
<td>-0.41</td>
<td>-0.15</td>
<td>-0.16</td>
<td>-0.44</td>
<td>0.41</td>
<td>0.26</td>
<td>0.23</td>
<td>0.23</td>
<td>0.19</td>
<td>0.40</td>
<td>0.49</td>
</tr>
<tr>
<td>9</td>
<td>Edit equality(Elites)</td>
<td>-0.19</td>
<td>-0.17</td>
<td>-0.44</td>
<td>-0.21</td>
<td>-0.19</td>
<td>-0.04</td>
<td>0.11</td>
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<td>0.11</td>
<td>0.21</td>
<td>0.11</td>
</tr>
<tr>
<td>10</td>
<td>Edit equality(Non-Elites)</td>
<td>-0.19</td>
<td>-0.16</td>
<td>-0.44</td>
<td>0.41</td>
<td>0.26</td>
<td>0.23</td>
<td>0.23</td>
<td>0.19</td>
<td>0.40</td>
<td>0.49</td>
<td>0.49</td>
</tr>
<tr>
<td>11</td>
<td>Talk equality(Elites)</td>
<td>-0.10</td>
<td>-0.25</td>
<td>-0.33</td>
<td>-0.13</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
<td>-0.13</td>
<td>-0.34</td>
</tr>
<tr>
<td>12</td>
<td>Talk equality(Non-Elites)</td>
<td>-0.18</td>
<td>-0.33</td>
<td>-0.38</td>
<td>0.23</td>
<td>0.22</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
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</table>

Table 5: Variable correlations
## Table 6: Regression analysis

<table>
<thead>
<tr>
<th>Group Characteristics + Activity</th>
<th>Model 1: Baseline</th>
<th>Model 2: Baseline + Activity</th>
<th>Model 3: Baseline + Activity + Group Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef</td>
<td>SE</td>
<td>Signif</td>
<td>Coef</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-2.75</td>
<td>***</td>
<td>-2.89</td>
</tr>
<tr>
<td>Previous Quality (ga)</td>
<td>0.28</td>
<td>**</td>
<td>0.05</td>
</tr>
<tr>
<td>Age</td>
<td>-2.19</td>
<td>***</td>
<td>-2.00</td>
</tr>
<tr>
<td>Popularity</td>
<td>-0.24</td>
<td>*</td>
<td>-0.10</td>
</tr>
<tr>
<td>#Edits</td>
<td>0.62</td>
<td>***</td>
<td>0.32</td>
</tr>
<tr>
<td>#Talks</td>
<td>-0.07</td>
<td>*</td>
<td>0.01</td>
</tr>
<tr>
<td>%Edits(Elites)</td>
<td>1.12</td>
<td>***</td>
<td>1.20</td>
</tr>
<tr>
<td>Edit equality(Elites)</td>
<td>0.22</td>
<td>***</td>
<td>0.05</td>
</tr>
<tr>
<td>Edit equality(Non-elites)</td>
<td>-1.21</td>
<td></td>
<td>0.05</td>
</tr>
<tr>
<td>%Talks(Elites)</td>
<td>0.16</td>
<td>**</td>
<td>0.13</td>
</tr>
<tr>
<td>Talk equality(Elites)</td>
<td>-0.06</td>
<td>ns</td>
<td>0.07</td>
</tr>
<tr>
<td>Talk equality(Non-elites)</td>
<td>-0.10</td>
<td>ns</td>
<td>0.07</td>
</tr>
<tr>
<td>Retention(Elites)</td>
<td>-0.09</td>
<td>*</td>
<td>0.04</td>
</tr>
<tr>
<td>Retention(Non-elites)</td>
<td>0.29</td>
<td>***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Significant codes: 0: *** 0.001: ** 0.01: * 0.05: ns
Table 7: Regression analysis, where #Edits and #Talks from Table 6 are replaced with #Edits(Non-elites) and #Talks(Non-elites)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1: Baseline</th>
<th>Model 2: Baseline + Activity</th>
<th>Model 3: Baseline + Activity + Group Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>5.57</td>
<td>5.97</td>
<td>6.76</td>
</tr>
<tr>
<td>Previous Quality (ga)</td>
<td>0.32</td>
<td>0.32</td>
<td>0.32</td>
</tr>
<tr>
<td>Age</td>
<td>2.14</td>
<td>1.27</td>
<td>1.53</td>
</tr>
<tr>
<td>Popularity</td>
<td>0.11</td>
<td>1.06</td>
<td>1.24</td>
</tr>
<tr>
<td>%Edits(Elites)</td>
<td>0.16</td>
<td>2.93</td>
<td>2.93</td>
</tr>
<tr>
<td>Edit equality(Elites)</td>
<td>0.15</td>
<td>2.11</td>
<td>2.11</td>
</tr>
<tr>
<td>Edit equality(Non-elites)</td>
<td>0.12</td>
<td>2.45</td>
<td>2.80</td>
</tr>
<tr>
<td>%Talks(Elites)</td>
<td>-0.06</td>
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<td>0.29</td>
</tr>
<tr>
<td>Talk equality(Elites)</td>
<td>-0.07</td>
<td>0.08</td>
<td>0.29</td>
</tr>
<tr>
<td>Talk equality(Non-elites)</td>
<td>-0.09</td>
<td>0.11</td>
<td>0.29</td>
</tr>
<tr>
<td>Retention(Elites)</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.29</td>
</tr>
<tr>
<td>Retention(Non-elites)</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.29</td>
</tr>
<tr>
<td>%Talks(Non-elites)</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.29</td>
</tr>
<tr>
<td>%Edits(Non-elites)</td>
<td>-0.09</td>
<td>0.13</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Significant codes: 0.001 *** 0.01 ** 0.05 *
<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Non-elite (b)</th>
<th>Elite (a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Membership Retention (H2)</td>
<td>(-) H2a is supported</td>
<td>(-) H2b is supported</td>
</tr>
<tr>
<td>EDIT Equality (H1)</td>
<td>(+) H1a is supported</td>
<td>(+) H1b is supported</td>
</tr>
</tbody>
</table>

Table 6: Overview of Results
REFERENCES


*Proceedings of the 2011 annual conference on Human factors in computing systems.*
Appendix II

Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia
Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

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ABSTRACT

Several past studies have commented on the uneven distribution of contributions in online social production communities while at the same time highlighting the successful end products of many such communities. These two seemingly paradoxical situations are made possible through smaller groups of highly devoted volunteers who act as catalysts in organizing and maintaining community outputs. These volunteers have been referred to as “knowledge janitors.” There is currently limited understanding of how the group composition and interaction patterns of knowledge janitors affect social production quality outcomes. This study provides answers to these questions in the context of Wikipedia. By analyzing 11,359 changes in Wikipedia article quality, we found that cohesiveness, diversity, and equal distribution of communication turn-taking of an article’s janitors increase the likelihood of that article’s quality improvement. These main findings are further refined by considering how the main effects differ at different development stages of an article. The study’s contributions to research and implications to practice are discussed.

Keywords: online social production, Wikipedia, Wikipedia janitors, group composition, group interaction, article quality
1. INTRODUCTION

Online social production communities have become an increasingly viable and popular way to create information products that are often of relatively high quality (Giles, 2005; Tapscott & Williams, 2006). Open source software such as Linux and R allow people to install and use the software with no cost as well as to contribute back to the improvement of the software. Peer recommendations such as Amazon’s book reviews and YouTube’s ratings rely on community submissions and social monitoring to produce reliable product reviews. Wikipedia, a peer content production, has become one of the world’s most popular sources of information; the quality of Wikipedia entries has repeatedly been found to be on par to other traditionally organized processes, carried out by professional editors over several years, such as the Encyclopedia Britannica (Giles, 2005; Tapscott & Williams, 2006).

While it is common knowledge that contributions in online social production communities follow a long tail distribution (Collier & Kraut, 2012; Zhu et al., 2012), the ways in which the most highly devoted volunteers act as catalysts in the development of high quality output are still not well understood. This study will address this research gap in the context of Wikipedia. A WikiProject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women's history) or a specific kind of task (for example, checking newly created pages). The English Wikipedia currently has about 2,000 WikiProjects.¹ Members of Wikiprojects are highly devoted volunteers who act as catalysts in the development of high quality articles, i.e., they are able to organize and keep Wikipedia articles stable. Following (Sundin, 2011), we refer to those individuals as Wikipedia janitors, indicating their essential role in the development and organization of content in Wikipedia (Chen et al., 2010; Choi et al., 2010; Sundin, 2011).

Focusing on Wikipedia janitors, this study aims to provide answers to the following

questions: What are the relationships between the *composition* of Wikipedia janitor groups (diversity, cohesiveness) and their *interactions* (communication turn-taking) on the article quality improvement?

The contributions of this study are twofold. First, this study complements the extant literature on online social production in general and Wikipedia in particular, by focusing on Wikipedia janitors rather than following the common approach of looking at the entire Wikipedia community (Kittur & Kraut, 2008; Ransbotham & Kane, 2011; Zhu et al., 2012). We unveil how the composition of Wikipedia janitor groups in a particular article and the way they interact with one another affect the likelihood of that article’s quality improvement. Second, as the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of collaboration, with the growing tendency of organizations to outsource complex tasks to large masses of workers via distributed labor networks using limited or no monetary incentives (Downs et al., 2010; Aniket Kittur et al., 2008; Ross et al., 2010), this study offers insights for organizations on how to achieve high quality outcomes in such online distributed labor networks.

2. THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

There are numerous research articles dealing with Wikipedia, as it is an excellent resource to examine online social production. There are four specific reasons for this. First, the underlying wiki technology records the full editing activity and all editors’ social interactions for each article. Second, Wikipedia’s articles can only be edited using the Wikipedia platform, allowing researchers to have a complete editing and social interaction history of each article. Third, any Internet user can contribute content to the articles, allowing researchers to examine group interactions in an uncontrolled setting. Fourth, there are formal guidelines and mechanisms for assessing and evaluating quality ratings of Wikipedia’s
articles, allowing researchers to have a somewhat objective measurement of group performance outcomes.

In Wikipedia, the contributions and involvement of editors may drastically vary over time (Ransbotham & Kane, 2011), with some editors moving from peripheral participation to full involvement (Bryant et al., 2005), while others abandoning the article (Brandes & Lerner, 2009; Halfaker et al., 2011). In contrast to the plethora of studies on the distribution of editor contributions, a recent sociotechnical investigation of Wikipedia proposes a change of research focus towards analyzing the importance of the “practices of fixing, erasing, voting, changing, proof-reading, and, […] inserting references to external sources“ for the construction of articles in Wikipedia (Sundin, 2011) – which are the main activities of Wikiproject members. Joining a Wikiproject can be considered as a proxy of an editor’s interest for or familiarity with a specific sub-domain, as well as of the willingness to contribute to the Wikipedia content in that specific sub-domain (Chen et al., 2010; Choi et al., 2010). In this article we refer to Wikipedia editors who joined at least one Wikiproject as *Wikipedia janitors*. We analyze how these Wikipedia janitors, through their essential roles in developing and organizing content in Wikipedia, improve the quality of articles.

Previous research claimed that the success of social production in Wikipedia depends on the ways in which peers self-organize and coordinate their work, e.g. by directly communicating with each other and by concentrating most of the editing among a subset of the editors (Arazy & Nov, 2010). Besides interaction patterns, the characteristics of those who participate in the group work appear to be important in increasing the quality of group outcomes (Butler et al., 2007; Liu & Ram, 2011). Because of the importance of Wikipedia janitors to the development of article content, we focus our analysis on the effect of group composition and interaction patterns of Wikipedia janitors on the change in article quality over time.
When members of a group coordinate their work through communication, their individual turn-taking dynamics may facilitate the formation of a common ground (Clark, 2005). Turn-taking is the set of communication practices by which collaboration is achieved in and through conversational turns (Sacks et al., 1974). Previous studies showed that articles in which a few editors do most of the work are also the ones in which these editors talk to each other on the article talk page (Aniket Kittur & Kraut, 2010). Kittur and Kraut (2008) found that coordination through communication is more efficient when there are few editors. In addition to its coordination role (Butler et al., 2007; Liu & Ram, 2011; Panciera et al., 2009), turn-taking may also be important for knowledge exchange (Woolley et al., 2010). Through laboratory experiments of small size (2-5 members) face-to-face groups, Woolley et al. (2010) showed that equality in distribution of turn-taking is positively correlated with group outcome across a variety of tasks. “In other words, groups where a few people dominated the conversation were less collectively intelligent than those with a more equal distribution of conversational turn-taking” (Woolley et al., 2010). The reason being that collective intelligence is a group intelligence that emerges from the knowledge exchange and consensus building of the individual members that is generally superior to simply aggregating the individual members’ knowledge. If the discussion is directed by a single individual who imposes a consensus view on the others, then that perspective would not be more powerful than the perspective of the particular individual (Heylighen, 2013). All this implies that an equal distribution of communication turn-taking between the Wikipedia janitors should result in better group performance in terms of higher article quality. Accordingly, we hypothesize:

**H1:** There is a positive relationship between the equality of distribution of communication turn-taking between Wikipedia janitors and article quality.

Besides interaction patterns, the characteristics of the individuals who participate in group work appear to be important in increasing the quality of group outcomes (Butler et al., 2007;
Diversity in group composition has been proposed as a requirement for a group to exhibit ‘wisdom of crowds’ effects (Surowiecki & Silverman, 2007). The literature concerning group diversity suggests that it may be either beneficial or detrimental in terms of group outcomes. On the one hand, more diversity in knowledge and experience helps group members to avoid biases and overlooking certain aspects; this can lead to improved outcomes. Heterogeneous groups appear to perform well because they have a relatively broad range of information, experiences, and perceptions to draw from. On the other hand, group heterogeneity and differences among individuals may result in conflict and diminished performance (Aral et al., 2008). Social categorization theory suggests that differences between peers may generate tensions and conflicts among them, which may, in turn, negatively influence group outcomes (Van Knippenberg et al., 2004). Recent research on the effect of group diversity on performance has established a curvilinear relationship, in the sense that moderate diversity correlates with higher performance, whereas extremes of too little or too much diversity are detrimental to group performance (Aral et al., 2008). Since group diversity appears to be a double-edged sword, we hypothesize:

**H2:** There is an inverted U curvilinear relationship between the diversity of Wikipedia janitors and article quality.

Previous literature on group processes and outcomes acknowledges that, when group members stay and work together over a period of time, they are able to develop a common ground, unspoken expectations and shared mental models of the task to be accomplished (Aral et al., 2008; Chen et al., 2010). This is especially important for key group members as turnover in the key roles of a work group may negatively influence the way team members interact or coordinate their work (Humphrey et al., 2009; Ransbotham & Kane, 2011). According to the theory of group cohesiveness, the stick-togetherness of group members is positively associated with group performance (Chansler et al., 2003; Festinger et al., 1950).
However, a recent paper argues otherwise. Examining close to 200 groups whose members worked together for a few hours on predefined tasks, Woolley et al. (2010) found that group cohesion was not correlated with group performance. We argue that, in online social production such as Wikipedia, where group size fluctuates dynamically as members come and leave at their own will (Brandes & Lerner, 2009; Bryant et al., 2005; Halfaker et al., 2011; Ransbotham & Kane, 2011), it is important that at least the Wikipedia janitors stick together to be able to improve the article quality over time (Zhu et al., 2012). Hence, we hypothesize:

**H3:** There is a positive relationship between the cohesiveness of Wikipedia janitors and article quality.

### 3. RESEARCH METHODOLOGY

To test the above hypotheses, we conduct a longitudinal analysis in a similar way to Kittur et al. (2008), i.e., for each quality assessment of an article, we consider the period between the previous and the current change in quality. A graphical representation of the considered time span of analysis is presented in Figure 1. Note that our analysis takes into account only those articles that receive at least two quality assignments during their life span. The instantiations of all the subsequent constructs in our model are computed relative to this time span.

[Insert Figure 1 about here]

### 3.1 Dependent Variable

**Change in Quality.** As dependent variable we indicate whether, following a quality assessment, an article was either promoted (to a superior quality class) or demoted (to a lower quality class). The Wikipedia community has developed formal guidelines and mechanisms for assessing and evaluating quality ratings of its articles in an inter-subjective manner, into a large spectrum of *quality ratings*. The ratings vary from a very low quality to the highest quality and are termed (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good
articles’, ‘A-class’, and ‘Featured articles’. These ratings are consistent with Wang and Strong’s multidimensional definition of data quality (Liu & Ram, 2011; Wang & Strong, 1996). An article is promoted to a higher rating or demoted to a lower rating only after an official assessment of peer reviewers. In order to maintain objectivity and neutrality, the assessments of good and featured articles are made by Wikipedians who did not participate in heavy or repeated edits of the article proposed for assessments (Liu & Ram, 2011). Previous studies have shown that Wikipedia’s internal quality ratings and the ratings from external raters are significantly correlated (Spearman’s $\lambda = 0.54$, $p < 0.001$) (Kittur & Kraut, 2008). Hence, even though they may not be completely objective and neutral, Wikipedia’s quality ratings constitute a valid proxy for article quality (Liu & Ram, 2011). This proxy is used to compute the dependent variable in this study.

### 3.2 Dataset

The dataset we use in this study is extracted from the June 2011 dump of English Wikipedia. The dataset includes full texts of Wikipedia pages and their complete edit history from the beginning of Wikipedia. Since our intention is to examine the influential factors of Wikipedia article quality, we selected an equal proportion of articles of different Wikipedia-designated quality levels as follows. We randomly sampled 60% of the articles (about 2.15 million of 3.6 million articles). We chose random sampling against purpose sampling (e.g. snowball sampling), because, for example, selecting articles that are more popular and attract more editors would not create a representative subset population. Random sampling ensures that each article has identical probability to be chosen independently of other articles it is connected to. Similar to Liu and Ram (2011), out of the selected articles, we extracted all the articles labeled as featured (fa), good (ga), B-class (b), and C-class (c), totalling a number of 84,915 articles. Note that we investigated featured, good, B-class, and C-class articles because these four represent well-distinguished, non-transitional quality classes (Nemoto et
al., 2011). We ensure unbiased statistics by choosing Wikipedia articles with equal likelihood to represent one representative quality class. Thus, by using random sampling, the insights are more likely to be generalizable to the entire Wikipedia articles as well. Finally, we identified all the changes in article quality during an article’s life span, ranging from 3-level demotion (fa→c) to 3-level promotion (c→fa). The resulting dataset contains in total 11,359 changes in article quality, on which we base our analysis. Table 1a and Table 1b give an overview of the counts and proportions of each type of change in article quality.

[Insert Table 1a and Table 1b about here]

3.3 Independent Variables

**Distribution of Communication Turn-Taking.** We operationalize the equality of distribution of communication turn-taking in the same manner as Woolley et al. (2010, p. p. 688). For each article, we counted the number of times each Wikipedia janitor contributed a discussion point on the talk page of that article. The distribution of these counts represents the distribution of *communication turn-taking* among the Wikipedia janitors who worked on the article ($TT_i, 1 \leq i \leq N$ with $N$ is the number of janitors). We then computed the coefficient of variation of communication turn-taking ($CV_{TT}$) as the ratio between the standard deviation and the mean of the turn-taking scores ($\mu_{TT}$): $CV_{TT} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (TT_i - \mu_{TT})^2 \mu_{TT}}$. To interpret this measure of equality, $CV_{TT}=0$ if there are for instance 16 communication turns in a talk page of 4 janitors who each communicate 4 times. That is, $CV_{TT}=0$ means an equality in the communication turn-taking of the janitors on the talk page of an article. The smaller the value of $CV_{TT}$ suggests the more equality in the distribution of communication turn-taking of the janitors on the talk page of an article.

**Group Diversity.** WikiProjects provide a valuable setting to quantify the amount of diversity among Wikipedia janitors according to their editing activity and interests (Chen et al., 2010,
p. p. 18). In this sense, we use the Blau index (Agresti, 2002) to measure the probability that two entities (e.g. Wikipedia janitors), taken at random from the dataset of interest (editorial team of an article), represent different types, i.e. do not share any Wikiproject in common (Blau, 1977). The formal definition of the Blau index is $\text{BI} = 1 - \sum_{k=1}^{K} p_k^2$, where $K$ is the number all possible categories (i.e., of Wikiprojects), and $p_k$ is the proportion of the Wikipedia janitors who share (i.e. are all members of) project $k$. A value of the Blau index equal to zero indicates that all Wikipedia janitors who are part of the editorial team of an article share at least one Wikiproject. If all Wikipedia janitors share no Wikiproject among them, the corresponding Blau index equals 1.

**Group Cohesiveness.** Group cohesiveness is achieved when the members of the group are committed to work together to accomplish a collective task (Guzzo et al., 1995; Hsu et al., 2011; Kidwell et al., 1997). Group cohesiveness refers to “the resultant of all the forces acting on members to remain in the group” (Festinger, 1950). In other words, group cohesiveness is the 'stick togetherness' of the group, the bonds of unity that hold group members together to achieve their common goals (Ren et al., 2012; Schultz, 1988). Members of strongly cohesive groups are more willing to participate readily and to stay with the group (Dyaram & Kamalanabhan, 2005). In line with these definitions, we instantiate group cohesiveness relative to the development process of articles in Wikipedia as the proportion of Wikipedia janitors who previously contributed to the article development, and stayed in the team during the most recent interval of quality change (Chansler et al., 2003; Dyaram & Kamalanabhan, 2005).

### 3.4 Control Variables

**Editing Effort Distribution.** This is an important control variable, as previous studies pointed to the long tail distribution of edits on Wikipedia articles (Kittur & Kraut, 2008; Wilkinson, 2008). Here we expect to see that such distributions exist among Wikipedia
janitors as well, and so we decide to control for it in our analysis. One of the most commonly used metrics to describe the inequality of a distribution (in this case, equality of contributions) is the Gini coefficient of homogeneity, with higher values indicating greater inequality (Dorfman, 1979). In the context of Wikipedia, a low Gini coefficient of the edit distribution means that the work is equally distributed among Wikipedia janitors; conversely, a large value of the Gini coefficient reflects situations where a few Wikipedia janitors are performing most of the work (Allison, 1978).

To account for exogenous variables, we also consider the following control variables related to Wikipedia articles that may influence the article quality: article age, article popularity, group size, and initial article quality. A detailed description of these variables and a summary of all the variables used in this study are presented in Table 2.

4. DATA ANALYSIS

Since the aim of our analysis is to identify influential predictors and gain insights into the relationship between the predictors and the outcome, we employ a regression model (Harrell, 2001, p. 97). A longitudinal analysis is conducted as follows: for each quality assessment of an article, we considered the period between the previous and the current change in quality. Similar to Kittur and Kraut (2008), the metrics computed in this time span are used in order to explain the change in article quality, as depicted in Figure 1.

As the scales/units of the main predictors are not easy to interpret (they are not natural metrics), we employ a standardized version of the binary logistic regression model. As explained in (Schielzeth, 2010), standardization facilitates not only a common scale of all the input variables so that the coefficients are better understood, especially in the presence of interactions, but also a comparison of the relative importance of the individual main effects: marginal effect size estimates. Table 3a shows the summaries of unstandardized (original)
and standardized datasets that are used for modeling. We note here that the original dataset is a subset of the main dataset, obtained by keeping only non-missing observations of the eight covariates (the main predictors and the controls variables). In this way, the meaning of promotion and demotion are not violated since the aforementioned articles cannot be promoted to any higher quality level than “fa” and cannot be demoted to any lower quality level than “c”.

We first consider a baseline model in which the covariates are the control variables. We refer to this as Model 1. Afterwards, similar to Kittur and Kraut (2008), we add Edits as the main predictor and all the interactions with the variables in Model 1. The resulting model is referred to as Model 2. Finally, in Model 3, which is the main contribution of this study, we add Communication, Diversity, and Cohesiveness as main predictors, along with the corresponding interaction effects. We computed the $AIC$ value corresponding to each model together with two summary measures for the goodness of fit: the Nagelkerke’s $R^2$ (also known as Cragg & Uhler’s $R^2$) and the chi-square test for goodness of fit ($chi-square GOF$) (Hosmer and Lemeshow, 1980; Hosmer et al., 1997). Values of $chi-square GOF$ larger than 5% indicate that the considered model is fit. A summary of the results of the logistic regression is presented in Table 4.

5. DISCUSSIONS OF THE FINDINGS

The results of our data analysis confirm that contribution inequality (Edits) among Wikipedia janitors has a positive effect on article promotion in Wikipedia. More precisely, a one standard deviation increase in the inequality of editing effort distribution (Edits) among Wikipedia janitors corresponds to an increase of 169% (i.e., $exp(0.99)-1$) in the likelihood for
an article to be promoted (vs. demoted), when all the other variables are kept at their mean level (see Table 4, Model 3).

With respect to our first main variable of interest, i.e., the distribution of communication turn-taking (Communication), our results show that unequal distribution of communication turn-taking is not favorable for promoting an article to a superior quality class. In other words, higher uniformity in the distribution of communication turns correlates with higher article promotion likelihood. A one standard deviation increase in the equality of communication turn-taking corresponds to an increase of 15% (i.e., exp(0.14)-1) in an article’s promotion likelihood (see Table 4, Model 3). This result confirms H1 and the finding of Woolley et al. (2010). It is worth noticing the consistency of the two results, given the obvious difference in the two study contexts: we study real-life groups working on fuzzy tasks for an extended period of time whereas Woolley et al.’s (2010) study laboratory-controlled face-to-face groups working on predefined tasks for a few hours. This remarkable consistency of results suggests that, regardless of the mode (offline or online), or the degree of certainty of the task, or the work duration, the more the communication turns are uniformly distributed among the group members, the higher the quality of group outcomes.

We found that the diversity of Wikipedia janitors has a significantly positive impact on the likelihood for an article to be promoted. A one standard deviation increase in diversity corresponds to a 12% (i.e., exp(0.12)-1) increase in the promotion likelihood of an article (see Table 4, Model 3). Following H2, we further tested for a quadratic effect of diversity: although we found a negative coefficient of the quadratic term, the coefficient was not significant. This does not offer sufficient support for H2. Looking at the interaction effect of the diversity variable with the control variables (see Table 4), one notable interaction is the interaction with group size where the positive effect of diversity became much stronger when the number of Wikipedia janitors increased. To dig deeper into this interaction effect, we run
additional analysis (see Figures 2a, b, c). Collectively these figures show that the effect of Wikipedia janitors’ diversity on an article’s promotion probability is positive when the article’s initial quality is “b” (indicating a less developed article) and, further, that this effect becomes stronger with the increasing size of Wikipedia janitors. However when the article’s initial quality is “ga” (indicating a more developed article), the size of Wikipedia janitors appears to undermine the effect of diversity, i.e., the effect of diversity on the probability for an article to be promoted becomes negative. Altogether these results imply having many diverse Wikipedia janitors is beneficial when the article is at a less developed stage, while having few and less diverse Wikipedia janitors is beneficial when the article is at a more developed stage.

[Insert Figures 2a, b, c]

Group cohesiveness is found to be the most important main effect relative to an article’s likelihood of promotion. A one standard deviation increase in group cohesiveness corresponds to a 68% (i.e., exp(0.61)-1) increase in an article’s promotion likelihood (see Table 4, Model 3). This result confirms H3. In contrast with Woolley et al. (2010), but in line with the theory of group cohesiveness (Festinger et al., 1950), this finding shows the importance of the stick-togetherness of the Wikipedia janitors for producing high quality outcomes. As with the diversity variable, the most notable interaction effect of this variable is its interaction with the size of the Wikipedia janitors, i.e., the higher the number of Wikipedia janitors working on an article, the more positive the effect of their cohesiveness on the article’s promotion likelihood. However when we dig deeper into this interaction, we found a marginal reverse effect when the article is at a less developed stage (see Figure 2b). This is peculiar because one would expect a tightly bonded group to be important in improving the quality of a less developed article, especially when the number of individuals working on the article is quite large. One possible explanation of this finding could be that people that stick
together typically think alike (homophily); having too many like-minded people at the early stage of article development may not be beneficial on the likelihood of the article being promoted to a higher quality level. In this case, the stick-togetherness of the Wikipedia janitors editing the article may be undermined by biases resulting from the fact that they think alike. Indeed we found a negative correlation between diversity and cohesiveness (corr = -0.42).

6. CONTRIBUTIONS AND IMPLICATIONS

Findings of this study have to be viewed in light of its limitations. With regard to generalizability and endogeneity, we acknowledge that several areas dealing with the dynamics of social interaction in online collaboration that were not examined in this study, such as the issues of social power or culture (Baym, 2006; Jiang et al., 2011). Pragmatically, there may be several perspectives for examining peer interactions in online social production communities. Conditions other than group interactions and group composition characteristics – such as users’ capabilities and goals, their interpretations of technology, and institutional contexts, power, or culture – may play key roles in causal explanations. Due to the possibility of omitted variable bias, simultaneous causality bias, and errors-in-variable bias, future research should examine our identified relationships using more controlled settings or methods such as instrumental variables regression. Nonetheless the findings of this study contribute to the extant literature and have important implications for practitioners.

This study contributes to the extant literature of online social production communities in general and Wikipedia in specific by investigating how the properties and interactions of the people who are most engaged in the production of the common goods, i.e., the Wikipedia janitors, affect quality outcomes. Linus’ law that “many eyes make all bugs shallow” have been repeatedly challenged by findings that show that, in reality, only few volunteers significantly contribute to common goods. However no study has ever investigated how the
few Wikipedia janitors contribute to the success of Wikipedia. Ours is a pioneering study that investigates the composition of the Wikipedia janitors, how they interact, and how their composition and interaction affect output quality. Through a longitudinal analysis of the composition of Wikipedia janitors, their communication turn-taking, and the quality changes (promotion or demotion) of articles they worked on, we found that the most important ingredient to an article’s likelihood of promotion is the cohesiveness of Wikipedia janitors. At the same time, however, cohesiveness implies lower diversity and this, in turn, may not be beneficial for an article at its early development stage. An interesting question for future research would be to explore further the tension between cohesiveness and diversity in other online social production communities, e.g., examine whether this dilemma persists in OSS projects (which produce technically more challenging output than Wikipedia) at different software development stages.

While comparisons between offline and online social production are not within the scope of the study, it is interesting to note here the similarities and differences between our findings and the findings of Woolley et al. (2010), which is perhaps the most comprehensive study of face-to-face group interactions to date. Our context is real-life groups working on fuzzy tasks for an extended period of time whereas Woolley et al. (2010) study laboratory-controlled face-to-face groups working on predefined tasks for a few hours. Despite the obvious contextual differences, we similarly found the positive effect of an equal distribution of communication turn-taking on output quality. However, while Woolley et al. (2010) found that group cohesiveness has no effect on output quality, we found it to be the most important antecedent. This difference can be possibly related to the different lengths of work duration of the groups. Future research could pursue a 2 x 2 x 2 research design that manipulates the interaction mode (offline or online), the degree of task certainty (low or high), and the work duration (short or long) for a more direct comparison of the different settings.
From a managerial perspective, organizations increasingly consider the outsourcing of knowledge tasks to large masses of workers via distributed labor networks using limited or no monetary incentives; this is possible, in part, due to the fact that the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of collaboration. While open collaborative innovation can potentially displace producer innovation at many parts of the economy (Baldwin and Hippel 2011), the fluid generativity of distributed innovation suggests that knowledge resources will be increasingly heterogeneous and often only temporarily integrated (Yoo et al. 2012). Reflecting from the Wikipedia case, having janitors (who could be individuals employed by the organization) tasked with constantly organizing and refining the collectively produced knowledge resources is important for organizations who would like to outsource knowledge tasks to large masses of online distributed workers. This study provides insights on the most effective composition of janitor groups, as well as on how they should interact with one another. While the focal organization may not be able to control the way janitors interact with one another, it should be able to define and alter their composition (diversity and cohesiveness) over time. Findings in this study can guide the organization in doing so.

REFERENCES


Figures and Tables

Figure 1: Analysis window

Table 1a: Total counts of quality changes (lines represent the starting quality, whereas columns represent the quality after the change)

<table>
<thead>
<tr>
<th>From/to quality</th>
<th>c</th>
<th>b</th>
<th>ga</th>
<th>fa</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>0</td>
<td>1285</td>
<td>284</td>
<td>16</td>
</tr>
<tr>
<td>b</td>
<td>6239</td>
<td>0</td>
<td>1974</td>
<td>191</td>
</tr>
<tr>
<td>ga</td>
<td>146</td>
<td>469</td>
<td>0</td>
<td>501</td>
</tr>
<tr>
<td>fa</td>
<td>60</td>
<td>180</td>
<td>14</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1b: Proportions of quality changes by initial quality and magnitude of changes in quality

<table>
<thead>
<tr>
<th>Initial quality/magnitude of change</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>InitialQuality=c</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0</td>
<td>0.81</td>
<td>0.18</td>
<td>0.01</td>
</tr>
<tr>
<td>InitialQuality=b</td>
<td>NA</td>
<td>NA</td>
<td>0.74</td>
<td>0</td>
<td>0.23</td>
<td>0.02</td>
<td>NA</td>
</tr>
<tr>
<td>InitialQuality=ga</td>
<td>NA</td>
<td>0.13</td>
<td>0.42</td>
<td>0</td>
<td>0.45</td>
<td>NA</td>
<td>NA</td>
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<td>0.24</td>
<td>0.71</td>
<td>0.06</td>
<td>0</td>
<td>NA</td>
<td>NA</td>
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</table>
### Table 2: Operational definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Main Effects</strong></td>
<td></td>
</tr>
<tr>
<td>Communication Effort Distribution (Communication)</td>
<td>Coefficient of Variation of Communication Turn Taking measured on article talk pages (Woolley et al., 2010), e.g. conversations are dominated by single group members.</td>
</tr>
<tr>
<td>Group Cohesiveness (Cohesiveness)</td>
<td>The proportion of Wikipedia janitors who previously contributed to the article development, and stayed in the team during the most recent interval of quality change (Chansler et al., 2003; Dyaram &amp; Kamalanabhan, 2005).</td>
</tr>
<tr>
<td>Group Diversity (Diversity)</td>
<td>Editorial team diversity measured using the Blau index (Blau, 1977), i.e. the probability that two entities chosen at random represent different types, with respect to the participation in Wikiprojects.</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
</tr>
<tr>
<td>Editing Effort Distribution (Edits)</td>
<td>Contribution inequality measured using the Gini Coefficient of the distribution of article editing effort (Allison, 1978; Dorfman, 1979; Espinosa et al., 2007).</td>
</tr>
<tr>
<td>Article Age</td>
<td>Duration from the creation of an article until the current change in quality.</td>
</tr>
<tr>
<td>Article Popularity</td>
<td>Number of web search hits.</td>
</tr>
<tr>
<td>Group Size</td>
<td>Number of Wikipedia janitors (i.e. WikiProject members and administrators) involved in the editing process.</td>
</tr>
<tr>
<td>Initial Quality</td>
<td>Quality label of an article at the beginning of the time span of analysis.</td>
</tr>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
</tr>
<tr>
<td>Change in Quality</td>
<td>Binary variable measuring whether an article was promoted (+1, i.e. to a superior quality standard) or demoted (-1; i.e. to an inferior quality standard).</td>
</tr>
</tbody>
</table>
Table 3a: Dataset Summary

<table>
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<tr>
<th>Independent Variables</th>
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<th>Standardized</th>
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<td></td>
<td>min</td>
<td>max</td>
</tr>
<tr>
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</tr>
<tr>
<td>Diversity</td>
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</tr>
<tr>
<td>Cohesiveness</td>
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<td>1.00</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Edits</td>
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<td>1.00</td>
</tr>
<tr>
<td>Article Age</td>
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<tr>
<td>Log (Article Popularity)</td>
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<td>Log (Group Size)</td>
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<tr>
<td>Initial Quality</td>
<td>count</td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>6445</td>
<td></td>
</tr>
<tr>
<td>b</td>
<td>1934</td>
<td></td>
</tr>
<tr>
<td>ga</td>
<td>2272</td>
<td></td>
</tr>
<tr>
<td>fa</td>
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<td></td>
</tr>
<tr>
<td>Dependent Variable (DV)</td>
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<td></td>
</tr>
<tr>
<td>Change in Quality</td>
<td>count</td>
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<tr>
<td>Demoted (-1)</td>
<td>7108</td>
<td></td>
</tr>
<tr>
<td>Promoted (+1)</td>
<td>4251</td>
<td></td>
</tr>
<tr>
<td>Total nr. of instances</td>
<td>11359</td>
<td></td>
</tr>
</tbody>
</table>

Table 3b: Variable Correlations

<table>
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<tr>
<th>Correlations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Age</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Log (Article Popularity)</td>
<td>0.34</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Log (Group Size)</td>
<td>0.40</td>
<td>0.31</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Edits</td>
<td>-0.06</td>
<td>-0.06</td>
<td>0.22</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Communication</td>
<td>0.08</td>
<td>0.26</td>
<td>0.34</td>
<td>0.33</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Diversity</td>
<td>0.30</td>
<td>0.24</td>
<td>0.79</td>
<td>0.22</td>
<td>0.26</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7. Cohesiveness</td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.44</td>
<td>-0.08</td>
<td>-0.13</td>
<td>-0.42</td>
<td>1</td>
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</table>
Table 4: Standardized Binary Logistics Models

<table>
<thead>
<tr>
<th></th>
<th>Baseline (Model 1)</th>
<th>Edits (Model 2)</th>
<th>All (Model 3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>Pr(&gt;</td>
<td>Z</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.60</td>
<td>***</td>
<td></td>
</tr>
<tr>
<td>Article Age</td>
<td>-0.36</td>
<td>***</td>
<td>1.20</td>
</tr>
<tr>
<td>Log (Group Size)</td>
<td>-0.57</td>
<td>***</td>
<td>1.10</td>
</tr>
<tr>
<td>Log (Article Popularity)</td>
<td>-0.08</td>
<td>***</td>
<td>1.10</td>
</tr>
<tr>
<td>Edits</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Article Age * Edits</td>
<td>-0.08</td>
<td>***</td>
<td>1.20</td>
</tr>
<tr>
<td>Log (Group Size) * Edits</td>
<td>0.54</td>
<td>***</td>
<td>2.30</td>
</tr>
<tr>
<td>Log (Article Popularity) * Edits</td>
<td>0.04</td>
<td>.</td>
<td>1.20</td>
</tr>
<tr>
<td>Communication</td>
<td></td>
<td>-0.14</td>
<td>***</td>
</tr>
<tr>
<td>Article Age * Communication</td>
<td>-0.10</td>
<td>***</td>
<td>1.30</td>
</tr>
<tr>
<td>Log (Group Size) * Communication</td>
<td>0.01</td>
<td>0.70</td>
<td>1.80</td>
</tr>
<tr>
<td>Log (Article Popularity) * Communication</td>
<td>-0.02</td>
<td>0.40</td>
<td>1.50</td>
</tr>
<tr>
<td>Diversity</td>
<td></td>
<td>0.12</td>
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</tr>
<tr>
<td>Diversity²</td>
<td></td>
<td>-0.06</td>
<td>0.28</td>
</tr>
<tr>
<td>Article Age * Diversity</td>
<td></td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>Log (Group Size) * Diversity</td>
<td>0.21</td>
<td>***</td>
<td>5.70</td>
</tr>
<tr>
<td>Log (Article Popularity) * Diversity</td>
<td>0.17</td>
<td>***</td>
<td>1.60</td>
</tr>
<tr>
<td>Cohesiveness</td>
<td></td>
<td>0.61</td>
<td>***</td>
</tr>
<tr>
<td>Article Age * Cohesiveness</td>
<td></td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Log (Group Size) * Cohesiveness</td>
<td>0.25</td>
<td>***</td>
<td>4.10</td>
</tr>
<tr>
<td>Log (Article Popularity) * Cohesiveness</td>
<td>0.05</td>
<td>*</td>
<td>1.40</td>
</tr>
<tr>
<td>AIC</td>
<td>13574</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo-R²</td>
<td>0.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-square GOF</td>
<td>0.27</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

***Significant at < 0.001; **Significant at < 0.01; *Significant at < 0.05
Figure 2a: Slopes of main effects - when taking into account the marginal effect of GroupSize, when all the other factors are kept fixed, using the following formula:

\[ \text{Slope(MainEffect)} = \text{Coef(MainEffect)} + \text{Coef(Interaction(MainEffect, GroupSize))} \times \text{DomainOfDef (GroupSize)} \]

Figure 2b: Slopes of main effects when the initial quality is “b”
Figure 2c: Slopes of main effects when the initial quality is “ga”
Appendix III

Knowledge Creation: Effects of Stick-Togetherness on the Emergence of Collective Intelligence: A Longitudinal Analysis
Effects of Stick-Togetherness on the Emergence of Collective Intelligence: A Longitudinal Analysis

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Bernadetta Tarigan  
ETH Zurich, Switzerland

Juliana Sutanto  
ETH Zurich, Switzerland

Introduction

While research has shown the existence of a “collective intelligence” emerging from interactions among group members in controlled laboratory settings, its existence, emergence and consequences in online settings are unclear. With more than 3.7 million articles, Wikipedia is a highly successful and prominent instance of online social production systems. This research uncovers the interplay between the factors influencing the quality of outcome in Wikipedia. Extending previous studies on online social production, our longitudinal analysis provides evidence that the ability of core groups of Wikipedians to stick together and collaborate over time is essential for producing high quality outcomes.

Research Problem

The understanding of the way in which high quality outcomes are produced in Wikipedia (and in online social production, in general) is still unclear [1]. Although researchers have studied for decades how well groups perform on specific tasks [2], they mostly have not attempted to study group interactions on a large scale or in the field. Most of studies were based on laboratory experiments, in controlled situations, which are fundamentally different from an open environment such as Wikipedia. More precisely, the contributions and involvement of editors in the Wikipedia community may drastically vary over time, with some editors moving from peripheral participation to full involvement [3], while others even abandoning Wikipedia [4]. Given this rapidly changing environment, Wikipedia articles that reach faster a higher quality level appear to be created by core Wikipedia contributors who have previously worked together on the development of other articles [5]. Below we propose to extend previous findings on collective intelligence and analyze the possible impact of the activity of core Wikipedians on the emergence of collective intelligence in Wikipedia.

Editing Effort Distribution. Prior studies have shown that Wikipedia holds a long tail architecture of participation [6], with a relatively small proportion of editors who perform most of the edits [7]. These core contributors set the direction of the work by their own efforts. Moreover, articles in which the workgroup structure includes a small core of leaders are more likely to increase in quality than articles in which work is evenly distributed amongst contributors, and that this effect becomes stronger as the number of involved contributors grows [8]. Relative to core Wikipedians, we ask whether this pattern still occurs. Consistent with the previous findings, we hypothesize that:

\[ \text{H1: Contribution inequality among core Wikipedians is positively related to an increase in the quality of Wikipedia articles.} \]

Communication Effort Distribution. When members of a group coordinate their work through communication, their individual turn-taking dynamics may facilitate the formation of a common ground [9]. Turn-taking is the set of communication practices by which collaboration is achieved in and through conversational turns [10]. Equality in
distribution of turn-taking has been shown in laboratory experiments to be positively correlated with the performance of groups across a variety of tasks [2]. If the manner in which communication between group members takes place is more uniformly distributed and thus not dominated by single group members, this corresponds to higher levels of group performance. Transferring this insight to Wikipedia, an equal distribution of distribution of turn-taking between editors who work together on an article should lead to the emergence of collective intelligence and, in turn, result in higher article quality:

**H2:** Equality of distribution of turn taking between core Wikipedians is positively related to an increase in the quality of Wikipedia articles.

**Group Cohesiveness.** Turnover in the key roles of a work group may negatively influence the way team members interact and coordinate their work [11, 12]. In this sense, the ability of Wikipedia community to determine its key members to stay together over longer periods of time and develop a common ground via collaboration (e.g., editing articles in the context of Wikipedia) can be understood as a quality indicator [13]. It is generally accepted that this stick-togetherness of groups (commonly referred as group cohesiveness) and performance are associated [14]:

**H3:** High cohesiveness among core Wikipedians is positively related to an increase in the quality of Wikipedia articles.

**Group Diversity.** Diversity in group composition has been proposed as a requirement for large group to exhibit the effect of ‘wisdom of crowds’ [15]. On the one hand, diversity in knowledge and experience helps the members of a group to avoid potential biases, which can lead to improved outcomes. On the other hand, heterogeneity of the group and differences among individuals may also result in conflict and diminished performance [16]. Because of the many peripheral contributors in Wikipedia who presumably ensure the emergence of the wisdom of crowds, potential biases seem to be rather unlikely in Wikipedia [17]. We can thus hypothesize that, in the case of core Wikipedians, too much diversity may correspond to a lack in common ground and negatively influence the outcome of collaboration [18]:

**H4:** High diversity of core Wikipedians corresponds to a decrease in article quality.

**Research Approach**

**Quality of Outcome in Wikipedia.** The Wikipedia community has developed formal guidelines and mechanisms for assessing and evaluating quality ratings of its articles in an inter-subjective manner, into a large spectrum of quality ratings. The ratings vary from a very low quality to the highest quality and are termed (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good articles’, ‘A-class’, and ‘Featured articles’. These ratings are consistent with Wang and Strong’s multidimensional definition of data quality [1]. An article is promoted to a higher rating or demoted to a lower rating only after an official assessment of peer reviewers. Previous studies have shown that Wikipedia’s internal quality ratings and the ratings from external raters are significantly correlated [8]. Hence, Wikipedia’s quality ratings, though not guaranteed to be completely objective and neutral, constitute a valid proxy for article quality [19]. This proxy is used to compute the dependent variable in this study. The operationalizations of all the constructs used in this paper are presented below.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Editing Effort Distr.</td>
<td>Contribution inequality measured using the Gini Coefficient of the distribution of article</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Communication Effort Distr.</td>
<td>Coefficient of variation of conversational turn-taking on article talk pages [2], e.g. when conversations are dominated by single group members</td>
</tr>
<tr>
<td>Group Cohesiveness</td>
<td>Group cohesiveness is achieved when the members of the group are committed to work together to accomplish their collective tasks or shared goals [21]. Group cohesiveness is the 'stick togetherness' of the group, the bonds of unity that hold group members together to achieve their common goals [22]. Members of strongly cohesive groups are more willing to participate readily and to stay with the group [23]</td>
</tr>
<tr>
<td>Group Diversity</td>
<td>Editorial team diversity measured using the Blau index [24], i.e. the probability that two entities chosen at random represent different types, with respect to the participation in Wikiprojects</td>
</tr>
<tr>
<td>Article Age</td>
<td>Duration from the creation of an article until the current change in quality</td>
</tr>
<tr>
<td>Article Popularity</td>
<td>Number of web search hits of the article title</td>
</tr>
<tr>
<td>Team Size</td>
<td>Number of core Wikipedians (i.e. WikiProject members and administrators) who participated in the editing process</td>
</tr>
<tr>
<td>Change in Quality</td>
<td>Quantification of the change in the quality label of an article (e.g. c→b, b→ga, ga→fa)</td>
</tr>
</tbody>
</table>

**Data Set.** The dataset we use in this study is extracted from the June 2011 dump of English Wikipedia. The dataset includes full texts of Wikipedia pages and their complete edit history from the beginning of Wikipedia. With the intention to study the relationship between collaboration and the quality of Wikipedia articles, we selected an equal proportion of articles of different Wikipedia designated quality levels as follows. We randomly sampled 60% of the articles (about 2.15 million of 3.6 million articles). We chose random sampling against purpose sampling (e.g. snowball sampling), because, for example, selecting articles that are more popular and attract more editors than the others would not create a representative sample. Similar to [1], out of the selected articles, we extracted all the articles labeled as featured (fa), good (ga), B-class (b), and C-class (c), totalling a number of 84,915 articles. Note that we investigated featured, good, B-class, and C-class articles because these four represent well-distinguished, non-transitional quality classes [5]. We ensure unbiased statistics by choosing Wikipedia articles with equal likelihood to represent one representative quality class. Thus, by using random sampling, the insights are more likely to be generalizable to the entire Wikipedia articles as well. For each of these articles, we identified all the quality assessments during their life span, distributed as follows: 2,259 fa-assessments, 8,564 ga-assessments, 47,258 b-assessments, and 55,037 c-assessments, totalling a number of number of 113,118 assessments.

**Data Analysis and Results**

We first consider a model (further referred as Model 1) in which we chose the following independent variables (IV): editing effort distribution and distribution of conversational turn-taking (accounting for group interactions), as well as group cohesiveness, and group diversity (accounting for group characteristics). To account for exogenous variables, we control for article age, article popularity, and team size (C). To partially address the issue of causality, we employ
a longitudinal analysis in a similar way to Kittur et al. [8], as follows: for each quality assessment of an article, we consider the period between the previous and the current change in quality. The instantiations of all the subsequent constructs in our model are computed relative to this time span. We use ordinal logistic regression, as the dependent variable (DV) represents either a positive or a negative change in article quality.

To assess the global goodness of fit for the above model, we employed the le Cessie - van Houwelingen - Copas - Hosmer unweighted sum of squares test [25]. A good fit is indicated by the large p-value (p=0.95>0.05). To test for the proposed hypotheses, we investigate the coefficients of the parameters related to editing effort distribution (H1), distribution of conversational turn-taking (H2), group cohesiveness (H3) and group diversity (H4). Values of exponentiated β-coefficients (further referred as “coefficients”) larger than one indicate the likelihood for the article to be promoted. The coefficients should be interpreted as the effect of an increase with one standard deviation in the level of an independent variable (IV) on the output (DV) when all the other predictors are fixed at their mean level.

With respect to group interactions, inequality of editing efforts of core Wikipedians significantly influences the likelihood of an article to be promoted (p<0.001). More precisely, a unit increase in inequality of editing effort corresponds to an increase of 61% in the likelihood for an article to be promoted, when all the other variables in the model are kept at their mean level (H1 is supported). This result is in line with previous research [26] in the sense that, in the case of promoted articles, only a small subset from the core Wikipedians who participate in the editing process indeed contribute to a large part of the edits. However, the effect of the communication effort distribution on the likelihood for an article to be promoted is very small (6.1%) and requires further investigation. Regarding group composition, we find that a unit of increase of group cohesiveness corresponds to an increase of 17% in the likelihood for an article to be promoted (H3 is supported). Finally, the effect of group diversity has been found to be not significant.

These results extend previous research on Wikipedia, that established that articles reaching faster a higher quality level appear to be created by groups of editors who have previously worked together on other articles [5], i.e., highly cohesive groups. This higher pre-existing social capital of co-workers has been found to be especially important in the early phase of the editorial team organization; once the general direction of the article is set, the editorial team is able to absorb new contributors (presumably resulting in a higher group diversity) in a more effective manner [5]. We thus propose to analyze the statistical interaction of team characteristics (both group cohesiveness and group diversity among core Wikipedians) with respect to the maturity level of the article. Model 2 adds each of these respective interactions. To assess the model validity, the p-value obtained from the le Cessie - van Houwelingen - Copas - Hosmer unweighted sum of squares test is by far larger than 0.05, indicating a good fit of the model (p=0.87). We found that the interaction between cohesiveness and article age to be significant (p<0.001) and positive. The interaction between group diversity and article age has been found to be not significant. Finally, one unit increase of group cohesiveness accounts for a 30.9% increase in the likelihood for an article to be promoted. We can thus conclude that, in order for an article to be promoted, it is vital for the core Wikipedians to stick together over time and develop a common ground [9], independent of the level of group diversity among them (given this constantly changing environment of Wikipedia).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model1: IV+Controls</th>
<th>Model2: IV+Controls+Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exp(Coef.)</td>
<td>S.E.</td>
</tr>
</tbody>
</table>

Variable | Model1: IV+Controls | Model2: IV+Controls+Interactions |
----------|---------------------|----------------------------------|
|          | Exp(Coef.) | S.E.                      | Exp(Coef.) | S.E. |
Independent Variables (IV)

<table>
<thead>
<tr>
<th>Variable</th>
<th>p-value</th>
<th>95% CI</th>
<th>p-value</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Editing Effort Distribution</td>
<td>1.616***</td>
<td>0.095</td>
<td>1.733***</td>
<td>0.098</td>
</tr>
<tr>
<td>Distribution of Conversational Turn-Taking</td>
<td>1.061***</td>
<td>0.049</td>
<td>1.010</td>
<td>0.049</td>
</tr>
<tr>
<td>Group Cohesiveness</td>
<td>1.173***</td>
<td>0.084</td>
<td>1.309**</td>
<td>0.216</td>
</tr>
<tr>
<td>Group Diversity</td>
<td>0.980</td>
<td>0.080</td>
<td>1.051</td>
<td>0.201</td>
</tr>
</tbody>
</table>

Interactions (I)

<table>
<thead>
<tr>
<th>Interaction</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Cohesiveness x Article Age</td>
<td>1.150***</td>
</tr>
<tr>
<td>Group Diversity x Article Age</td>
<td>1.040</td>
</tr>
<tr>
<td>Group Cohesiveness x Group Diversity</td>
<td>1.299</td>
</tr>
</tbody>
</table>

Notes: Controls are: article age, article popularity, team size.
Dependent variable (DV): change in article quality (i.e., promotion/demotion).
Signification codes: *p < .05, **p < .01, ***p < .001.

Goodness of fit: p=0.95; LR \( \chi^2 \): 4206.63; Pseudo-\( R^2 \)=0.19
Goodness of fit: p=0.87; LR \( \chi^2 \): 4442.28; Pseudo-\( R^2 \)=0.20

Conclusion

Although online collaboration has found broad acceptance in practice, research or studies both on the factors influencing and on the quality of outcome of online collaboration are still underdeveloped. Our work examines how group interactions and group characteristics influence the outcome of social production in Wikipedia. The results suggest that having core Wikipedians who lead editing activities among themselves is beneficial in terms of the quality of the outcome, which is in line with the results of Kittur and Kraut [8]. Our main finding is that the stick-togetherness of core Wikipedians is essential in achieving highly qualitative articles, independently of the degree of group diversity. These results open a link to further controlled studies such as experiments observing the emergence of collective intelligence in online social production groups. An immediate point of interest would be to investigate team collaboration and peer content production in the context of another similar and rapidly growing resource, Wikia. A further direction worth investigating would be to analyze and test patterns of social collaboration in communities of open source software development (e.g., Linux, Apache, GitHub, or SourceForge).

References


Appendix IV

Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia
Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

MIHAI GRIGORE, BERNADETTA TARIGAN, JULIANA SUTANTO, Swiss Federal Institute of Technology, Zurich
CHRYSANTHOS DELLAROCAS, Boston University

EXECUTIVE SUMMARY

Several past studies have commented on the uneven distribution of contributions in online social production communities while at the same time highlighting the successful end products of many such efforts. These two seemingly paradoxical situations are made possible through smaller groups of highly devoted volunteers who act as catalysts in organizing and maintaining community outputs. These volunteers have been referred to as “knowledge janitors.” There is currently limited understanding of how the group composition and interaction patterns of knowledge janitors affect social production quality outcomes. This study provides answers to these questions in the context of Wikipedia. By analyzing 9,520 changes in Wikipedia article quality, we found that cohesiveness, diversity, and equal distribution of communication turn-taking of an article’s janitors increase the likelihood of that article’s quality improvement. These main findings are further refined by considering how our main effects differ at different development stages of an article. The study’s contributions to research and implications to practice are discussed.

Keywords: online social production, Wikipedia, Wikipedia janitors, group composition, group interaction, article quality

1. INTRODUCTION

Online social production communities have become an increasingly viable and popular way to create information products that are often of relatively high quality (Giles, 2005; Tapscott & Williams, 2006). While it is common knowledge that contributions in online social production communities follow a long tail distribution (Collier & Kraut, 2012; Zhu et al., 2012), the ways in which the most highly devoted volunteers act as catalysts in the development of high quality output are still not well understood. This study will address this research gap in the context of Wikipedia. A WikiProject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women’s history) or a specific kind of task (for example, checking newly created pages). The English Wikipedia currently has about 2,000 WikiProjects.1 Members of Wikiprojects are highly devoted volunteers, who act as catalysts in the development of high quality articles, i.e., they are able to organize and keep Wikipedia articles stable. Following (Sundin, 2011), we refer to those individuals as Wikipedia janitors, indicating their essential role in the development and organization of content in Wikipedia (Chen et al., 2010; Choi et al., 2010; Sundin, 2011). Focusing on Wikipedia janitors, this study aims to provide answers to the following questions: What are the relationships between the composition of Wikipedia janitor groups (diversity, cohesiveness) and their interactions (communication turn-taking) on an article’s quality improvement?

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Our analysis is based on the June 2011 dump of English Wikipedia. The Wikipedia community has developed formal guidelines and mechanisms for assessing the quality of its articles in an intersubjective manner. Wikipedia articles are assigned quality ratings ranging from (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good articles’, ‘A-class’, and ‘Featured articles’. Occasionally, community members can request a reassessment of an article’s quality. Quality reassessments might result in an article’s promotion (to a higher quality rating) or demotion (to a lower quality rating). We use article rating changes as our proxy for changes in quality and we correlate them to the activity of Wikiproject groups working on those articles prior to such rating changes to derive our results.

2. RESEARCH HYPOTHESES

When members of a group coordinate their work through communication, their individual turn-taking dynamics may facilitate the formation of a common ground (Clark, 2005). Turn-taking is the set of communication practices by which collaboration is achieved in and through conversational turns (Sacks et al., 1974). Through laboratory experiments of small size (2-5 members) face-to-face groups, Wolley et al. (2010) showed that equality in distribution of turn-taking is positively correlated with group outcome across a variety of tasks. All this implies that an equal distribution of communication turn-taking between the Wikipedia janitors should result in better group performance in terms of higher article quality. Accordingly, we hypothesize:

**H1:** There is a positive relationship between the equality of distribution of communication turn-taking between Wikipedia janitors and article quality.

Besides interaction patterns, the characteristics of the individuals who participate in group work appear to be important in increasing the quality of group outcomes (Butler et al., 2007; Liu & Ram, 2011). Diversity in group composition has been proposed as a requirement for a group to exhibit ‘wisdom of crowds’ effects (Surowiecki & Silverman, 2007). The literature concerning group diversity suggests that it may be either beneficial or detrimental in terms of group outcomes. On the one hand, more diversity in knowledge and experience helps group members to avoid biases and overlooking certain aspects; this can lead to improved outcomes. Heterogeneous groups appear to perform well because they have a relatively broad range of information, experiences, and perceptions to draw from. On the other hand, group heterogeneity and differences among individuals may result in conflict and diminished performance (Aral et al., 2008). Since group diversity appears to be a double-edged sword, we hypothesize:

**H2:** There is an inverted U curvilinear relationship between the diversity of Wikipedia janitors and article quality.

Previous literature on group processes and outcomes acknowledges that, when group members stay and work together over a period of time, they are able to develop a common ground, unspoken expectations and shared mental models of the task to be accomplished (Aral et al., 2008; Chen et al., 2010). This is especially important for key group members as turnover in the key roles of a work group may negatively influence the way team members interact or coordinate their work (Humphrey et al., 2009; Ransbotham & Kane, 2011). According to the theory of group cohesiveness, the stick-togetherness of group members is positively associated with group performance (Chansler et al., 2003; Festinger et al., 1950). Hence, we hypothesize:

**H3:** There is a positive relationship between the cohesiveness of Wikipedia janitors and article quality.
3. RESEARCH METHODOLOGY

To test the above hypotheses, we conduct a longitudinal analysis in a similar way to Kittur et al. (2008), i.e., for each quality assessment of an article, we consider the period between the previous and the current change in quality. Our independent variable is the change of quality of an article. Our dependent variables include appropriate operationalizations of turn taking, diversity and cohesiveness, as well as a number of control variables, including: article age, article popularity, group size, and initial article quality. These are described in full detail in the paper.

4. BRIEF SUMMARY OF KEY RESULTS

With respect to our first main variable of interest, i.e., the distribution of communication turn-taking (Communication), its effect has been found to be positive and significant when the initial quality is ‘B-Class’ (that is, in formative stages). This result partially confirms H1 and the finding of Woolley et al. (2010). It is worth noticing the consistency of the two results, given the obvious difference in the two study contexts: we study real-life groups working on fuzzy tasks (i.e., the development of Wikipedia articles) for an extended period of time, whereas Woolley et al. (2010) study laboratory-controlled face-to-face groups working on predefined tasks for a few hours. This remarkable consistency suggests that, regardless of the mode (offline or online), or the degree of certainty of the task, the more the communication turns are uniformly distributed among the group members, the higher the quality of group outcomes. Interestingly, we observe that effect is not significant when initial quality is ‘Good Article’. This indicates that the impact of communication turns is important in an earlier, formative stage of an article’s life but, perhaps, once an article stabilizes, the nature of the discussion changes, so communication turn-taking becomes less important.

With respect to the diversity of Wikipedia janitors, it has a significantly positive impact on the likelihood for an article to be promoted. Delving deeper, our results show that the effect of Wikipedia janitors’ diversity on an article’s promotion probability is significant only when the article’s initial quality is ‘B-Class’ (indicating a less developed article), suggesting that diversity is most important in early, formative phases of content creation. Looking at the interaction term of Diversity and group size we notice that it is positive and significant when initial quality is ‘B-Class’ (indicating a less developed article) whereas it is negative and significant when initial quality is ‘Good Article’. These findings suggest that diversity works to the favor of larger groups when articles are in their formative stage (perhaps because larger, diverse groups can contribute more comprehensive content), whereas it is detrimental when articles have already converged (perhaps, because the persistence of a variety of viewpoints may prevent articles from further stabilizing).

A salient contribution of our research is the finding of group cohesiveness to be the most important main effect relative to an article’s likelihood of promotion. A one standard deviation increase in cohesiveness corresponds to a 14% increase in the probability for an article to be promoted. This result confirms H3.

5. CURRENT STATUS

The paper has been completed and is currently under review at a journal. We are therefore in a position to give a full presentation at the conference.
REFERENCES


Appendix V

Knowledge Creation: The Impact of Elite vs. Non-Elite Contributor Groups in Online Social Production Communities: The Case of Wikipedia
The impact of elite vs. non-elite contributor groups in online social production communities: The case of Wikipedia

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1. INTRODUCTION

Online social production communities have become an increasingly viable and popular way to create information products that are often of relatively high quality (Giles, 2005; Tapscott & Williams, 2006). While it is common knowledge that contributions in online social production communities follow a long tail distribution (Collier & Kraut, 2012; Zhu et al., 2012), the ways in which the most highly devoted volunteers act as catalysts in the development of high quality output are still not well understood. This study will address this research gap in the context of Wikipedia. A WikiProject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women's history) or a specific kind of task (for example, checking newly created pages). The English Wikipedia currently has about 2,000 WikiProjects. Members of WikiProjects are highly devoted volunteers, who act as catalysts in the development of high quality articles, i.e., they are able to organize and keep Wikipedia articles stable. We refer to those individuals as Wikipedia elite editors, indicating their essential role in the development and organization of content in Wikipedia (Chen et al., 2010; Choi et al., 2010; Sundin, 2011). This study aims to provide answers to the following questions: How important are elite editor groups (vs. the long tail of un-organized occasional contributors) to Wikipedia article quality outcomes? What are the relationships between the composition of Wikipedia elite editor groups (diversity, cohesiveness) and their interactions (communication turn-taking) on an article’s quality improvement? How do elite groups interact with occasional contributors and do such interactions make a difference on outcomes?

Our analysis is based on the June 2011 dump of English Wikipedia. The Wikipedia community has developed formal guidelines and mechanisms for assessing the quality of its articles in an inter-subjective manner. Wikipedia articles are assigned quality ratings ranging from (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good articles’, ‘A-class’, and ‘Featured articles’. Occasionally, community members can request a reassessment of an article’s quality. Quality reassessments might result in an article’s promotion (to a higher quality rating) or demotion (to a lower quality rating). We use article rating changes as our proxy for changes in quality and we correlate them to the activity of WikiProject groups working on those articles prior to such rating changes to derive our results.

2. INITIAL RESEARCH HYPOTHESES

The first set of questions we tackled focuses on elite groups, trying to understand how aspects of their composition and interactions correlate with an article’s quality improvement.


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When members of a group coordinate their work through communication, their individual turn-taking dynamics may facilitate the formation of a common ground (Clark, 2005). *Turn-taking* is the set of communication practices by which collaboration is achieved in and through conversational turns (Sacks et al., 1974). Through laboratory experiments of small size (2-5 members) face-to-face groups, Woolley et al. (2010) showed that *equality in distribution of turn-taking* is positively correlated with group outcome across a variety of tasks. All this implies that an equal distribution of communication turn-taking between the Wikipedia janitors should result in better group performance in terms of higher article quality. Accordingly, we hypothesize:

**H1:** *There is a positive relationship between the equality of distribution of communication turn-taking between Wikipedia janitors and article quality.*

Besides interaction patterns, the characteristics of the individuals who participate in group work appear to be important in increasing the quality of group outcomes (Butler et al., 2007; Liu & Ram, 2011). Diversity in group composition has been proposed as a requirement for a group to exhibit ‘wisdom of crowds’ effects (Surowiecki & Silverman, 2007). The literature concerning group diversity suggests that it may be either beneficial or detrimental in terms of group outcomes. On the one hand, more diversity in knowledge and experience helps group members to avoid biases and overlooking certain aspects; this can lead to improved outcomes. Heterogeneous groups appear to perform well because they have a relatively broad range of information, experiences, and perceptions to draw from. On the other hand, group heterogeneity and differences among individuals may result in conflict and diminished performance (Aral et al., 2008). Since group diversity appears to be a double-edged sword, we hypothesize:

**H2:** *There is an inverted U curvilinear relationship between the diversity of Wikipedia janitors and article quality.*

Previous literature on group processes and outcomes acknowledges that, when group members stay and work together over a period of time, they are able to develop a common ground, unspoken expectations and shared mental models of the task to be accomplished (Aral et al., 2008; Chen et al., 2010). This is especially important for key group members as turnover in the key roles of a work group may negatively influence the way team members interact or coordinate their work (Humphrey et al., 2009; Ransbotham & Kane, 2011). According to the theory of group cohesiveness, the stick-togetherness of group members is positively associated with group performance (Chansler et al., 2003; Festinger et al., 1950). Hence, we hypothesize:

**H3:** *There is a positive relationship between the cohesiveness of Wikipedia janitors and article quality.*

### 3. RESEARCH METHODOLOGY

To test the above hypotheses, we conduct a longitudinal analysis in a similar way to Kittur et al. (2008), i.e., for each quality assessment of an article, we consider the period between the previous and the current change in quality. Our independent variable is the change of quality of an article. Our dependent variables include appropriate operationalizations of turn taking, diversity and cohesiveness, as well as a number of control variables, including: article age, article popularity, group size, and initial article quality. These are described in full detail in the paper.
4. SUMMARY OF INITIAL RESULTS

With respect to our first main variable of interest, i.e., the distribution of communication turn-taking (Communication), its effect has been found to be positive and significant when the initial quality is 'B-Class' (that is, in formative stages). This result partially confirms H1 and the finding of Woolley et al. (2010). It is worth noticing the consistency of the two results, given the obvious difference in the two study contexts: we study real-life groups working on fuzzy tasks (i.e., the development of Wikipedia articles) for an extended period of time, whereas Woolley et al. (2010) study laboratory-controlled face-to-face groups working on predefined tasks for a few hours. Interestingly, we observe that effect is not significant when initial quality is 'Good Article'. This indicates that the impact of communication turns is important in an earlier, formative stage of an article's life but, perhaps, once an article stabilizes, the nature of the discussion changes, so communication turn-taking becomes less important.

With respect to the diversity of Wikipedia janitors, it has a significantly positive impact on the likelihood for an article to be promoted. Delving deeper, our results show that the effect of Wikipedia janitors' diversity on an article's promotion probability is significant only when the article's initial quality is 'B-Class' (indicating a less developed article), suggesting that diversity is most important in early, formative phases of content creation. Looking at the interaction term of Diversity and group size we notice that it is positive and significant when initial quality is 'B-Class' (indicating a less developed article) whereas it is negative and significant when initial quality is 'Good Article'. These findings suggest that diversity works to the favor of larger groups when articles are in their formative stage (perhaps because larger, diverse groups can contribute more comprehensive content), whereas it is detrimental when articles have already converged (perhaps, because the persistence of a variety of viewpoints may prevent articles from further stabilizing).

A salient contribution of our research is the finding of group cohesiveness to be the most important main effect relative to an article's likelihood of promotion. A one standard deviation increase in cohesiveness corresponds to a 14% increase in the probability for an article to be promoted. This result confirms H3.

5. ONGOING WORK

We have established results that relate aspects of elite-editor group composition and interaction to quality outcomes in Wikipedia articles. We are currently working towards exploring the impact of the long tail of occasional and generally un-coordinated contributors on article quality improvement outcomes, looking for patterns of such activity that correlate with success. We are also examining whether and how the interaction of elite editor groups with long tail contributors makes a difference in article quality. Our overarching goal is to develop theories of online social production efforts, in particular quantifying the role of coordinated elite groups. We anticipate that our additional analyses will be completed by June. If our submission is accepted we will present the full set of results at SCECR in June.
REFERENCES


Appendix VI

Knowledge Creation: Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia
Understanding the “Few that Matter” in Online Social Production Communities: The Case of Wikipedia

EXTENDED ABSTRACT

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ABSTRACT
Several past studies have commented on the uneven distribution of contributions in online social production communities while at the same time highlighting the successful end products of many such efforts. These two seemingly paradoxical situations are made possible through smaller groups of highly devoted volunteers who act as catalysts in organizing and maintaining community outputs. These volunteers have been referred to as “knowledge janitors.” There is currently limited understanding of how the group composition and interaction patterns of knowledge janitors affect social production quality outcomes. This study provides answers to these questions in the context of Wikipedia. By analyzing 9,520 changes in Wikipedia article quality, we found that cohesiveness, diversity, and equal distribution of communication turning of an article’s janitors increase the likelihood of that article’s quality improvement. These main findings are further refined by considering how our main effects differ at different development stages of an article. The study’s contributions to research and implications to practice are discussed.

Keywords: online social production, Wikipedia, Wikipedia janitors, group composition, group interaction, article quality

INTRODUCTION

Online social production communities have become an increasingly viable and popular way to create information products that are often of relatively high quality (Giles, 2005; Tapscott & Williams, 2006). While it is common knowledge that contributions in online social production communities follow a long tail distribution (Collier & Kraut, 2012; Zhu et al., 2012), the ways in which the most highly devoted volunteers act as catalysts in the development of high quality output are still not well understood. This study will address this research gap in the context of Wikipedia. A WikiProject is a group of contributors who want to work together as a team to improve Wikipedia. These groups often focus on a specific topic area (for example, women's history) or a specific kind of task (for example, checking newly created pages). The English Wikipedia currently has about 2,000 WikiProjects.¹ Members of Wikiprojects are highly devoted

volunteers, who act as catalysts in the development of high quality articles, i.e., they are able to organize and keep Wikipedia articles stable. Following (Sundin, 2011), we refer to those individuals as Wikipedia janitors, indicating their essential role in the development and organization of content in Wikipedia (Chen et al., 2010; Choi et al., 2010; Sundin, 2011). Focusing on Wikipedia janitors, this study aims to provide answers to the following questions: What are the relationships between the composition of Wikipedia janitor groups (diversity, cohesiveness) and their interactions (communication turn-taking) on an article’s quality improvement?

Our analysis is based on the June 2011 dump of English Wikipedia. The Wikipedia community has developed formal guidelines and mechanisms for assessing the quality of its articles in an inter-subjective manner. Wikipedia articles are assigned quality ratings ranging from (in increasing order): ‘Stub’, ‘Start’, ‘C-class’, ‘B-class’, ‘Good articles’, ‘A-class’, and ‘Featured articles’. Occasionally, community members can request a reassessment of an article’s quality. Quality reassessments might result in an article’s promotion (to a higher quality rating) or demotion (to a lower quality rating). We use article rating changes as our proxy for changes in quality and we correlate them to the activity of Wikiproject groups working on those articles prior to such rating changes to derive our results.

**RESEARCH HYPOTHESES**

When members of a group coordinate their work through communication, their individual turn-taking dynamics may facilitate the formation of a common ground (Clark, 2005). Turn-taking is the set of communication practices by which collaboration is achieved in and through conversational turns (Sacks et al., 1974). Through laboratory experiments of small size (2-5 members) face-to-face groups, Woolley et al. (2010) showed that equality in distribution of turn-taking is positively correlated with group outcome across a variety of tasks. All this implies that an equal distribution of communication turn-taking between the Wikipedia janitors should result in better group performance in terms of higher article quality. Accordingly, we hypothesize:

**H1**: There is a positive relationship between the equality of distribution of communication turn-taking between Wikipedia janitors and article quality.

Besides interaction patterns, the characteristics of the individuals who participate in group work appear to be important in increasing the quality of group outcomes (Butler et al., 2007; Liu & Ram, 2011). Diversity in group composition has been proposed as a requirement for a group to exhibit ‘wisdom of crowds’ effects (Surowiecki & Silverman, 2007). The literature concerning group diversity suggests that it may be either beneficial or detrimental in terms of group outcomes. On the one hand, more diversity in knowledge and experience helps group members to avoid biases and overlooking certain aspects; this can lead to improved outcomes. Heterogeneous groups appear to perform well because they have a relatively broad range of information, experiences, and perceptions to draw from. On the other hand, group heterogeneity and differences among individuals may result in conflict and diminished performance (Aral et al., 2008). Since group diversity appears to be a double-edged sword, we hypothesize:
H2: There is an inverted U curvilinear relationship between the diversity of Wikipedia janitors and article quality.

Previous literature on group processes and outcomes acknowledges that, when group members stay and work together over a period of time, they are able to develop a common ground, unspoken expectations and shared mental models of the task to be accomplished (Aral et al., 2008; Chen et al., 2010). This is especially important for key group members as turnover in the key roles of a work group may negatively influence the way team members interact or coordinate their work (Humphrey et al., 2009; Ransbotham & Kane, 2011). According to the theory of group cohesiveness, the stick-togetherness of group members is positively associated with group performance (Chansler et al., 2003; Festinger et al., 1950). Hence, we hypothesize:

H3: There is a positive relationship between the cohesiveness of Wikipedia janitors and article quality.

RESEARCH METHODOLOGY

To test the above hypotheses, we conduct a longitudinal analysis in a similar way to Kittur et al. (2008), i.e., for each quality assessment of an article, we consider the period between the previous and the current change in quality. Our independent variable is the change of quality of an article. Our dependent variables include appropriate operationalizations of turn taking, diversity and cohesiveness, as well as a number of control variables, including: article age, article popularity, group size, and initial article quality.

SUMMARY OF KEY RESULTS

With respect to our first main variable of interest, i.e., the distribution of communication turn-taking (Communication), its effect has been found to be positive and significant when the initial quality is ‘B-Class’ (that is, in formative stages). This result partially confirms H1 and the finding of Woolley et al. (2010).

With respect to the diversity of Wikipedia janitors, it has a significantly positive impact on the likelihood for an article to be promoted. Delving deeper, our results show that the effect of Wikipedia janitors’ diversity on an article’s promotion probability is significant only when the article’s initial quality is ‘B-Class’ (indicating a less developed article), suggesting that diversity is most important in early, formative phases of content creation.

A salient contribution of our research is the finding of group cohesiveness to be the most important main effect relative to an article’s likelihood of promotion. A one standard deviation increase in cohesiveness corresponds to a 14% increase in the probability for an article to be promoted. This result confirms H3.

CURRENT STATUS

The paper has been completed and is currently under review at a journal. We are therefore in a position to give a full presentation at the conference.
REFERENCES


Appendix VII

Knowledge Reuse: The Impact of Sentiment-Driven Feedback on Knowledge Reuse in Online Communities
THE IMPACT OF SENTIMENT-DRIVEN FEEDBACK ON KNOWLEDGE REUSE IN ONLINE COMMUNITIES

Original Empirical Research

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Abstract

Knowledge reuse is of increasing importance for organizations. Despite the extant research, the ways peers are motivated to reuse knowledge with the help of Wiki technologies are still not well understood. The purpose of this work is to study the motivation for knowledge reuse in a prominent instance of online social production, Wikipedia. The study of knowledge reuse in Wikipedia is important, since Wikipedia has been able to leverage the benefits of efficient knowledge reuse in order to produce knowledge goods of relatively high quality. This research explores: (1) how Wikipedia editors communicate their feedback towards each other’s work in peer conversations, and (2) to what extent sentiment-driven feedback impacts the level of knowledge reuse in Wikipedia. The results show that displaying sentiment-driven feedback positively influences the level of knowledge reuse. Our study further shows a significant difference in the level of knowledge reuse between editors who share mainly positive or mainly negative sentiments. Specifically, displaying mainly positive feedback corresponds to a superior level of knowledge reuse than displaying mainly negative feedback. We contribute to the extant literature of online social production communities in general, and Wikipedia in specific, by providing a first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse. Implications for theory and practice are discussed.

Keywords: Knowledge Reuse, Sentiment-Driven Feedback, Affective Communication Affect in Information Systems Research, Online Social Production, Online Collaboration.

1 This research received financial support from Swiss National Science Foundation Grant No.: 100018_146444
Introduction

Knowledge represents an essential resource for organizations in today’s economic environment. Successful organizations build or have built dynamic capabilities to create, acquire, share, use, and reuse knowledge (Alavi and Leidner, 2001; Argote et al., 2003; Argote and Miron-Spektor, 2011; Khodakarami and Chan, 2014). Being “localized, embedded and invested” in practice, knowledge represents a critical asset that may prevent organizations from spending time and resources on redeveloping already existing solutions (Carlile, 2002). By leveraging knowledge that already exists, knowledge reuse has been shown to enhance efficient and effective problem solving in organizations (Gray, 2001). However, infrequent or even lack of knowledge reuse continue to be important issues for organizations, although managers nowadays pay significant attention to knowledge reuse (Liu et al., 2013; Rozwell, 2009).

The rise of Internet technologies has facilitated increased access to peers, resources, information and knowledge - even outside the boundaries of traditional organizations. In this sense, new forms of organizing – such as online social production - have emerged and have opened substantial opportunities to research knowledge processes at unprecedented scales (Puranam et al., 2013). Online social production has become an increasingly viable and popular way to create knowledge goods that are often of relatively high quality (Faraj et al., 2011; Giles, 2005; von Hippel and von Krogh, 2003). Although information technologies have been subject to extensive research for their role to facilitate reuse of knowledge among peers who hold knowledge (Nonaka and Takeuchi, 1995), empirical research on knowledge reuse in online social production is still lacking. Indeed, whereas knowledge reuse in traditional organizations has been relatively well researched, see (Majchrzak et al., 2013b; Markus, 2001), knowledge reuse in online communities continues to be under-researched (Haefliger et al., 2008; von Krogh et al., 2012).

Wikipedia, a prominent exemplar of online social production community, has become one of the world’s most popular sources of knowledge, with more than four million articles. The quality of Wikipedia entries has repeatedly been found to be on par to traditionally organized processes, carried out by professional editors over several years, such as the Encyclopedia Britannica (Giles, 2005; Tapscott and Williams, 2006). Given the importance of technology-fostered knowledge reuse, there are three specific reasons for considering Wikipedia as a resource for examining a success story of Wiki-enabled knowledge reuse. First, the underlying Wiki technology records the full editing and interaction activity for each article; thus Wikipedia enables its users to integrate others’ knowledge for efficient knowledge reuse (Grant, 1996). Second, Wikipedia’s articles can only be edited using the Wikipedia platform, allowing researchers to have a complete editing and social interaction history of each article. Third, any Internet user can contribute knowledge to the articles, allowing researchers to examine group interactions in an uncontrolled setting.

The extant literature on motivation to contribute to online social production established that peers follow diverse motivational drives (e.g., the pleasure involved in completing a task) and social signals (e.g., community belonging and social recognition) (Benkler, 2006; Puranam et al., 2013). Moreover, previous research on factors that motivate contribution of knowledge in communities of practice has focused mostly on factors explaining why peers contribute their personal knowledge (Carlile, 2004; Carlile and Rebentisch, 2003), with little research on why peers reuse the knowledge contributed by others in online social production communities (Yates et al., 2010). Evidence that intrinsic motivation positively influences knowledge reuse
with the help of electronic repositories has been found through a field survey on customer service (Kankanhalli et al., 2011). A recent study in the context of organizational Intranets supported by Wikis showed that knowledge shaping promotes knowledge reuse through improved integration of knowledge (Majchrzak et al., 2013). Our research objective is to provide an explanation of the motivational factors that lead to the success story of knowledge reuse in Wikipedia. We aim to provide answer to the following research question: "How and why do Wiki editors reuse knowledge?"

To answer this question, we conduct a longitudinal analysis of peers’ editing and interaction activity in Wikipedia. We build on the findings of Markus (2001) on knowledge reuse. Specifically, one of the aspects stressed by Markus (2001) is that successful knowledge reuse is in part a matter of how to provide incentives for contributions. In this study, we regard knowledge reuse among Wikipedia editors as an aspect of collaboration that is influenced by specific communication practices. We examine the way Wikipedia editors communicate their feedback towards others’ work and explore to what extent this acts as an incentive to reuse knowledge. In particular, we investigate whether affective communication (Te’eni, 2001; Zhang, 2013) in form of sentiment-driven feedback in discussions between Wikipedia editors motivates collaborative work, using knowledge reuse as a proxy for collaboration. In doing so, we contribute to the extant literature on knowledge reuse (Majchrzak et al., 2013b; Markus, 2001) by providing the first building block for research on the role of peer feedback on developing and sustaining Wiki-based knowledge reuse.

In the next section, we discuss the related work and the conceptual background of our research. Following this, we present our research model and methodology. The dataset used in this study consists of a complete revision history dump of Simple English Wikipedia. We employ methods from sentiment analysis, compute Wikipedia-specific metrics, and use regression analysis in order to produce and analyze our data. After presenting our results, we conclude the paper with an outlook for further research.

Related Work and Theory Development

Theoretical Findings on Motivations for Knowledge Reuse and the Role of Peer Feedback

Previous studies have systematically reported that traditional organizational repositories are not suitable to efficiently and effectively leverage the knowledge within organizations (Rafaeli and Ariel, 2008; Yates et al., 2010). In a recent attempt to explain knowledge reuse in communities of practice, Majchrzak et al. (2013b) focused on the unique affordance of Wiki technologies to foster online knowledge integration for knowledge reuse. Contributing knowledge to a Wiki may involve not only contributing the knowledge of one’s domain expertise but also integrating knowledge already contributed to the Wiki in order to make it more logically organized. In a Wiki-based knowledge-sharing context, knowledge reuse can often be visibly observed and tracked (Chi et al., 2008; Grudin and Poole, 2010).

Besides the recent interest in Wiki technologies for supporting communities of practice within traditional organizations, Wikis have been intensively investigated as a cornerstone of online social production communities. Online social production communities (also referred to as commons-based peer production) have two defining characteristics: (1) they are based on

http://simple.wikipedia.org
the online collaboration of volunteers who carry out productive activities primarily for social and psychological purposes than for financial remuneration (Benkler, 2006; Shirky, 2010); (2) the online production apparently happens in the absence of governance mechanisms based on price mechanisms or hierarchical, managerial structures (Aaltonen and Lanzara, 2011; Benkler, 2006). The first characteristic has motivated a bulk of studies in online social production communities to examine the motivational drivers of the participating individuals (e.g., Benkler, 2006; Ghosh, 2005; Hahn et al., 2008; Lerner and Tirole, 2002; Shah, 2006; Stewart and Gosain, 2006; Weber, 2004). These motivational drivers range from altruism and enjoyment to solving challenging problems, social recognition, and future employment benefit. The second characteristic of online social production communities has motivated research on the governance mechanisms of such communities (e.g., Feller et al., 2008; Mehra, 2012; Singh, 2010). Such communities are typically governed by self-organization (Crowston et al., 2007), a rather slow and difficult process to ensure global coordination out of local interactions between people. Self-organization is fostered by Internet technologies that keep a detailed trace of the community members’ interactions while they are interacting in real-time (Lanuible et al., 2010). For example, the extant literature on online social production communities has examined the role of Internet technologies in enabling peers to interact with each other (Burnett, 2000; Preece, 2001); usability and sociability are factors that make online communities successful (Preece, 2001; Tarmizi and Vreede, 2005). Based on these findings, Porra and Parks (2006) suggest that the sustainability of online social production communities requires persistent people, continuous support by an online space, and flexibility for alternative sub-communities to emerge. Ginsburg and Weisband (2002) conclude from their survey that volunteerism is an important aspect for the success of online social production communities.

Following this line of reasoning, our research focuses on the examination of what motivates individuals to collaborate in online social production, with an emphasis on knowledge reuse in Wikipedia. In this sense, in an attempt toward establishing a theory of knowledge reuse, Markus (2001) stressed that successful knowledge reuse is in part a matter of how to provide incentives for high quality contributions. Indeed, intrinsic motivation has been found to positively influence knowledge reuse through electronic repositories (Kankanhalli et al., 2011). Feng et al. (2004) further emphasized the importance of developing supportive working relationships online.

In online settings, the focus of attention changes from the relationship between peers and the technology to the relationship between peers and the community; peers who never physically meet or know each other get to communicate and work collectively. Empathy has been found to be essential in encouraging peers to work together online (Leimeister et al., 2006; Maloney-Krichmar and Preece, 2005; Skopik et al., 2009). In the case of online social production communities, the apparent lack of formal authority may be compensated by individuals who mentor and encourage each other towards contributing knowledge (Eseryel, 2009). That is, providing sentiment-driven feedback (or affective feedback) may act as a powerful motivational factor towards superior work outcomes (Bateman and Organ, 1983; Zhu et al., 2013). Further results from offline settings acknowledge that strategic use of feedback may increase recipients’ motivation to adhere to their goals (Fishbach et al., 2010). Concretely, sentiment-driven feedback has been recognized to intrinsically motivate goal pursuit; this happens through the affective experience that sentiment-driven feedback is able to produce (Fishbach et al., 2010). An elaboration of the concepts of sentiment-driven feedback, affective communication, and affect in online settings, as well as their usage in information systems research are discussed in the following section.
Sentiment-Driven Feedback and its Motivating Role for Knowledge Reuse

Sentiment-driven feedback (often used also as affective feedback) is a form of communication used to express affect, such as praise (e.g., “well written”) or criticism (e.g., “badly written”) (Nelson and Schunn, 2009). Affect – also commonly referred to as sentiment, emotion, or mood – represents “general moods (happiness, sadness) or specific emotions (fear, anger, envy)” as reaction to things one thinks about, actions one takes, or to various stimuli (Ajzen, 2001, p. 29; Barrett and Russell, 1999; VandenBos, 2006). The study of affect has received growing attention among social psychologists and information systems researchers (Scherer et al., 2004; Van der Heijden, 2004; Zhang, 2013). Recent research studies acknowledge the increasing importance of affect on information systems usage and on online work behavior. In this context, affect has been shown to be efficiently externalized through computer-mediated communication (Harris and Paradice, 2007). The intensity of affect has further been recognized as a means for coping with communication complexity to achieve communication goals; affect is a suitable means to motivate and to inform (Te'eni, 2001). Stieglitz and Dang-Xuan (2013) investigate the relationship between affect and information diffusion in microblogging websites and find that affective Twitter messages tend to be retweeted more often and more quickly compared to neutral ones. Moreover, Aggarwal et al. (2012) focus on affect in social media and study the effects of negative posts from employee blogs. They reveal the potentially positive influence of negative posts, in the sense that negative posts may act as catalyst that can exponentially increase the awareness of employee blogs.

Transferring these insights to our study, we argue that intrinsic motivations for knowledge reuse may be, at least partially, explained by the display of affect in inter-editor conversations. Indeed, the articulation of affect both in spoken discourse and in written text (Te’eni, 2001) – that is, affective communication - has the potential to act as awareness catalyst. Affective communication helps coordinating group activity by fostering group bonds (Spoor and Kelly, 2004). Our reasoning is in line with the work of Kankanhalli et al. (2011), who found that intrinsic motivation positively influences knowledge reuse through electronic repositories. To support this reasoning for online social production communities, we first consider prior research on Wikipedia that has shown that an intensification in peer collaboration usually occurs after the initiation of conversations among editors on talk pages (Crandall et al., 2008). Moreover, peer influence exerted across social ties among peers was found to be a significant predictor of future collaborative behavior in Wikipedia (Crandall et al., 2008). Discussion pages offer Wikipedia editors the means to communicate their achievements and constantly receive feedback on the progress of their work (Reagle, 2010). Peers need to feel that their engagement is beneficial to the organization or community (Haefliger et al., 2011; Stahlbrost and Bergvall-Kareborn, 2011). This perception of appreciation (i.e., affect) can be transmitted through affective communication in form of sentiment-driven feedback on discussion pages in Wikipedia. We further argue that affective communication in form of sentiment-driven feedback in inter-editor discussions may act as intrinsic motivator for knowledge reuse in Wikipedia.

In this study, (1) we focus our analysis on how Wikipedia editors communicate their feedback on others’ contribution on discussion pages and (2) we explore to what extent
affective communication in form of sentiment-driven feedback on discussion pages impacts the level of knowledge reuse in Wikipedia. In doing so, we integrate the analysis of specific peer content collaboration - the editing process of Wikipedia articles - with the analysis of informal discourse - the intensity of affective communication between Wikipedia editors. We formally hypothesize that:

**H1:** The display of sentiment-driven feedback in inter-editors communication corresponds to increased levels of knowledge reuse than in the case of neutral feedback.

The orientation and intensity of affective communication can range on a scale from being very positive to very negative (Barrett and Russell, 1999). The distinction between positive and negative sentiments, on the one hand, and neutral statements in conversations, on the other hand, could be useful for explaining collective behavior, as sentiments become externalized instances on the collective level (Scherer et al., 2004). Depending on the sensitivity to attitudes and changes in disposition voiced in affective communication (Te'eni, 2001), peers should be influenced differently by positive or negative feedback. In this sense, making a habit of dispensing positive feedback is more likely to motivate peers to perform with confidence and autonomy, than giving negative feedback (Lickerman, 2012). However, negative feedback is needed when something is being done incorrectly, in order to give peers the opportunity to improve the result. Research has shown that, when possible, positive feedback should be used in public, whereas negative feedback is rather effective for correcting problems, behaviors and attitudes in private (Fishbach et al., 2010). Accordingly, we hypothesize that:

**H2:** Displaying positive feedback in inter-editors communication corresponds to greater levels of knowledge reuse than displaying negative feedback.

**Research Method**

**Data Set**

Wikipedia relies on the open-source model, that is, providing free products and services for peer review and for the mutual benefit of the peer community (Bezroukov, 1999). In the case of Wikipedia, the term “open” refers to the fact that any Internet user has access to the knowledge produced by other peers, can freely contribute with knowledge, but, at the same time, cannot exert exclusive rights over the collective innovation (Lakhani and Panetta, 2007). This enables the constant refinement of article knowledge through collaboration, which is considered one of the main added values of Wikipedia.

To support collaborative writing and editing of textual content by its own community of readers, Wikipedia uses a Wiki technology. The resulting *article pages* represent the main source of knowledge used by regular Wikipedia readers. Almost all of Wikipedia articles can be edited by anyone with Internet access. In order for any user to visualize the dynamics of article changes, the *revision history* provides the functionality to chronologically track previous versions of the article by time stamp, editor, actual text resulting from the edit, and editor comments. Besides article pages, Wikipedia hosts free-form discussion pages called *talk pages* for each article. Concretely, editors use talk pages in order to plan and discuss their work, that is, to support and coordinate their work, share and ask for feedback, report vandalism, or refer to edit guidelines (Schneider et al., 2010).
In this sense, sentiment-driven feedback emerges from “social interactions that occur in the context of inter-personal relationships” (Andersen and Guerrero, 1998). In Wikipedia, social interactions often happen on discussion pages, in form of feedback to others’ work. Feedback may be classified as either being sentiment-driven (positive or negative), or neutral. Table 1 presents examples of sentiment-driven feedback (both positive and negative), along with neutral feedback expressed by editors on on Wikipedia’s “Talk:NASA”, “Talk:Water_on_Mars”, and “Talk:Jupiter” entries:

<table>
<thead>
<tr>
<th>Type of Feedback</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sentiment-driven feedback</strong></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>“Many Modules ! Brilliant ! Precise ! Do you know, looking at the changes log, I think the guardians of this page are overworked and under-appreciated. I do hope I can be of assistance wherever possible. Keep up the great work! Don't give up!” – Penyulap (talk) 01:08, 18 March 2011 (UTC)³</td>
</tr>
<tr>
<td>Negative</td>
<td>“Not only is it a bit lengthy, but it has very unusual organization for a wikipedia page... perhaps inappropriately so [...] I hate to merely be a critic, but I'm not nearly qualified enough to attempt rewriting or reorganizing this article. :)” – The2crowrox (talk) 00:58, 5 November 2010 (UTC)⁴</td>
</tr>
<tr>
<td>Neutral feedback</td>
<td>“In the table at the beginning, the amount of hydrogen stated is 85.8 to 89.8%. The source (Williams, Dr. David R. &quot;Jupiter Fact Sheet&quot;, NASA) states that the amount of gas is &quot;89.8% (2.0%)&quot;, meaning 89.8% plus or minus 2%” - Barras (talk) 18:50, 19 July 2009 (UTC)⁵</td>
</tr>
</tbody>
</table>

Table 1. Examples of positive, negative, and neutral feedback on article talk pages in Wikipedia

Articles from Simple English Wikipedia - a spin-off of Wikipedia written using basic English vocabulary and uncomplicated grammar constructions - are usually not new; their editors use articles from Wikipedia and attempt to bring them to a simple form. The dump we used in this study was created in March 2011 and contains over 200,000 pages (out of which around 70,000 are article pages), totaling approximately 16 gigabytes of XML data. Along with anonymous users, there are over 170,000 registered users who contributed to approximately 3 million revisions from the creation of Simple English Wikipedia in 2003. The average number of revisions per page is 14.35 and Simple English Wikipedia has over 700 active,

⁴ retrieved from: http://en.wikipedia.org/wiki/Talk:Water_on_Mars
⁵ retrieved from: http://simple.wikipedia.org/wiki/Talk:Jupiter
registered users with at least one edit or logged action in the past month. Because of the extremely large size of Wikipedia’s revision history and the limited computational power, many previous analyses used only samples of data in order to save computation costs (Arazy and Nov, 2010; Javanmardi and Lopes; Muller-Birn et al., 2009; Viegas et al., 2007). However, as there is no general guideline on how to obtain a good sample from Wikipedia, and since complete revision histories are necessary for computing revision-based metrics (such as knowledge reuse), we instead use a complete revision history dump (as of October 2011) of Simple English Wikipedia.

Measurement & Construct Operationalizations

We compute Wikipedia-specific, revision-based measures on the peers’ editing activity of article pages (knowledge reuse), as well as mining affect from feedback posted on article talk pages (sentiment-driven feedback) corresponding to each article. To address H1 and H2, we employ monthly time series analyses of the relationship between knowledge reuse and the amount of (positive and negative) sentiments in inter-editors affective communication. Below we present the operationalizations and measurements we employ for sentiment-driven feedback and knowledge reuse.

Sentiment-Driven Feedback in Inter-Editor Communication

Sentiment-driven feedback is mined from inter-editor communication on Wikipedia article talk pages. To do so, we apply sentiment analysis to distinguish sentiment-driven feedback from neutral feedback. Below we present the approach in detail. Sentiment analysis broadly classifies textual statements into ‘objective statements’ that express factual information and into ‘subjective statements’ that reflect holder’s attitudes or perceptions (Banea et al., 2008; Furuse et al., 2007; Pang and Lee, 2008; Wiebe and Mihalcea, 2006). It represents a systematic, computer-based analysis of written text or speech excerpts for extracting the attitude of the author or speaker about a specific topic (Pang and Lee, 2008). Sentiment analysis aims to establish the overall orientation (positive or negative) and intensity (weak or strong) of the sentiments expressed in statements previously classified as subjective. However, sentiments may often be expressed in a subtle manner, making subjectivity analysis often “more difficult than subsequent polarity classification, so improvements in subjectivity classification promise to positively impact sentiment classification” (Mihalcea, 2007). As Wikipedia editors often use informal vocabulary when writing comments on talk pages, this adds difficulties to the task of identifying subjectivity.

Recent algorithms for sentiment analysis are able to detect positive and negative sentiment strength in short informal texts (Akkaya et al., 2009; Paltoglou and Thelwall, 2010; Shanmugasundaram et al., 2009). In our analyses, we use SentiStrength (Thelwall et al., 2011; Thelwall et al., 2010) to analyze the level of sentiments on article talk pages in Wikipedia. SentiStrength provides a scoring range from −5 (very negative) to +5 (very positive). In case of texts showing an equal amount of positive and negative sentiments, the algorithm is able to predict which of the two orientations is the prevalent one. Figure 1 shows the distribution of the total monthly amount of positive (Figure 1a) and negative (Figure 1b) sentiments expressed by editors on article talk pages.

Evaluation of sentiment analysis. SentiStrength performs best on short texts, such as Twitter postings (Nielsen, 2011) and Wikipedia article talk pages. An evaluation of SentiStrength on short informal texts from Twitter showed that it performs with 96.9% accuracy on positive sentiment strength detection, while the detection of negative sentiment strength yielded 95.1% accuracy (Thelwall et al., 2010). To evaluate the performance of SentiStrength on
Wikipedia, we constructed a random set consisting of 200 sentences from conversations in Simple English Wikipedia talk pages. To produce a gold standard for the evaluation of SentiStrength, the data set was classified by two independent judges (i.e., annotators) in terms of the sentiment scores from −5 (very negative) to +5 (very positive). The annotators were asked to send the results to the authors on an individual basis. Out of the 200 sentences, the two annotators agreed on 194 cases. The remaining six disagreement cases were adjudicated by a neutral judge, thus obtaining the gold standard of human ratings. The results of SentiStrength were then evaluated against the gold standard.

To validate the use of SentiStrength for the sentiment analysis, we use precision (P) and accuracy (A) as evaluation metrics (Menditto et al., 2007; Powers, 2011). For classification tasks, the terms “true positives”, “true negatives”, “false positives” (type I error), and “false negatives” (type II error) are used to compare the results of the classifier against the gold standard (Goutte and Gaussier, 2005). The terms “positive” and “negative” refer to the result indicated by the classifier, whereas the terms “true” and “false” refer to whether that result corresponds to the gold standard. Precision is the proportion of correctly labeled examples, i.e., the proportion of the true positives against all the positive results (both true positives and false positives). Accuracy is the proportion of true results (both true positives and true negatives) in the population. While accuracy is the proximity of measurement results to the true value, precision represents the reproducibility of the measurement (Cohen, 1998). Table 2 below summarizes the results of the evaluation we performed on the gold standard, with respect to three classes: negative, positive, and the overall sentiment score.

<table>
<thead>
<tr>
<th>SentiStrength Evaluation</th>
<th>Negative sentiment</th>
<th>Positive sentiment</th>
<th>Overall sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision (P)</td>
<td>0.83</td>
<td>0.93</td>
<td>0.98</td>
</tr>
<tr>
<td>Accuracy (A)</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Table 2. Results of the evaluation of SentiStrength against the gold standard in terms of precision and recall for the negative, positive, and the overall sentiment scores.

The results of our evaluation are consistent with the results of the evaluation of SentiStrength on Twitter. SentiStrength is thus suitable for sentiment analysis on Wikipedia article talk pages.
Figure 1. Distribution of total amounts of (a) positive and (b) negative sentiments on article talk pages corresponding to each month from the creation of Simple English Wikipedia.
Knowledge Reuse

Knowledge reuse enables repetitive use of existing knowledge for creating new knowledge. Repetitive use refers to knowledge that is systematically stored in a repository and that can be retrieved and reused without the cost of its re-invention (Kankanhalli et al., 2011). In a firm context, knowledge reuse is defined as “one individual or group within the firm using knowledge generated by a different individual or group within the same firm in order to be more effective and productive in their work” (Alavi and Leidner, 1999, p. 143; Alavi and Leidner, 2001). In this sense, Majchrzak et al. (2013b) reported that the use of Wiki technologies may improve collaboration, work processes, and knowledge reuse in companies. However, quantifying the amount of knowledge being reused is not trivial. One of the settings in which knowledge reuse has been often derived from observable data is software development. Specifically, code reuse in software development, as the name implies, is the employment of previously written code (i.e., objects) as an alternative to writing new (possibly identical), code to perform the same or similar function (Banker et al., 1994). Code reuse has been previously measured in terms of the reuse leverage metric. Concretely, the reuse leverage within an application is defined as the total number of objects used, divided by the number of new objects built (Banker et al., 1992). For example, if a software application consists of 400 objects (i.e., used objects), of which 100 had to be programmed from scratch (i.e., new objects), the reuse leverage would be 4.0. To indicate how much of a software application can be attributed to reuse (Poulin, 1992), the reuse ratio can be expressed as the ratio of the number of objects that are reused (i.e., 300 = 400-100) to the number of new objects (i.e., 100) is 3:1 = 3.0. Similar to a software application, in the case of Wikipedia, an article represents a dynamic and systematic transformation of existing knowledge. Below we describe the quantification of knowledge reuse in the context of Wikipedia, based on the reuse ratio.

Knowledge Reuse in Wikipedia. The ongoing process of knowledge reuse is facilitated by the Wiki technology and is captured by the revision history functionality. The revision history facilitates the chronological tracking of all the previous versions of an article by the text resulting from the article edits. In order to contribute to the development of an article, an editor starts editing the knowledge already contributed in the current revision. In other words, an editor reuses existing knowledge in the previous article revision to create a new article revision. The amount of knowledge reuse between two consecutive article revisions can be quantified as the amount of knowledge from the previous revision that is being reused in the current revision. Similar to reuse ratio in software development (Banker et al., 1992) and inspired by the work of Turek et al. (2010) on Wikipedia revision history metrics, we compute the level of knowledge reuse relative to any two consecutive revisions of the same article page as the reuse ratio of the number words from the previous revision that were reused (e.g., copied, moved elsewhere, or restored) to the number of words that have been newly created in the current revision.

For a given Wikipedia article page, we compute the overall level of knowledge reuse between its revisions as a mean of pairwise levels of knowledge reuse, weighted by the proportion of editors who contributed to the creation of each specific revision from the total number of article editors. In this way, we account for the effect of the number of edits and of editorial team size, which vary from article to article. A value of 1 shows equal amounts of reused and new words. A value of 2 (i.e., 2:1) indicates that the number of reused words is two times larger than the number of newly created words. Conversely, a value of 0.5 (i.e., 1:2) indicates that the number of reused words is two times larger than the number of newly created words.
Figure 2 shows the distribution of the monthly average amount of knowledge reuse extracted from the edit logs of article pages.

**Measurement considerations.** There are two considerations that we employed in the computation of knowledge reuse. The first consideration refers to the adaptation of the measurement of knowledge reuse from software development (Banker et al., 1992). Since reuse in software development employs code (i.e., objects) as units of analysis, reuse in Wikipedia should conversely employ as unit of analysis individual key concepts or key phrases expressed in Wikipedia articles. However, unlike in the case of software development, where the code is automatically compiled, in the case of Wikipedia, the automatic recognition of domain-specific key concepts or phrases from natural language text is not a trivial task (Boudin and Morin, 2013; Erbs et al., 2014). We thus decided to employ the measurement of knowledge reuse in Wikipedia articles at word level. To avoid taking into account common words that are not informative, we employed a linguistic processing, consisting of three steps. First, we divided the textual content into individual strings of characters, called tokens. Second, for each token representing a word, we reduced inflected words to their word stem (such as the verbs “represents” and “representing” to “represent”). Finally, we removed non-informative words that tend to occur very often (i.e., employed stop-words filtering), such as articles, prepositions, conjunctions, adverbs, or verbs (for instance “a”, “the”, “is”, “an”, “in”, “it”, “that”, etc.). In addition, for the measurement of knowledge reuse, we discarded from the count consecutive word revisions for which the corresponding edit distance was smaller or equal to one (Gonzalo, 2001). The rationale is that such a small edit distance indicates that the word underwent a minor spelling correction, rather than a substantial change in its meaning. All together, this linguistic processing aims at reducing the potential pitfall of the choice of individual words as the level of analysis for the measurement of knowledge reuse. Relative to the second adaptation used in this study, our measurement of knowledge reuse does not penalize repetitive consecutive edits done by the same peers (Turek et al., 2010). The rationale for this was that it is difficult to establish clear criteria on how to group consecutive revisions made by the same editors. Since the time elapsed between consecutive edits done by the same editor may vary up to months or years, we decided to treat every revision as stand-alone and compute the knowledge reuse with respect to the previous revision.
Analysis and Results

To test hypotheses H1 and H2, we examine both the distribution of sentiments on article pages and level of knowledge reuse between editors on the corresponding article pages. Similar to Turek et al. (2010), we use the number of edits on an article as a proxy in order to avoid taking into account articles that are in very initial stages of development. After analyzing the distribution of edits, similar to Turek et al. (2010), we decided to use a threshold of 30 edits for analyzing those articles whose knowledge is a result of collaboration among their editors. For those article pages having an overall number of revisions greater than this threshold, we compute the distribution of sentiments over time on their corresponding article talk pages. In order to prepare our dataset for hypothesis testing, we first perform a time series analysis of all article pages with respect to the amount of both knowledge reuse and sentiments expressed during conversations among their editors. Following our analyses of Wikipedia article pages and article talk pages, we group article pages by the following criteria:

- **presence or absence of sentiments** - article pages containing subjective (S) statements on the corresponding article talk pages are grouped in an S-cluster (1239 article pages), while the ones containing only objective (O) statements are grouped in an O-cluster (742 article pages);

- **positive versus negative sentiments** - each article page belonging to the S-cluster is grouped into either a P-cluster if the main orientation of sentiments displayed in the corresponding talk page is positive (P, 794 articles), or an N-cluster, if the orientation is mainly negative (N, 445 articles); in order to decide upon the main orientation of the sentiments, for all the statements on a talk page, we compared the sum of positive
sentiment strengths with the corresponding negative one; the orientation was decided by
the category corresponding to the higher sum.

To quantify whether the presence or absence of subjectivity in the content of article talk
pages influences the level of knowledge reuse, we compute monthly averages of the level of
knowledge reuse for each S- and O-clusters according to their article pages’ revision flows.
Results are shown in Figure 3 (a). We first compare the obtained discrete distributions of the
levels of knowledge reuse. On the one hand, the median level of knowledge reuse in the case
of sentiment-driven feedback (S) appears to be close to 2, indicating that the number of
reused words is almost twice as much as the number of newly created words. On the other
hand, in the case of neutral feedback (O), the sub-unitary level of knowledge reuse shows that
the number of newly created words appears to overcome the number of reused words. As
expected, the median level of knowledge reuse computed for the O-cluster is significantly
lower than the median of the S-cluster (Mann-Whitney U test; Z=–10.26, p<0.001, r=0.76). A
linear regression shows that the presence and absence of sentiments significantly explain
the level of knowledge reuse (adj. $R^2 = 0.6388$, p < 0.001), which confirms H1. In other words, as
expected, providing feedback appears to be beneficial for knowledge reuse in Wikipedia.

![Figure 3](image.png)

**Figure 3.** Distribution of knowledge reuse scores (a) computed for each of the two subject groups,
according to the sentimentality (S) or the objectivity (O) of content on their corresponding article
talk pages and (b) of articles classified in the S category, grouped by the positivity (P) or the
negativity (N) of the content on their corresponding article talk pages

For the articles contained in the S-cluster, we compare mainly positive (P) and mainly
negative (N) orientation of subjective content on article talk pages. The results are shown in
Figure 3 (b). The median level of reuse for the article pages of the P-cluster is significantly
higher than the one corresponding to the N-cluster (Mann-Whitney U test; Z=–8.61, p<0.001, r=0.64). The mainly positive or mainly negative orientation of subjectivity
also explains a significant proportion of variance in the level of knowledge reuse using a
linear regression (adj. $R^2 = 0.4284$, p < 0.001). This means that, indeed, providing positive
feedback appears to be more effective in Wikipedia with respect to knowledge reuse than
providing negative feedback. The median level of knowledge reuse in the case of positive feedback (P) appears to be more than two times higher than in the case of negative feedback (N). This result further confirms H2.

In a nutshell, we confirmed that receiving (especially positive, rather than negative) feedback in form of sentiments that are expressed in inter-editor conversations is beneficial in terms of sustaining knowledge reuse in Wikipedia; moreover, giving either positive or negative feedback appears to be more effective than providing no feedback at all.

Discussion and Implications

This paper investigated how peers are motivated to reuse knowledge in online social production by conducting a longitudinal analysis of peers’ editing and interaction activity in Simple English Wikipedia. In line with the findings of Markus (2001) on knowledge reuse, we considered knowledge reuse among Wikipedia editors as an essential aspect of collaboration that is influenced by specific communication practices. Specifically, we examined the way peers in Wikipedia communicate their feedback and support towards the work of other peers; we quantified to what extent providing sentiment-driven feedback acts as incentive towards the reuse of knowledge among peers. We found that peer content collaboration in Wikipedia - in terms of higher levels of knowledge reuse - appears to be strongly influenced by sentiment-driven feedback in inter-editor discussions. We also confirmed a significant difference in the level of knowledge reuse between editors who share mainly positive or mainly negative feedback. Indeed, displaying mainly positive sentiments in form of peer feedback corresponds to a superior level of knowledge reuse than displaying mainly negative sentiments. We contribute to the extant literature of online social production communities in general, and Wikipedia in specific, by providing the first building block for research on the role of sentiment-driven feedback on developing and sustaining Wiki-based knowledge reuse.

The findings of this study have to be viewed in light of several limitations. With regard to generalizability and endogeneity, we acknowledge that several areas dealing with the dynamics of social interaction in online collaboration were not examined in this study, such as the issues of social power or culture (Baym, 2006; Jiang et al., 2011). Pragmatically, one can take several other perspectives for examining the role of sentiment-driven feedback in online social production communities. Conditions other than peer feedback – such as group interactions, group composition characteristics, peers’ capabilities and goals, their interpretations of technology, and institutional contexts, power, or culture – may play key roles in causal explanations. Due to the nature of our observational data and the possibility of omitted variable bias, simultaneous causality bias, and errors-in-variable bias, we cannot make strong causal claims and future research should examine our identified relationships using more controlled settings or methods such as instrumental variables regression or controlled experiments. Moreover, the limitations of the measurement of knowledge reuse are discussed in detail in the “Measurement & Construct Operationalizations” section. Furthermore, there exist no clear guidelines on how to select the articles for analysis; similar to Turek et al. (2010), we decided to use a threshold of 30 edits for analyzing those articles that are a result of peer collaboration. We acknowledge that this choice may introduce a bias in selecting only those articles where editors appear motivated. In order to filter out articles that are not a result of peer collaboration, alternative methods could be filtering out either relatively new articles based on their age, or those articles that have not received enough attention from the community, based on the number of times they have been read. Finally, the accuracy of the identification of sentiments in article talk pages is limited by the performance
of SentiStrength; a manual evaluation of the performance of the sentiment analysis algorithms has been presented in the “Measurement & Construct Operationalizations” section. Future research may want to use and compare alternative approaches from sentiment analysis in order to perform a more detailed comparison and benchmark of the results.

Nonetheless, by examining the talk pages of all articles in Simple English Wikipedia (no sampling was done), our study provides important insights for the literature on online social production. Thereby we provide the first building block for research on how to understand peer collaboration in online social production communities in terms of knowledge reuse. Wikipedia provides an unprecedented amount of data that enabled us to 1) fully use the information provided by the edit history in order to quantify the amount of knowledge reuse, and 2) exploit the multitude of informal language in order to identify subjectivity in the content of article talk pages. Wikipedia is indeed an ideal environment for studying the cumulative effect of social and sentiment-driven interactions among editors on collaborative work. By extending previous work on knowledge reuse, our study contributes to the existing research on online social production along several dimensions of interests to researchers and practitioners.

From a theoretical perspective, the collective ethics of online social production appears to be in conflict with traditional policies, perceptions, and theories of organizational work (Arvidsson, 2008; Banks and Deuze, 2009; Puranam et al., 2013; Sanger, 2009). Indeed, social production systems raise a series of challenges for traditional organization, as it so far has been shown that peers do not necessarily follow the normal signals generated by firms or markets, either as employees in the firms following managerial directions, or as individuals in the markets following price signals (Benkler and Nissenbaum, 2006; Tapscott and Williams, 2006). In this sense, a micro-foundation of peer production is important to develop up-to-date theoretical concepts for management and organizational sciences. In order to design efficient policies that boost an innovative, networked economy, a systematic empirical analysis and an empirically grounded theoretical understanding of knowledge processes in peer production is needed. Relative to the focus of this paper, knowledge reuse in online communities continues to be under-researched (Haefliger et al., 2008; von Krogh et al., 2012). Although Majchrzak et al. (2013a) provided comprehensive theorizing of how peers engage in knowledge sharing via online knowledge conversations, a theoretical understanding of technology-enabled knowledge reuse in online communities is still lacking. This exploratory study helps to discover strategies to encourage collaboration and foster knowledge reuse in online communities and make the crowd sustainable without relying either on markets or hierarchies (Metiu and Kogut, 2001; Stephen and Suzanne, 2006).

Our results open a link to further controlled studies such as experiments observing the affective implication of individuals who reuse content. Researchers may transfer and test our findings from Wikipedia to more general scenarios involving peer collaboration. An immediate point of interest would be to investigate team collaboration and online social production in the context of another similar and rapidly growing resource, Wikia. With more than 370,000 established communities, Wikia is fundamentally different from the Wikipedia community in terms of having more permissive guidelines and policies, as well as a high number of small, topic-centered communities. Another direction worth investigating would be to analyze and test patterns of social collaboration in communities of open source software development (OSS) (e.g., Linux, Apache, GitHub, or SourceForge).
From a *managerial perspective*, organizations increasingly consider the outsourcing of knowledge tasks to large masses of workers via distributed labor networks using limited or no monetary incentives; this is possible, in part, due to the fact that the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of collaboration. While open collaborative innovation can potentially displace producer innovation at many parts of the economy (Baldwin and von Hippel, 2011; Maiolini and Naggi, 2011), the fluid generativity of distributed innovation suggests that knowledge resources will be increasingly heterogeneous and often only temporarily integrated (Yoo et al., 2012). Reflecting from the Wikipedia case, having insights about practical mechanisms to motivate the refinement of the collectively produced knowledge resources is important for organizations that would like to outsource knowledge tasks to large masses of online distributed workers. This study provides insights that positive feedback appears to be an effective way to motivate collaborative work in online social production.


Appendix VIII

Knowledge Reuse: Increasing the Willingness to Collaborate Online: Analysis of Sentiment-Driven Interactions in Peer Content Production
INCREASING THE WILLINGNESS TO COLLABORATE ONLINE: AN ANALYSIS OF SENTIMENT-DRIVEN INTERACTIONS IN PEER CONTENT PRODUCTION

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<td>17. Online Communities and Digital Collaborations</td>
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<td>08-Sep-2011</td>
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<tr>
<td>Complete List of Authors:</td>
<td>Grigore, Mihai; Goethe University Frankfurt, Economics and Business Administration, Business Information Systems Rosenkranz, Christoph; Goethe University, Economics and Business Administration</td>
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<td>Keywords:</td>
<td>Online Collaboration, Peer Content Production, Affective Communication, Virtual Teamwork, Social Interaction, Online Trust</td>
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Abstract:

We investigate mechanisms that trigger collaborative work behavior in online peer communities. We regard the collaboration among Wikipedia editors as a social process influenced by specific communication practices. We analyze and quantify the way Wikipedia editors communicate their feedback and support towards each others’ work in form of sentiments and opinions, and explore to what extent this influences online trust among them. We show that peer content production in Wikipedia is influenced by sharing sentiments during discussions among editors. At the global level, sharing sentiments positively influences the level of online trust. We also find a significant difference in the amount of online trust among editors who share mainly positive or mainly negative sentiments. We further suggest that providing and receiving especially supportive feedback expressed in form of positive sentiments and opinions may be beneficial in terms of virtual teamwork.
INCREASING THE WILLINGNESS TO COLLABORATE ONLINE: AN ANALYSIS OF SENTIMENT-DRIVEN INTERACTIONS IN PEER CONTENT PRODUCTION

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Abstract

We investigate mechanisms that trigger collaborative work behavior in online peer communities. We regard the collaboration among Wikipedia editors as a social process influenced by specific communication practices. We analyze and quantify the way Wikipedia editors communicate their feedback and support towards each others’ work in form of sentiments and opinions, and explore to what extent this influences online trust among them. We show that peer content production in Wikipedia is influenced by sharing sentiments during discussions among editors. At the global level, sharing sentiments positively influences the level of online trust. We also find a significant difference in the amount of online trust among editors who share mainly positive or mainly negative sentiments. We further suggest that providing and receiving especially supportive feedback expressed in form of positive sentiments and opinions may be beneficial in terms of virtual teamwork.

Keywords: Online Collaboration, Peer Content Production, Affective Communication, Virtual Teamwork, Social Interaction, Online Trust
Introduction

Online communities are a key topic of interest for both researchers and practitioners, especially since Hagel and Armstrong (1997) claimed that commercial success in the online area belongs to those businesses that organize electronic communities. Online users increasingly not only consume the Internet to seek information, but also use it as a virtual communication and collaboration platform. These interactive and collaborative mechanisms have found their way into scientific discourse and discussion mostly under the umbrella term “Web 2.0” (Vossen and Hagemann 2007). Web 2.0 is usually associated with technologies that facilitate interactive information sharing, interoperability, and collaboration on the World Wide Web, leading to the development of social networks and social media (Musser and O’Reilly 2007). The main building blocks of Web 2.0 are principles and technologies that allow an interactive and user-oriented design of Internet applications. Blogs (web logs), wikis, or podcasts allow users to easily create content on their own, to discuss issues of interest, to express opinions, facts, or to share information with others without needing to understand the underlying technologies (Vossen and Hagemann 2007). Web 2.0 further allows various levels of user involvement, as well as unique and unprecedented opportunities for engaging users into mass collaboration.

The emergence of these information and communication technologies fundamentally enables geographically dispersed people to come together with little cost, exchange ideas, and coordinate their activities (Leimeister et al. 2006; Preece 2000; Preece 2001; Rheingold 1993). This phenomenon has led to an increase in the number of online communities that focus on coordinated efforts of volunteers to produce intellectual work – so-called peer production (Benkler 2006; Benkler and Nissenbaum 2006). This raises a series of challenges for traditional organization theory, as social peer production systems organize creative mass collaboration through coordination without relying either on markets or on managerial hierarchies to organize decentralized production (Benkler 2006; Stephen and Suzanne 2006). Peer content production further offers major advantages over markets and managerial hierarchies in terms of resource allocation and information processing (Andreev et al. 2010; Benkler 2002; Taddeo and Vaccaro 2011). Wikipedia, the online encyclopedia “that anyone can edit”, is a prominent example of peer content production, where voluntary contributors coordinate their work and develop mutual understanding on the collaboratively created content of encyclopedic articles (Kittur and Kraut 2010; Tkac 2010).

Recent years have seen increasing research efforts on investigating how community design affects user behavior in online communities and social networks (Crandall et al. 2008; Ren et al. 2009; Ren et al. 2007; Wang et al. 2009). The effects of social interactions on longitudinal user behavior, however, are barely explored, and neither are the effects of such interactions on user collaboration in online communities and peer production entirely understood. Mass collaboration works surprisingly well, despite its lack of mechanisms of formal authority (Eseryel 2009). However, a major recurring problem for providers of online communities is that a significant part of community members do not contribute with content. That is, even when online platforms provide appropriate tools for collaboration, a large number of their user communities end up being underdeveloped simply because of both non-participative and non-collaborative user behavior (Ling et al. 2005; Maloney-Krichmar and Freence 2005; Susan et al. 2005). Despite the large body of literature on how to build viable online communities (Farzan et al. 2011; Gurzick and Lutters 2009; Lin 2008; Maher et al. 2011; Rosenkranz and Feddersen 2010), we still have no deep understanding of the underlying factors driving online collaboration and peer production. Traditional incentivizing methods are usually unsuitable for such online environments (Bishop 2007). Non-participative online behavior might also be a significant issue for the trend to increasingly “crowdsource” tasks to large masses of workers, for example, by using micro-task markets such as Amazon’s Mechanical Turk² (Downs et al. 2010; Kittur et al. 2008; Ross et al. 2010), where there is a constant need to convince users to provide content for your service in case one either has limited or cannot provide monetary incentives.

The aim of this paper is to provide a novel theoretical perspective on understanding the mechanisms driving productive social interactions online with almost no centralized control. We seek to identify

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1 http://en.wikipedia.org/wiki/Main_Page
2 https://www.mturk.com/mturk

3 Thirty Second International Conference on Information Systems, Shanghai 2011
factors that motivate users to contribute, and that positively influence online collaborative work. For doing this, we analyze and discuss peer content collaboration in the particular case of Wikipedia article editing. Our study regards the collaboration among Wikipedia editors as a social process influenced by specific communication practices. More concretely, we investigate whether affective communication (Te’eni 2001) among Wikipedia editors acts as an intrinsic motivator of collaborative work behavior. We analyze how users communicate their feedback and support towards each others’ work in form of sentiments and opinions expressed during conversations, and explore to what extent peer feedback influences online trust among Wikipedia editors. Our aim is to provide insights towards what makes large-scale collaboration and peer content production in online communities sustainable and productive without relying either on markets or hierarchies (Metiu and Kogut 2001; Stephen and Suzanne 2006).

We discuss the related work and the theoretical background of our research in the next section. Afterwards, we describe and discuss our research method. The dataset used in this study consists of a complete revision history dump of Simple English Wikipedia. We employ methods from opinion mining and sentiment analysis to our data. First, we find that sentiments expressed in inter-editor conversations correspond to an increased level of online trust of co-editors on the corresponding article pages. Second, we show a significant difference in the level of online trust between editors who share mainly positive or negative impressions respectively. Finally, we show that reaching mature states of article content is not necessarily linked to the strength of sentiments expressed as feedback in Wikipedia discussions. We discuss our results and conclude with an outlook on further research, as well as on the implications of our study.

Background and Related Work

User Contributions in Online Communities: The “Lurker Problem”

Most traditional research on online communities focuses on the role of information technology in enabling people to interact with each other (Burnett 2000; Preece 2001), on the factors of usability and sociability (Preece 2001; Tarmizi and Vreede 2005), as well as on what principles make online communities successful. For example, Porra and Parks (2006) suggest that the sustainability of online communities requires persistent people, continuous support by an online space, and flexibility for alternative sub-communities to emerge. Ginsburg and Weisband (2002) conclude from their survey that volunteerism is an important aspect for the success of online communities.

Although online communities are becoming increasingly relevant to business (Parameswaran and Whinston 2007), many of them fail and participation drops to zero (Ling et al. 2005). Regardless of the size of online communities, it has been observed that only a small fraction of registered users actively contribute to the process of creating and managing content. In the context of online environments, “lurkers” are usually perceived as users who consume the available information, without further contributing with any content (Gensollen et al. 2007). It is an important and difficult challenge to design technical features of online communities and seed their social practices in a way that generates ongoing contributions from a larger fraction of the participants (Ling et al. 2005). In this context, Ren et al. (2007) developed a theoretical framework to distinguish identity-based from bond-based attachment to online communities. While common identity refers to users who appreciate the community as a whole, common bond attachment refers to users who appreciate other individuals in the group. Fiedler and Sarstedt (2010) performed an evaluation of the influence of social interaction on both common identity and common bond attachment in online communities. They provided valuable insights into the complex relationships underlying user behavior in online communities by showing that both network effects and collectivism influence, among others, membership robustness, and loyalty to the online community.

Designers of online communities usually face the problem of determining what makes lurkers become active contributors, as previous efforts on understanding why lurkers do not contribute (Maloney-Krichmar and Preece 2005; Susan et al. 2005) do not provide sufficient insights for affecting an established lurking behavior. For example, Rafaeli and Raban (2005) stress the importance of passive reading as a likely precondition for both participating and building a sense of online community. Antin

3 http://simple.wikipedia.org
and Cheshire (2010) investigate the way readers learn to get involved in the Wikipedia community, and propose theoretical insights for re-casting lurkers as more valuable participants in online environments. They claim that research on how different categories of users pay attention to the content may reveal insights about particular users’ attitudes, behaviors, and intentions. In a study investigating habit formation in online communities, Gan et al. (2009) find that there exist both intrinsic and extrinsic motivations influencing user participation. Preece et al. (2004) reveal that a significant proportion of lurkers do not belong to the category of self-interested individuals taking advantage of others’ work. Lurkers may even be willing to contribute, but are usually hold back by already developed beliefs and values (Bishop 2005). In fact, Preece et al. (2004) identify five important reasons why lurkers do not contribute in any way to the community: there are both no needs and no encouragements to post, lurkers needed to know more about the group before getting involved, they think they are being helpful by being altruistic lurkers, or they are simply not able to use the software functionalities.

To understand the motivation behind technology-mediated social cooperation, Preece and Shneiderman (2009) propose the “Reader-to-Leader” framework. As prior studies (Shah 2006) report that once their needs are met, users are more likely to leave the community than continuing to contribute, Preece and Shneiderman (2009) claim that getting users to revisit online social environments may represent an important premise for users to start contributing content and possibly becoming collaborators. On the one hand, Bishop (2007) recommends that, in order to successfully challenge lurking behavior, community providers should at first attempt to change lurker beliefs by using persuasive discourse, that is, by countering the beliefs of actors and providing them with new information (Chambliss and Garner 1996). On the other hand, Murphy et al. (2003) argue whether using persuasive texts represents an effective way of changing lurker beliefs, and, consequently, lurking behavior. Although challenging these predefined lurker beliefs may generate an increased individual participation in online communities, Bishop (2007) points out that none of the previous theoretical attempts (suggesting that participants are either goal-driven or need-driven) are entirely appropriate for understanding lurking behavior in such settings. Moreover, further empirical studies on the progression from reading to other forms of user participation in online communities are needed (Antin and Cheshire 2010).

**Online Collaborative Work: The Role of Affectivity and Trust in Online Settings**

What drives people to collaborate in an online setting, becoming active co-workers? Collaboration is a process involving “two or more contributors discussing, cooperating, and working together to create something or share information” (Denning and Yaholkovs 2008). It takes coordination for people to perform things together and it takes communication to achieve that coordination (Clark 2005). The basis for communication and coordination is shared knowledge, or common ground, between people (Clark 1996, p. 120). Developing mutual understanding and shared beliefs (i.e., a common ground) is an essential aspect of collaboration (Convertino et al. 2008; Convertino et al. 2009). Moreover, participation in any collaborative activity requires a unique motivation to share psychological states with others (Tomasello et al. 2005). Convertino et al. (2009) propose two types of common ground: process and content. Process common ground encompasses “I know that you know that I know how”; content common ground includes “I know that you know that I know what” (Convertino et al. 2009). Process coordination implies continuous communication of shared rules, timing, conventions, and manner in which the interaction will be conducted (procedural and strategic knowledge). In contrast, content coordination requires exchanging content and mutually checking and signaling understanding to establish a grounded content as result of collaborative work.

Sproull and Kiesler (1991) stretch the importance of developing supportive interpersonal relationships online, especially since the rise of the Internet. In an online setting, the focus of attention changes from the relationship between a person and technology to the relationship between a person and other people; people who never physically meet or know each other get to communicate and work collectively. Especially trust and empathy are found to be essential in encouraging people to work together online (Leimeister et al. 2006; Maloney-Krichmar and Preece 2005; Skopik et al. 2009).

Trust building increases members’ willingness to collaborate, while shared values and the satisfaction with previous user interactions have a positive impact both on trust online and on returning behavior of virtual community members (Wu et al. 2010). Thus, one may count as beneficial the willingness to suspend doubt about others, and start working on group tasks with a positive expectation that the group
activity will be completed (Meyerson et al. 1996). Moreover, research on trust in virtual teams suggests that the initial willingness to show trusting actions leads swiftly to actual trust, and that frequent communication between team members helps to promote trust among them (Wallace 2001). The probability of engaging in trusting behavior is further likely to increase as a result of the “anticipated positive and negative motivational consequences” (Deutsch 1958).

Empathy has been shown to have a significant influence on trust in online settings (Feng et al. 2004). Communication partners who interact in an empathically accurate and supportive way appear to be most trusted by other online participants (Feng et al. 2004). Empathic accuracy itself does not guarantee trust, and, in order to win other’s trust online, it is not nearly enough to correctly infer the other’s feeling, but also to provide supportive feedback. Eseryel (2009) further discusses how the lack of formal authority in online communities is efficiently compensated by individuals who mentor and encourage each other to contribute to the team. Shared affect, that is, subjective experience of feeling - sentiment or emotion - as reaction to things one thinks about, actions one takes, or to various stimuli (VandenBos 2006), helps coordinating group activity through fostering group bonds and group loyalty (Spoor and Kelly 2004).

Moreover, affective communication among group members plays a key role in the articulation of sentiments, emotions, or moods both in spoken discourse and in written text. Affective information can be transferred through computer-mediated communication, while message receivers are able to successfully decode affective information (Harris and Paradice 2007). In a recent preliminary study, Lee et al. (2010) investigate whether emotional expressions in threaded discussions influence the quality of knowledge in online communities. More precisely, they argue that emotional expression in inter-user communication is a trigger for sharing experiences in such communities, and they propose that the degree of emotional expression is positively associated with the degree of sustaining dialogues, and with the quality of knowledge created.

In the specific case of peer content production in Wikipedia, an analysis of collaboration patterns occurring during article editing revealed that an intensification in collaboration usually occurs after the initiation of conversations among editors (Crandall et al. 2008). Peer influence exerted across social ties among editors can be further used as predictor of future editing behavior (Crandall et al. 2008). Social capital (Shah et al. 2001) represents both a cause and an effect of social selection in Wikipedia, in the sense that articles that reach faster a higher quality level appear to be created by groups of editors who have previously worked together on other articles (Nemoto et al. 2011). This higher pre-existing social capital of co-workers is reported to be especially important in the early phases of Wikipedia article definition and team organization. Once the general direction of the article is set, the team then appears to be able to absorb new contributors more effectively (Nemoto et al. 2011).

To sum up, users who tend to interact and communicate in a supportive way are most likely to be trusted by other online participants. Both pre-existing social capital and supportive feedback among participants appear to have a positive impact both on building trust online, as well as on returning behavior of virtual community members. Trust building has further been shown to increase members’ willingness to collaborate in online settings. Moreover, Convertino et al. (2009) stress the differences between the process of sharing knowledge that supports common ground in conversations (content coordination), on the one hand, and the process of building common ground in the context of complex team activities (process coordination), on the other hand. In the context of teamwork in Wikipedia, we regard the peer content collaboration (i.e., article editing) as a process of content coordination. We further see the communication among Wikipedia contributors as one means by which editors plan editing actions, and develop a shared understanding of the edit policies, procedures, and timing which are meant to guide their interactions (i.e., process coordination). We aim to identify factors that lead to building a sense of trust among Wikipedia editors, and that further drive them towards collaborating on article content.

As a first step, we propose to investigate whether affective communication practices among Wikipedia editors positively affect the level of trust online, and act as intrinsic motivators of peer content collaboration. More precisely, we focus our investigations on how Wikipedia editors communicate their feedback and support towards each others’ work in form of sentiments and opinions expressed in inter-editor discussions, and to further explore to what extent this impacts the collaborative article editing process in Wikipedia. We analyze the level of subjectivity (or, more specifically, the level of sentiments, cf. section “Research Model”) in inter-user communication with regard both to the level of trust between users and to the user collaboration in content creation. For doing so, we propose to integrate the analysis...
of specific peer content collaboration - the editing process of Wikipedia articles - with an analysis of informal discourse - the level of sentiments in discussions between Wikipedia editors. This leads us to formulating a general research question:

**GRQ:** What enables a foundation of trust among peer content contributors? Do peers mentor and encourage others to contribute?

From this, we draw two subsequent, more focused research questions we address in this study:

**RQ1:** Is online trust in Wikipedia affected by providing feedback about editors’ contributions? If so, does sharing supportive feedback increase promoting a higher level of online trust?

**RQ2:** To what extent is sharing feedback on others’ work beneficial in terms of collaboration effectiveness in Wikipedia?

**Research Design and Method**

**The Data Set**

The online encyclopedia Wikipedia uses a wiki technology to support collaborative writing and editing of textual content by its own community of readers. The resulting *article pages* represent the main source of contents used by regular Wikipedia readers. In order for any user to visualize the dynamics of article changes, the *revision history* functionality provides a track of chronologically ordered summaries about the previous versions of the article such as time stamp, editor, actual text resulting from the edit, and comments.

Besides the underlying wiki-based collaboration mechanism, Wikipedia contributors communicate among each others using specific mechanisms such as *talk pages* and *user talk pages*. While performing edits on article entries, Wikipedia editors tend to initiate conversations on article talk pages in order to plan and discuss their work, that is, coordinate their work, share and ask for feedback, report vandalism, or refer to edit guidelines (Schneider et al. 2010). Examples of both supportive and negative editor feedback on Wikipedia’s “Talk:NASA” and “Talk:Water_on_Mars” entries are shown below:

“Many Modules ! Brilliant ! Precise ! Do you know, looking at the changes log, I think the guardians of this page are overworked and under-appreciated. I do hope I can be of assistance wherever possible. Keep up the great work ! Don't give up !Penyulap (talk) 01:08, 18 March 2011 (UTC)”

“Not only is it a bit lengthy, but it has very unusual organization for a wikipedia page... perhaps inappropriately so. Also, in some places it isn't written with proper encyclopedic style [...] I hate to merely be a critic, but I'm not nearly qualified enough to attempt rewriting or reorganizing this article. :)The2crowrox (talk) 00:58, 5 November 2010 (UTC)”

Because of the extremely large size of Wikipedia’s revision history and the limited computational power, many previous analyses used only samples of data in order to save computation costs (Arazy and Nov 2010; Javanmardi and Lopes; Muller-Birn et al. 2009; Viegas et al. 2007). However, as there are no general guidelines on how to obtain a good sample from Wikipedia, and since complete revision histories are necessary for computing revision-based metrics, we instead use a complete revision history dump of Simple English Wikipedia, a spin-off of Wikipedia written using basic English vocabulary and uncomplicated grammar constructions. Articles from Simple English Wikipedia are usually not new; their editors use articles from Wikipedia and try to bring them to a simple form. The dump was created in March 2011 and contains over 200,000 pages, out of which around 70,000 are article pages, totaling approximately 16 gigabytes of XML data. Along with anonymous users, there are over 170,000 registered users who contributed to approximately 3 million revisions from the creation of Simple English Wikipedia. The average number of revisions per page is 14.35. Currently, there are over 700 registered users with at least one edit or logged action in the past month.

5 retrieved from: http://en.wikipedia.org/wiki/Talk:Water_on_Mars

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*Thirty Second International Conference on Information Systems, Shanghai 2011*
Research Model

To explore factors that shape socially collaborative behavior, we propose to investigate the role of emotions as perceived feedback and as motivational factor of collaboration in Simple English Wikipedia. We argue that trust-implying actions of Wikipedia editors help to establish or reinforce an emotional sense of trust and commitment, since positive affect usually circulates among those who express their trust behaviorally, just as negative affect arises among those who ‘betray’ or act distrustfully toward each other (Boyle and Bonacich 1970; Lewis and Weigert 1985). Since emotions are rather transient states of subjectivity and may rapidly decay to the neutral state (Barrett and Russell 1999), we suggest to focus on sentiments and opinions. We propose that those may be more useful for explaining collective behavior, as they, in contrast to emotions, more often become externalized instances on the collective level (such as “public opinion” or “collective sentiment”) (Scherer et al. 2004). We further use the umbrella term subjectivity to refer to both sentiments and opinions, which are, in fact, commonly addressed together in the specific literature of the opinion mining and sentiment analysis research field (Pang and Lee 2008; Wiebe and Mihalcea 2006). We observe whether the amount of subjectivity (i.e., the linguistic expression of private states such as opinions, sentiments, or emotions on talk pages, Banea et al. 2008; Furuse et al. 2007; Wilson et al. 2005) is related to building a grounded content (i.e., article page content) as result of collaborative editing. Specifically, we formulate the following hypotheses:

\[ H_1: \text{The total amount of sentiments on talk pages (whether positive or negative) positively influences the trust between editors on corresponding article pages. (RQ1)} \]

\[ H_2: \text{Positive sentiments during discussions on talk pages are associated with increased trust between editors on corresponding article pages. (RQ1)} \]

\[ H_3: \text{Semantic convergence of content on article pages corresponds to an increased amount of sentiments on corresponding talk pages. (RQ2)} \]

Research Method

We compute Wikipedia-specific, revision-based measures on the editing process of article pages (trust and content convergence), as well as mining the sentiments expressed on talk pages. To address the above hypotheses, we employ monthly time series analyses of: 1) the user trust that is mediated by the amount of sentiments in inter-user communication, and 2) the level of subjectivity (in terms of sentiments expressed on talk pages) as a measure of coordination effort that is mediated by the convergence of article contents. Below we present each of the measures we use in our analyses.

Sentiment Analysis of Editor Interactions

Subjectivity analysis broadly classifies textual statements into objective statements that express factual information and into subjective statements that reflect holder’s attitudes or perceptions (Banea et al. 2008; Furuse et al. 2007). Opinion mining or sentiment analysis represents a systematic, computer-based analysis of written text or speech excerpts, for extracting the attitude of the author or speaker about a specific topic. Sentiment analysis provides a more fine-grained examination compared to subjectivity analysis, aiming to establish the overall orientation (positive or negative) and intensity (weak or strong) of the opinions or sentiments expressed by statements previously classified as subjective (Pang and Lee 2008). However, subjectivity may often be expressed in a subtle manner, making subjectivity analysis often “more difficult than subsequent polarity classification, so improvements in subjectivity classification promise to positively impact sentiment classification” (Mihalcea 2007). Moreover, Wikipedia editors often use informal vocabulary when writing comments on talk pages, which adds difficulties to the task of identifying subjectivity.

Recent sentiment analysis algorithms are able to detect positive and negative sentiment strength in short informal texts with a reasonable degree of success (Akkaya et al. 2009; Paltoglou and Thelwall 2010; Shanmugasundaram et al. 2009). In our analyses, we use the SentiStrength tool (Thelwall et al. 2011; Thelwall et al. 2010) to analyze the level of sentiments on talk pages in Wikipedia. SentiStrength provides a scoring range from −5 (very negative) to +5 (very positive). Also, in case of texts showing an equal amount of positive and negative sentiments, the algorithm is able to predict which of the two orientations
is the prevalent one. Figure 1 shows the distribution of the total monthly amount of sentiments expressed by editors in talk pages.

![Figure 1. Distribution of total amounts of (a) positive and (b) negative sentiments on talk pages corresponding to each month from the creation of Simple English Wikipedia](image)

**Online Trust as a Measure of Editor Team Quality**

Williamson (1993) considers trust as one’s subjective likelihood to engage in collaboration with agents who are perceived as potentially performing “beneficial or at least not detrimental” actions. Trust can in general be conceptualized as “a latent variable resulting from distinct but related (formative) indicators (i.e., propensity to trust and perceived trustworthiness), which lead to (reflective) indicators (i.e., behaviors of cooperation and monitoring between team members)” (Costa and Anderson 2010). In the case of virtual teams, perceived trustworthiness has been shown to accelerate the formation of trust and leads to more solid forms of trust in virtual teams (Hwang et al. 2004). The initial willingness to show trusting actions has been found to lead swiftly to actual trust, and frequent communication between team members helps to promote and gain others’ online trust (Wallace 2001). Fen et al. (2004) further observe that communication partners who are willing to share feedback and interact in a supportive way are most trusted by other online participants.

Josang (2007) elaborates editor’s trust towards the correctness of an entry in Wikipedia as perceived reliability of the information provided by other editors. Similar to Turek et al. (2010), we compute the amount of online trust established between two Wikipedia editors of the same article page as the number of words produced by the first author and reused (e.g., copied, moved elsewhere, or restored) by the second one. This indicates a notion of online trust in the sense of “a willingness to show trusting actions” (Wallace 2001). For a given Wikipedia article page, we compute the overall online trust between its editors as a mean of pairwise trust values, weighted by the proportion of editors who contributed to the creation of each specific revision from the total number of article editors. In this way, we reduce the effect of large number of edits on the same page. Figure 2 shows the distribution of the monthly average amount of online trust extracted from the edit logs of article pages.
Christopher and Amit (2007) define the semantic convergence of Wikipedia articles as a state in which the content of the article remains stable despite the ongoing edits. More precisely, a document is considered semantically stable if a high semantic similarity between the current version and the previous $k$ revisions can be established.

To measure the semantic similarity between two article revisions, we use the vector-space model for representing the semantics of the content of those revisions (Erk and Pado 2008). For each pair of vector-space representations of edit revisions, we compute their cosine similarity score as the angle between two vectors which represents the inner products of those vectors, the lengths being normalized to the unit (Turney and Pantel 2010). The value of the cosine ranges from -1 (the angle is 180 degrees and the vectors point in opposite directions) to +1 (the angle is 0 and the vectors point in the same direction). We consider a Wikipedia article as mature if its content converges over the series of edits.

In the next section we show the way we employ the three measurements (sentiments, trust, and convergence) in our analysis.

Analysis and Results

To address hypotheses H1 and H2, we examine both the distribution of sentiments on article pages and the trust between editors on the corresponding talk pages to accomplish two related tasks. First, we want to discover whether there is any significant difference between the presence or the absence of sentiments in the talk pages, and the amount of trust between editors. Second, we check if we can observe any discrepancy in terms of trust levels corresponding to positive and negative orientations of sentiments.

In order to prepare the data for tests, we first perform a time series analysis of all article pages with respect to the trust of their editors. We select all talk pages and store the time stamps of their edits. For those talk pages having an overall number of revisions greater than 30 (approximately double of the average amount of edits per article), we compute the distribution of sentiments over time on their corresponding article pages. We then attempt to discover to what extent sentiments on talk pages trigger collaborative behavior on the corresponding article pages.

To test the third hypothesis, we similarly perform a time series analysis of all talk pages with respect to the sentiments expressed by editors. This time we select all the article pages having an overall number of revisions greater than 30 and divide them into two clusters, whether their content is convergent or not. We aim at discovering whether an increased amount of sentiments on the talk pages corresponds to semantic convergence of content on article pages.

Maturity of Article Pages and Semantic Convergence of Content

Christopher and Amit (2007) define the semantic convergence of Wikipedia articles as a state in which the content of the article remains stable despite the ongoing edits. More precisely, a document is considered semantically stable if a high semantic similarity between the current version and the previous $k$ revisions can be established.
Following our analyses of Wikipedia article pages and talk pages, we group article pages by the following criteria:

- **Presence or absence of sentiments**: article pages containing sentimental (S) statements on the corresponding talk pages are grouped in an S-cluster (1239 article pages), while the ones containing only objective (O) statements are grouped in an O-cluster (742 article pages);

- **Positive versus negative sentiments**: we group each article page belonging to the S-cluster into either a P-cluster, if the main orientation of sentiments expressed in the corresponding talk page is positive (P, 794 articles), or an N-cluster, if the orientation is mainly negative (N, 445 articles); in order to decide upon the main subjectivity orientation, for all the statements on a talk page, we compared the sum of positive sentiment strengths with the corresponding negative one; the orientation was decided by the category corresponding to the higher sum;

- **Convergent versus non-convergent content**: article pages whose content has reached a semantically stable state and are thus considered mature are grouped into the C-cluster (1084 article pages), while the others are grouped under the NC-cluster (897 article pages).

To quantify whether the presence or the absence of sentiments in the content of talk pages influences the trust between editors on article pages, we compute monthly averages of trust for each S- and O-clusters according to their article pages’ revision flows. Results are shown in Figure 3 (a). We first compare the obtained discrete distributions of trust scores using the Mann-Whitney U test. The median level of trust computed for the O-cluster is significantly lower than the median corresponding to the S-cluster (Z = -10.26, p < 0.001, r = 0.76). A linear regression reveals that the presence and the absence of sentiments significantly predict the level of online trust (adj. \( R^2 = 0.6388, p < 0.001 \)).

![Figure 3](image_url)

**Figure 3.** Distribution of online trust scores (a) computed for each of the two subject groups, according to the sentimentality (S) or the objectivity (O) of content on their corresponding talk pages and (b) of articles classified in the S category, grouped by the positivity (P) or the negativity (N) of the content on their corresponding talk pages

For the articles contained in the S-cluster, we perform a second U test relative to mainly positive (P) and mainly negative (N) sentiment orientation of subjective content on talk pages. We obtain that the median trust for the article pages of the P-cluster is significantly higher than the one corresponding to the N-cluster (Z = -8.61, p < 0.001, r = 0.64). The results are displayed in Figure 3 (b). The mainly positive or mainly negative orientation of sentiments also explains a significant proportion of variance in the level of online trust using a linear regression (adj. \( R^2 = 0.4284, p < 0.001 \)).

However, we did not find a significant difference in terms of trust among editors between convergent (C-cluster) and non-convergent (NC-cluster) article pages (Mann-Whitney U test, p = 0.17).
We summarize the results drawn from our data set with regard to our hypotheses:

**Sentiments versus level of online trust:**

**H1:** There is strong statistical evidence that sharing sentimental statements (either positive or negative) on talk pages positively influences the online trust between editors on article pages.

**H2:** There is strong statistical evidence that positive sentiment orientation during discussions on talk pages is associated with increased online trust between editors on article pages.

**Content convergence versus amount of sentiments:**

**H3:** There is no statistical evidence that semantic convergence of the content of article pages corresponds to an increased amount of sentiments on talk pages.

On the one hand, our confirmation of H1 and H2 let us conclude that sentiments in discussions on talk pages positively influence the perception of online trustworthiness among Wikipedia editors. On the other hand, a high amount of sentiments does not necessarily imply maturity of content on article pages (rejection of H3).

**Discussion**

We described and analyzed peer content collaboration in Wikipedia using measures for sentiment strength, online trust between editors, and maturity of content based on the revision history of Simple English Wikipedia articles. Thereby we provided a first building block for research on how to effectively motivate users to collaborate in online peer production communities. We exemplary studied the way Wikipedia editors give feedback, mentor, encourage, or criticize other editors by means of positive or negative statements on talk pages. We tested three specific hypotheses concerning user collaboration. We found that peer content collaboration in Wikipedia (in terms of higher levels of online trust among editors) is influenced by peer feedback in form of sharing sentiments during inter-editor discussions (H1). We showed that, at the global level, sharing sentiments positively influences the level of online trust. Specifically, Wikipedia talk pages where editors express their affective implication present an increased level of online trust among editors, reflected in the editing of article pages. We also found a significant difference in the amount of trust between editors who share mainly positive or mainly negative sentiments (H2). We conclude that reaching mature states of content on article pages does not particularly imply increased amounts of sentiments (seen as feedback between editors) shared on talk pages (H3). Our results extend the approach of Wierzbicki et al. (2010), who considered online trust among editors as a relevant aspect of peer content collaboration in Wikipedia. We further suggest that receiving (especially positive) feedback in form of sentiments expressed in inter-editor conversations may be beneficial in terms of virtual teamwork.

To our knowledge, we are the first to examine the relationship of the semantic information (provided by the content on Wikipedia article pages via sentiment analysis) with respect to revision-based measures (provided by trust online and maturity of article content). Our findings let us conclude that the approach we considered in this study provides significant insights for researchers looking for factors that influence productive social behavior. We therefore provide a suitable means for analyzing the social interactions in collaborative online communities. Our concepts also create awareness for possible deficiencies and pitfalls. For example, we draw from our findings that it might be very useful to strive for early communication activities on talk pages that include sentimental statements and provide a motivation for other users. This should create trust earlier and may further reduce transaction costs by creating this trust, specifically the costs of cooperation and specialization (Hill 1995).

Wikipedia further provides an unprecedented amount of data suitable for mining practices in computer-based collaborative work. The data set we used in our analyses enabled us to: 1) fully use the information provided by the edit history of highly edited articles (we perform no sampling over the time dimension) to employ revision-based measurements, and 2) exploit the multitude of informal language phenomena (specific to user-generated content) in order to identify subjectivity in the content of talk pages. Additionally, Wikipedia represents an ideal environment for studying the cumulative effect of social and affective interactions among editors on collaborative work. In fact, recent investigations found social interaction to be both a cause and an effect of social selection in Wikipedia: articles that reach faster a
higher quality level appear to be created by groups of editors who have previously worked together on other articles (Nemoto et al. 2011). In a more general setting, our findings may illustrate that the need for explicit coordination does not necessarily come along with the maturity stage of collaboration. We propose that we need to further compare individual profiles (e.g., activity patterns, coordination efforts, or communication activities) of users whose group collaboration reaches mature stages in order to distinguish whether affective implication is a matter of individual work habits or if it indeed comes along as a consequence of social interaction among users. In this sense, Aral et al. (2009) further stretch the increasing importance of clearly separating social influence from homophily in order to be able both to understand how behavior spreads (i.e., what enables social contagion, and what makes behaviors propagate viral), as well as to effectively design and support policies that encourage or combat the spread of specific behaviors in online communities.

Our research offers several advantages to researchers and practitioners interested in the social dynamics of online communities, peer content production, and virtual collaboration. First, we offer a form for carrying out explanation and prediction. The application of our approach illustrates its potential for analyzing users of online communities, their behavior, their relations, and their activities in form of online collaboration and peer content production. Second, our research is capable of guiding both research and practice of online collaboration. If a “sound” understanding of online collaboration as a socially productive process is among the desired goals, researchers and practitioners may benefit from our insights on how to conceptualize the relationship between collaborators, affective communication, and trust. In particular, our findings on online trust in the context of subjectivity show a great potential for gaining insights on the way peer production develops with almost no centralized control. We acknowledge other areas dealing with the dynamics of social interaction in online collaboration, such as the analysis of gestures, problems of culture, or issues of social power as important (Baym 2006; Jiang et al. 2011). Pragmatically, there may be several perspectives for examining social interaction in online communities. Conditions other than sentiments or trust – users’ capabilities, characteristics and goals, their interpretations of technology, their work practices, and institutional contexts, power, or culture – may play key roles in causal explanations. Our results open a link to further experiments observing the affective implication of individuals who share a high value of trustworthiness.

Our work is not without limitations regarding both the semantic analysis of content and the generalizability of our findings. Each processing step is limited to the accuracy of the measurements we compute. For instance, the online trust measurement does not penalize repetitive edits in any way (Turek et al. 2010). We are also aware of the potential deficiencies associated with the existent behavioral approaches to measuring trust (McEvily 2011). Moreover, the accuracy of the identification of sentiments in talk pages is limited by the performance of the SentiStrength tool. Thelwall et al. (2010) performed an evaluation of SentiStrength on short informal texts, and reported that it performs with 96.9% accuracy on positive sentiment strength detection, while the detection of negative sentiment strength yielded 95.1% accuracy. Among the current sentiment analysis approaches, SentiStrength also performs best on Twitter postings (Nielsen 2011). We plan to use and compare alternative approaches from sentiment analysis in order to perform a more detailed comparison and benchmark of the results. Furthermore, the semantic convergence of articles takes into account only revision-based heuristics. An improvement to this measurement would be to compute the convergence only for those articles proven to meet a minimum standard of quality.

As regards generalizability, there are several characteristics that make Wikipedia significantly different from other online communities and virtual environments: established edit policies and norms, many active volunteers, the presence of administrators, as well as established social reputation among users. Moreover, if we consider the main usages of Wikipedia talk pages (request edit coordination, discuss controversial edits, ask for feedback, report vandalism, or refer to edit guidelines (Schneider et al. 2010)), researchers may even transfer and test our findings from Wikipedia to more general scenarios involving peer collaboration. An immediate point of interest would be to investigate team collaboration and peer content production in the context of another similar and rapidly growing resource, Wikia.6 With more than 34,000 of established wikis, Wikia is fundamentally different from the Wikipedia community in terms of having more permissive guidelines and policies, as well as a high number of small, topic-centered communities. A further direction worth investigating would be to analyze and test patterns of social

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6 http://www.wikia.com/Wikia
collaboration in open source software development communities (e.g., Linux, Apache, GitHub, and SourceForge).

At a higher level, a large number of processes are currently increasingly conducted electronically (Overby 2008), as the trend of virtual collaborations that are organized without markets or managerial hierarchies is emerging in the context of information production systems. Understanding the factors that drive socially productive behavior is therefore increasingly important, as the virtual, self-organizing workplace constantly evolves towards more spontaneous and decentralized forms of mass collaboration (Tapscott and Williams 2006). Despite that the effect of virtualization of organizational structures on collaborative work has been in focus for some time (Assmann et al. 2010; Korsgaard et al. 2010; Markus 2004; Picot et al. 2008), the investigation of organizational behavior change has only shown that user online involvement in peer production does not necessarily follow the normal signals generated by either market-based or hierarchical models (Andreev et al. 2010; Benkler and Nissenbaum 2006). If both issues of motivating user contribution and organizing peer collaboration are overcome, then peer production of information potentially presents a systematic advantage over markets and firms in matching the best available human capital to the best available information inputs (Benkler 2006).

Conclusion

Online collaboration is becoming more and more important. Although the concept has found broad acceptance in practice, research or studies both on the factors influencing and on the effects of online collaboration are still underdeveloped. In this paper, we attempt to transfer concepts from sentiment analysis to the study of peer content collaboration in Wikipedia as a social process. To our knowledge, we are the first to examine the trust behavior modeled by the subjective user implication. Our main finding is that sharing feedback in form of sentiments and opinions positively affects online trust in inter-user interactions. We hope that our transfer of concepts will be useful for other researchers and practitioners who investigate factors that shape online collaborative behavior. As Wikipedia has a series of specific qualities that make it difficult to generalize, we intend to apply our approach to other wiki communities (such as Wikia).

As further work, we propose to analyze the amount of sentiments in peer production communities supporting social networking. It would be worthwhile to investigate the evolution of affective implication of users in connection to changes in the group collaborative behavior. Moreover, at the community level, one may investigate whether the amount of sentiments contained in discussions can be correlated to the frequency of interactions between members. Furthermore, we intend to replicate and test our findings by further performing controlled experiments with regard to the level of trust and the amount of sentiments.

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Online Communities and Digital Collaborations


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Appendix IX

Knowledge Application: Is Improvising Worth Your Time? Challenges in Fostering Knowledge Application in Time-Critical Work Environments
Is Improvising Worth Your Time? Fostering Knowledge Application in Time-Critical Work Environments

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Abstract
Business decision makers have spent and continue to spend a great deal of resources to invest in information systems to support knowledge application. Yet, companies continue to encounter issues with knowledge application, mostly because of knowledge workers’ recurring difficulties in using the knowledge management systems (KMS). In response to the recurring difficulties with the existing KMS, knowledge workers often employ workarounds. The aim of this study is to enrich the current literature on knowledge application by analyzing the impact of workarounds on knowledge work performance in a time-critical environment. Through survey of 158 knowledge workers in a time-critical environment, we find that employing workarounds does not bring performance gains. In order to achieve superior work performance, such knowledge workers should continuously use and attempt to improve the existing KMS, instead of finding workarounds that may only bring temporary solutions. Contributions to the body of literature on knowledge management and information systems are outlined.

Keywords: workarounds in time-critical tasks, knowledge application, improvisation, knowledge management systems, knowledge work
Introduction

Knowledge is a key asset for organizations to remain competitive and create value in today's constantly changing business environment (Foss and Pedersen, 2002; Saleh et al., 2013). To effectively and efficiently leverage their knowledge assets, many enterprises implement knowledge management systems (KMS). KMS are a class of information systems (IS) designed to facilitate the management of organizational knowledge (Alavi and Leidner, 2001). More precisely, theoretically, KMS are information systems developed to support and enhance the organizational processes of knowledge creation, retrieval, storage, transfer, and application (Alavi and Leidner, 2001; Romano et al., 2001). However, in practice, organizations continue to encounter issues with respect to their knowledge creation, retrieval, storage, transfer, and application through their KMS. In response to these challenges, IS researchers investigated how organizations could achieve efficient and effective knowledge management processes through KMS.

Among the essential processes, knowledge application is arguably the most valuable process as it is the process of applying existing knowledge to solve specific problems and deriving business value from it (Lee and Sukoco, 2007). Yet knowledge application has been recognized as being the most understudied process in the knowledge management literature (Alavi and Tiwana, 2002; Datta, 2010).

Knowledge remains in many cases an intangible asset unless organizations are able to strategically apply that knowledge to gain economic benefits (Benbya et al., 2004; Fitzgerald et al., 2014). Yet, systematic research on knowledge application in terms of work performance in organizations is largely missing from the body of literature on knowledge management. Despite the extant literature on IS-enabled knowledge management processes (Massa and Testa, 2009), little research has empirically examined the effect of knowledge application on work performance in organizations (Zheng et al., 2010). Indeed, IS-enabled knowledge management plays an essential role in the ability of enterprises to apply existing knowledge effectively and to create new knowledge (Alavi and Leidner, 2001). However, successful KMS adoption and use do not guarantee that the systems will efficiently support knowledge application. In this sense, it is necessary to understand whether and how the adopted KMS are able to enhance work performance throughout the organization (Ahearne et al., 2008).

Although successful IS adoption and its efficient use are prerequisites for KMS success, post-adoption patterns of KMS use reportedly reveal that IS is often used differently than the intended use case design (Azad and King, 2008). Where mismatches occur between the expectations of IS use and the actual work practice, users may implement workarounds in order to handle recurring “exceptions to workflow” (Ferneley and Sobrepererez, 2006). The practice of workarounds usually consists of deviating from the initially designed use cases, or even bypassing the use of the system entirely (Koopman and Hoffman, 2003). Although workarounds are widespread IS post-adoption phenomena in organizations, the current literature does not provide a consistent view towards the impact of workarounds in knowledge application on work performance. Instead, the current body of literature suggests that workarounds may have an ambivalent character, i.e. may exert positive or negative effects on performance, depending on the context of the research (Mainemelis, 2010).

Our motivation in this research is to contribute to an improved theoretical and empirical understanding of the effect of workarounds on knowledge application success by means of superior work performance in a
time-critical environment. Our study addresses important but still unanswered questions: Do workarounds undermine the performance of knowledge workers in time-critical tasks? Or is it rather the case that workarounds represent a viable alternative to the use of existing KMS in time-critical tasks? In this paper we analyze the impact of workarounds on work performance by means of survey of employees in customer service department in a large IT organization; we contrast the employment of workarounds with the use of existing KMS in terms of knowledge application.

Building on a simplified version of DeLone and McLean’s updated IS success model (DeLone, 2003; DeLone and McLean, 1992), we find that in order to achieve superior work performance, knowledge workers should focus their activities on using the existing KMS. This means that improving the functionalities of the existing KMS should come before creating workarounds. The key contribution of this work to the current stream of literature on workarounds is to bring empirical evidence that workarounds employed in time-critical tasks do not necessarily lead to improved work performance in organizations. Instead, it is advisable for knowledge workers to cope with the existing KMS.

We proceed as follows. First, we review the current literature on information systems and knowledge management on the employment of workarounds in knowledge application and derive our research model. Second, we present the setting of the study and the method we obtained data. Next, we analyze the data, by contrasting the practice of workarounds with the use of existing KMS in terms of work performance. We report the differences between the two practices. We conclude by reviewing the limitations and contributions of our work.

**IS-Enabled Knowledge Management and IS Workarounds**

**KM Processes**

Information systems play an essential role in leveraging knowledge assets in organizations (Benbya and Belbaly, 2005; Lai, 2013; Sambamurthy and Subramani, 2005; Wasko and Faraj, 2005). Research on IS-enabled knowledge management in organizations has increasingly grown for several decades. The main streams of research include theoretical perspectives on the role of IS in knowledge management (von Krogh, 2009), empirical investigations of the drivers of KMS use (Jarvenpaa and Staples, 2000; McLure Wasko and Faraj, 2000) and of the determinants of KMS success (Merali et al., 2012; Mills and Smith, 2011; Schultze and Boland Jr, 2000), as well as examinations of KMS use in practice (Alavi and Leidner, 1999). Most notably, knowledge management systems facilitate four intertwined knowledge processes: (1) creation, (2) retrieval and storage, (3) transfer, and (4) application (Holzner and Marx, 1979; Massa and Testa, 2009; Pentland, 1995). Knowledge creation represents the development of new knowledge or replacement of existing knowledge with new knowledge from either internal or external sources (Pentland, 1995). Knowledge retrieval and storage refer to the processes of making knowledge more structured and accessible (Stein and Zwass, 1995). Knowledge transfer can generally be subdivided into knowledge sharing, i.e., the process by which knowledge is acquired and made available to those who need it (Appleyard, 1996; Majchrzak et al., 2004) and knowledge reuse, i.e., the process by which shared knowledge is being enriched or used further to create new knowledge (Argote and Ingram, 2000). Knowledge application is the process of applying existing knowledge to solve specific problems and
deriving value from it; that is, incorporating knowledge into an organization’s products, processes or services (Massa and Testa, 2009). Although all these processes are essential in achieving effective knowledge management using KMS (Alavi and Leidner, 2001), knowledge application has been recognized as being the most understudied process in the knowledge management literature (Alavi and Tiwana, 2002; Datta, 2010). Indeed, most of the literature consistently analyzed the role of information systems as effective means to (1) create, (2) retrieve and store, or (3) transfer knowledge (Arling and Chun; Benbya, 2011; Gold et al., 2001; Khalifa and Liu, 2003; Leidner et al., 2012; Romano et al., 2001; Sarin and McDermott, 2003), while (4) knowledge application has by far received less attention (Alavi and Tiwana, 2002; Datta, 2010). Yet this may be surprising, since efficient knowledge application is considered an antecedent of achieving superior work performance (Lee and Sukoco, 2007).

Knowledge Application

Previous studies on knowledge processes highlights that knowledge creation without its application may lead to a missing opportunity to leverage knowledge as a driver of organizational performance (Alavi and Leidner, 2001). Yet, systematic research on knowledge application in organizations is largely missing in the literature of knowledge management. The extant literature on knowledge management has often assumed that knowledge creation and accumulation implicitly lead to knowledge application (Datta 2010). Successful examples of knowledge management in practice reveal that organizations should develop viable routines that not only allow for effective storage of knowledge, but also for efficient application of that knowledge (Bhatt, 2001). In this sense, knowledge assets are of value for the organization up to the extent that they are applied whenever they are needed in the day-by-day operations of an organization (Dröge et al., 2003; Seleim and Khalil, 2007; Zahra and George, 2002). However, in practice, organizations continue to encounter issues in knowledge application, mainly because leveraging knowledge through KMS is often not easy to achieve (Benbya and Van Alstyne, 2011; Walsham, 2001). Understanding the factors that hinder knowledge application in organizations is thus of crucial importance.

Role of IS in Knowledge Application

To explain potential shortcomings in knowledge application in organizations, the IS literature is a suitable research venue. IS-enabled knowledge management plays an essential role in the ability of enterprises to manage existing knowledge effectively, see Kulkarni et al.’s knowledge management success model (2006). Over the last decades, IS literature has proposed several research models to explain technology use in organizations (Beaudry and Pinsonneault, 2010; Setia et al., 2013; Venkatesh et al., 2012). Most of these models have focused on how users accept IS, such as the technology acceptance model (Davis et al., 1989), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). In this sense, successful IS adoption has been found to be an antecedent of work performance, such as in the case of the IS success model of DeLone and McLean (2003). Subsequent research on adoption and use of technology (Burton-Jones and Straub Jr, 2006; Devaraj and Kohli, 2003) has further analyzed how users change their habit (Polites and Karahanna, 2013), attitudes towards technology (Ward et al., 2008), knowledge (Nambisan et al., 1999), work procedures and communication patterns during IS use (Beaudry and Pinsonneault, 2010; Sundaram et al., 2007).
Successful KMS adoption is not a guarantee, but rather a prerequisite that the IS will efficiently support knowledge application in the post-adoption phase (Zheng et al., 2010). Notably, while most of the attention of the IS community has focused on the positive or negative performance outcomes during the IS adoption phase (Lapointe and Rivard, 2005), little research has investigated the effect of IS use on performance in the post-adoption phase (Kane and Labianca, 2011). It is thus necessary to understand whether and how the adopted KMS are able to enhance work performance throughout the organization (Ahearne et al., 2008). This is in line with several calls for more consistent IS research into post-adoption behaviors (e.g., (Lapointe and Rivard, 2007)).

**IS Workarounds in Knowledge Application**

Post-adoption patterns of IS use in organizations repeatedly reveal that IS is often used differently than their intended use case design (Azad and King, 2008). Where mismatches occur between the expectations of IS use and the actual work practice, users may implement IS workarounds (Ferneley and Sobrepererez, 2006; Kobayashi et al., 2005) such as “informal temporary practices for handling exceptions to workflow” (Drum et al., 2014) or improvisations in business processes (Crossan et al., 2005; Cunha et al., 1999). More recently, workarounds have been comprehensively defined as “goal-driven adaptation, improvisation [...] of an existing work system in order to overcome, bypass, or minimize the impact of obstacles, exceptions, anomalies, mishaps, established practices, management expectations, or structural constraints that are perceived as preventing that work system or its participants from achieving a desired level of efficiency, effectiveness, or other organizational or personal goals.” (Alter, 2014). The practice of workarounds may thus range from deviating from the initially designed IS use cases, e.g., modifying existing software or their use cases (Sañá and Faraj, 2010), to bypassing the use of the system entirely (Koopman and Hoffman, 2003), as a manifestation of unease with an imperfect system (Hirschheim and Klein, 1994; Marakas and Hornik, 1996).

Although workarounds are an IS post-adoption phenomenon, the extant literature does not provide a consistent view towards the outcome of workarounds in knowledge application. Instead, the current body of literature suggests that workarounds may have an ambivalent character, i.e. may exert positive or negative effects on work performance, depending on context of the research (Mainemelis, 2010). On the one hand, IS research has acknowledged the potential of workarounds in IS to create viable organizational processes, to improve existing processes, and even to innovate (Boudreau and Robey, 2005; Ciborra, 2004; McGann and Lytinen, 2008; Pentland and Feldman, 2008; Rüder et al., 2014; Wagner and Newell, 2006). For example, users may create workarounds in form of custom methods in order to compensate shortcomings of technology functionalities (Davison et al., 2013; Huuskonen and Vakkari, 2013; Mason et al., 2002; Strong and Volkoff, 2010). On the other hand, workarounds have further been regarded as deviations from defined routines that may threaten performance using IS (Azad and King, 2012; Bagayogo et al., 2013; Ignatiadis and Nandhakumar, 2009; Lapointe and Rivard, 2005). It is thus not clear whether workarounds in knowledge application are beneficial or detrimental in terms of work performance (Halbesleben et al., 2008). What is missing from the current literature is a consistent perspective towards the impact of workarounds on performance in time-critical knowledge application tasks (Orlikowski and
To address this research gap, we proceed by contrasting the usage of traditional KMS with the practice of workarounds in terms of KM success in a time-critical enterprise context. To do so, we employ a simplified version of DeLone and McLean’s updated IS success model (2003).

Research Hypotheses

We first consider DeLone and McLean’s (2003) updated IS success model as the starting point to derive the hypotheses of our theoretical model. The model is further used to contrast the practice of workarounds with the use of existing KMS in terms of work performance (Kulkarni et al., 2007). Previous studies found positive relationships between system quality and IT use (Caldeira and Ward, 2003; Fitzgerald and Russo, 2005). For instance, system quality, measured as perceived ease of use is positively related to behavioral intentions to use the system (Venkatesh et al., 2003). Other studies operationalized system use as extent of use and found a positive effect of perceived ease of use on system use (Hsieh and Wang, 2007; Igbaria and Tan, 1997). Accordingly, we hypothesize:

\[ H1: \text{KMS quality has a positive effect on KMS use.} \]

There exists strong support for the positive effect of system quality on net benefits. Most of the studies have found a significant relationship (Agarwal and Prasad, 1999; Hsieh and Wang, 2007; Wixom and Todd, 2005; Yang and Yoo, 2004), while only several others have found no significant association (Chau and Hu, 2002; Subramanian, 1994). Moreover, the technical performance of an IS was found to indirectly affect the perceived value of the system, mediated by user satisfaction (Weill and Vitale, 1999). The quality of an IS was further found to be related to organizational efficiency (Farhoomand and Drury, 1999). Another study found the relationship between system quality and impact of use to be positive at all operational, tactical, and strategic levels (Bradley et al., 2006). We thus hypothesize:

\[ H2: \text{KMS quality has a positive effect on work performance.} \]

Previous IS literature found that IS use positively affects performance. For instance, Yuthas & Young (Yuthas and Young, 1998) found that the duration of system use correlates with performance. In this sense, many studies report positive relationships between system use and net benefits, measured as task performance or improvements in job performance (D’Ambra and Rice, 2001; Kositanurit et al., 2006; Seddon, 1997). Thus we can hypothesize:

\[ H3: \text{KMS Use has a positive effect on work performance.} \]

User satisfaction has been previously found to positively influence the frequency and duration of use (Guimaraes and Igbaria, 1997). In line with this result, Winter et al. (1998) found that satisfaction with the system is correlated to the amount of use. Several other studies have found a significant correlation between self-reported system use and user satisfaction (Torkzadeh and Doll, 1999). Given these results and the positive impact of system quality on system use, we may hypothesize:
H4: Satisfaction with quality of knowledge mediates the effect of KMS quality on knowledge application.

System quality, measured in terms of technical performance of an IS was found to indirectly affect the perceived value of the system, mediated by user satisfaction (Weill and Vitale, 1999). As regards to the impact of user satisfaction on net benefits, previous research has shown a strong effect of the former on the latter (Gelderman, 1998; Iivari, 2005). In this sense, user satisfaction has been found to improve performance and to increase productivity and effectiveness (Igbaria and Tan, 1997; McGill and Klobas, 2005; Rai et al., 2002). Yet similar results were found when evaluating the relationship between user satisfaction and organizational performance of IT systems (Law and Ngai, 2007). Given these results and the positive impact of system quality on net benefits, we may hypothesize:

H5: Satisfaction with quality of knowledge mediates the effect of KMS quality on work performance.

Figure 1 below presents our research model. The four main constructs are depicted from the updated IS success model of DeLone and McLean (2003). We build our investigations on this model and to contrast the employment of workarounds with the use of existing knowledge management systems. The next section of this paper emphasizes the research setting and the way we empirically test this research model.

Figure 1: Research model to contrast the use of workarounds against the use of existing KMS
Methodology

In order to test our research model for the use of both existing KMS and workarounds, we use a cross-sectional survey design (Boudreau et al., 2004; Burton-Jones and Straub Jr, 2004; Straub et al., 2004). We contend that employing a survey is appropriate to extract generalizable insights from the use of workarounds and compare these against the use existing KMS.

Research Setting/Design

Our research on workarounds practices in knowledge application is situated at the customer service department of a large technology provider. The customer service department under study provides support to technical problems encountered by clients. It is not unusual for the customer service department to cover countless technology-related products and services, such as software, hardware, or network related issues. Given that the complexity of IS infrastructures has significantly increased in the last years, clients may nowadays encounter a wider range of technical problems that in turn require increasingly complex solutions. Consequently, clients may often need to wait considerably longer or even contact customer service specialists several times before their enquiries are adequately addressed. The customer service department under study faces two important challenges in supporting their clients. First, clients expect instant answers to their questions, as customer service is a first contact place for them to relate to their technical problems, making their work time-critical (Reddy et al., 2006; Workman and Bommer, 2004). In this sense, Heckman and Guskey (1998) assert that “help unavailable when needed” is one of the major reasons for service delivery failure in the help desk, as it may lead to user dissatisfaction more often than not. Second, an important goal for the customer service department is to reduce call handling duration via continuous tracking and assessment of efficiency. It is thus required to develop mechanisms that enable customer service specialists to time-efficiently solve the overwhelming customer enquiries.

InfoWeb, KnowledgeBase, and workarounds. The customer service department has two KMS that guide the customer service specialists when solving time-critical customer cases, namely InfoWeb and KnowledgeBase. These two knowledge management systems are deeply embedded in the customer service practice. The solutions provided to customers are in the form of actionable knowledge to solve customer enquiries, which are stored in both InfoWeb and KnowledgeBase. Usually, customer service specialists attempt to find answers to client enquiries using primarily the InfoWeb platform. If answers in terms of actionable knowledge are not to be found in InfoWeb (see screenshot in Figure 2), customer service specialists have the alternative to gain in-depth technical knowledge with the help of the KnowledgeBase platform (see screenshot in Figure 3). Although InfoWeb and KnowledgeBase were designed to complement each other in the customer service practice, it appears that customer specialists have repeatedly encountered difficulties in applying relevant knowledge from these two systems when dealing customer requests. In this sense, a significant proportion of customer specialists have been employing custom methods (i.e. workarounds) to help them compensate the shortcomings of InfoWeb and KnowledgeBase. It is not unusual for customer service practice to make use of workarounds, as this practice has been documented in a series of studies before (Alter, 2014; Lederman and Parkes, 2005). In the next section we present the data collection procedure, as well as the way we contrasted the practice
of workarounds against InfoWeb and KnowledgeBase in terms of work performance in a time-critical context.

![Figure 2: Screenshot of InfoWeb](image)

![Figure 3: Screenshot of KnowledgeBase](image)

**Data Collection**

Data for this study was collected from surveying customer service specialists. A total of 158 responses were returned. Respondents were customer service specialists (102 male and 56 female), 46% of them had more than 5 years of experience in customer service, while 53% activated for at least 2 years in the
current position. 65% of respondents were 35 or less. The descriptive characteristics of the sample are included in the first two columns of Table 1 in Appendix C.

**Content Validity.** We acknowledge that surveys alone have intrinsic limitations with regard to uncovering fine-grained insights into the phenomenon under research. These insights can be better addressed via qualitative research. In this study, to ensure content validity and a greater level of insight for the items used in the survey, we employed the approach proposed by Burton-Jones and Straub (Burton-Jones and Straub, 2006). Following our literature review on KMS and before creating the measures that tie together the constructs in our research model, we interviewed customer service specialists to gain a comprehensive understanding of the practices in knowledge application at the customer service department. We specifically asked about the functionalities and the use of the knowledge management systems from the point of view of customer service specialists. This step was essential to identify all the important aspects of the knowledge application practice at the department under study and ensure that the survey is constructed according to these issues identified during interviews. Moreover, we included appropriate instrument design and data collection procedures (Soliman and Beaudry, 2010) such as neutral wording of the items for each construct. We further reduced the threat of common method bias by ensuring anonymity of the respondents, assuring them that there were no right or wrong answers, and requesting that they answer each question as honestly as possible (Podsakoff et al., 2003). Finally, with the help of interviews, we captured the whole spectrum of *channels of knowledge* (i.e., InfoWeb, KnowledgeBase or workarounds) used by customer service specialists in the KMS practice.

In a nutshell, data from interviews indicate a low or vastly unexploited potential of search functionalities in both InfoWeb and KnowledgeBase. On the one hand, search in KnowledgeBase appears to be difficult to use and is by far not exploited at its potential: customer service specialists are not fully aware of how to refine search results and thus prefer not to use KnowledgeBase for solving customer cases; on the other hand, InfoWeb does not offer suitable support for refining the output of the search, but appears to contain more comprehensive applicable knowledge than KnowledgeBase. The interviews further revealed that especially KnowledgeBase contains an insufficient number of records, which determined customer service specialists to tend to avoid using it and look for alternatives instead. In addition to using of InfoWeb, customer service specialists have started employing different workarounds. A summary of all the issues identified following our interviews is presented in Table 1 below.

<table>
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<th>Aspect</th>
<th>Summary of finding</th>
<th>Interview quotation</th>
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<tbody>
<tr>
<td><strong>Search in InfoWeb</strong></td>
<td>The search engine in InfoWeb is very sensitive to the keywords that are typed in</td>
<td>“In InfoWeb if I use the wrong word I might get no answers […] one word makes a difference. In Google I just enter any word and it still gives me answers.”</td>
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<tr>
<td></td>
<td>The search in InfoWeb is slow</td>
<td>“I think [that the search in InfoWeb] could be faster, […] it would be easier if it would be like a Wiki, Wikipedia type of solutions or something like that and the searches would be fast”</td>
</tr>
<tr>
<td><strong>Search in KnowledgeBase</strong></td>
<td>The search in KnowledgeBase provides many irrelevant answers</td>
<td>“The organisation [in KnowledgeBase] is so bad [...] In KnowledgeBase I might have like a thousand answers. And then I start clicking. And at the same time I have a customer waiting for</td>
</tr>
</tbody>
</table>
an answer ...;"

"It's like you [type in a query] and you search ... and the KnowledgeBase offers you ... any possible kind of answer"

<table>
<thead>
<tr>
<th>Creation of a novel search tool, independent of InfoWeb and KnowledgeBase</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Our [...] team is totally different from the other groups. We have made a Java-based search tool&quot;;</td>
</tr>
<tr>
<td>&quot;The tool is developed by our colleagues ... it's one additional tool in this house... it tries to find all the documents which are containing the word that you are looking for ...&quot;.</td>
</tr>
</tbody>
</table>

Search workarounds

<table>
<thead>
<tr>
<th>Development of customer-specific guides, as alternative to search from InfoWeb and Knowledge Base</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;[…] we have also made for ourselves like a guide, where you can find all the [customer specific] information. And if the information is not there, and we find an answer to that question, we just add it in that guide.”</td>
</tr>
<tr>
<td>&quot;Sometimes we use the guide that we have. We have the most [frequent problems described] there. […] And it's it takes about minute or two to find all the needed information from this guide. […] the simplest way, and the fastest way is to use this guide, where where we can find all the information.”</td>
</tr>
<tr>
<td>&quot;We have created Excel files where there are certain problems or programs [described]. What to do in case of if the password is locked... So we can first look at the Excel file”</td>
</tr>
</tbody>
</table>

Table 1: Summary of interview insights

**Construct Measurement**

Based on findings from previous studies, theoretical deliberations, and the insights gained from interviews with customer service specialists, we created measures that tie together the constructs in the research model. All constructs were operationalized with reflective indicators (Jarvis et al., 2003). We discuss the definition, operationalization, and source of the main constructs in the model as follows.

**Measuring system quality.** System quality refers to the desirable characteristics of an information system (Petter et al., 2008). Over time, several instruments have been proposed to measure system quality factors (Rivard et al., 1997; Yap et al., 2007). Among them, system features has been developed and validated as a dimension of system quality construct in the IS success model (Petter et al., 2008). For our research setting, according to the insights gathered during interviews, we focus our investigation on the most prevalent system feature used by customer support specialists, namely the search functionality. Relative to a technology functionality, **simplicity** is defined as the directness and singleness of a functionality, a combination of elements that results in ease of comprehending the meaning of the functionality (Galitz, 2007). In this sense, **simplicity of search** is the most prevalent system functionality used by customer service specialists in their work, see construct “Simplicity of search functionality” in Table 1 Appendix A.
Measuring user satisfaction. Satisfaction with the quality of a system has been overly used in the previous IS literature (Durcikova and Gray, 2009; Rai et al., 2002). In this study, we are focused on satisfaction with the quality of knowledge as indicator for the choice of a channel of knowledge as support in the knowledge application process, see construct “Satisfaction with quality of knowledge in Table 1 Appendix A.

Measuring system use. Knowledge application is “the phase in which existing knowledge is brought to bear on the problem at hand” in order to support organization’s processes, products or services (Alavi and Tiwana, 2002). Empirical studies have adopted several measures of knowledge application, the most commonly employed being employed by Choi et al. (2010). We use an adaptation of this self-reported measure in order to quantify the extent to which customer service specialists use customer-specific knowledge from a channel of knowledge in order to solve a customer case, see construct “Knowledge application” in Table 1 Appendix A.

Measuring work performance. There are several ways to measure work performance, the most encountered are in terms of work efficiency and work effectiveness at the individual level. As stressed by Petter et al. (2008), a key point to consider when measuring organizational benefits is that researchers must ensure that the person self-reporting organizational benefits is indeed in the position to offer accurate information on work performance. In our research setting, customer service specialists are confronted on a daily basis with up-to-date summaries of their performance from the previous day and of the overall week; the interviews revealed that they are aware of how they perform during each day. In service industries, such is the present case, the primary need for knowledge management systems is to reduce variation in organizational processes, thereby increasing efficiency; as customer support specialists have clear time targets that need to be achieved, they have to stay effective over their work (Schmenner, 2009). In this context, time becomes a key parameter for performance measurement. Notably, we ensured that the self-reported work efficiency is correlated with the actual efficiency figures, confirming that customer service specialists are well aware of their efficiency figures. Although we have attempted to get the actual efficiency figures, this was not possible because of confidentiality issues. Details on the measurement are presented under construct “Work efficiency” in Table 1 Appendix A.

As controls we consider factors that have been previously shown in the literature to impact knowledge application and work efficiency. We included the demographic variables of gender, age, experience, experience in the current position and work experience, as well as variables characterizing the work environment, namely job stress level, training, sourcing from colleagues, and task analyzability. An overview of all the variables is presented in Table 1 Appendix A.

Conceptual Validation. Before administering the survey, we assessed the conceptual validity of the items by adopting Moore and Benbasat’s (Moore and Benbasat, 1991) procedure. The conceptual validation was carried out using structured sorting (with variable category labels). The goal was to gain a clear indication of the validity of constructs used, i.e., confirm that the items are indeed measuring what they are supposed to measure. A set of 5 judges (researchers with substantial experience in the fields of information systems and knowledge management) was used for sorting the items. The sorting was organized in a web environment. Based on the sorting results, we revised the scales and similarly
conducted a second sorting that indicated good construct validity. Following this positive result, we distributed the questionnaire to customer service specialists. Appendix A shows a detailed summary of construct operational definitions and scales.

**Data Analysis and Results**

We used the partial least squares (PLS) modeling technique for our data analysis, as it is suitable for causal-predictive analysis (Henseler et al., 2012; Straub et al., 2004). Given that this study was an early attempt to develop a model for knowledge application and work performance benefits, PLS therefore was appropriate. As a general rule, the minimum sample size for a reliable survey should at least be 10 times as many observations as there are number of constructs (Sarstedt et al., 2011). As there were 13 constructs in our study, a sample size of 158 was deemed appropriate. Below we present the assessment of both the measurement model and the structural model.

**Measurement Model Evaluation and Common Method Bias**

The questionnaire consisted of reflective constructs whose validities were evaluated as follows. The strength of the measurement model was demonstrated through convergent validity, i.e., the extent to which two or more items measure the same construct. The convergent validity of these constructs was assessed in three ways: (1) item reliability (i.e., Cronbach’s alpha), (2) composite reliability, and (3) average variance extracted (i.e., AVE) for each construct. The generally accepted threshold for item and composite reliability is 0.7 (Gefen et al., 2011), whereas the threshold for average variance extracted is 0.5 (Hair et al., 2013). As shown in Tables 1-3 in Appendix C, all our items load well on the respective constructs: all constructs have item and composite reliability of over 0.7 and AVE of over 0.5. Tables 1-3 in Appendix D further present the latent variable correlations among the constructs in our research model. The item loadings should be considerably higher than the cross-loadings on other constructs (Straub et al., 2004). This is supported in our results so that indicator reliability and discriminant reliability is present in our measurement model (Hair et al., 2013). Tables 1-3 in Appendix C further allow us to check for the Fornell-Larcker criterion in order to ensure discriminant validity (Fornell and Larcker, 1981). The results show that the square root of the AVE of each latent construct is higher than the construct’s highest correlation with any other latent construct, indicating good discriminant validity (Hair et al., 2011). Altogether we conclude that the convergent and discriminant validities of the constructs are satisfactory, thus our items measure the respective constructs appropriately. Given the satisfactory measurement model, our hypotheses could then be tested by examining the structural model.

**Structural Model Evaluation**

Tables 1 and 2 in Appendix B show the evaluation results of the structural model - the $R^2$ coefficients and the path coefficients along with their respective significance levels from PLS analysis - for work efficiency (Table 1 Appendix B) and knowledge application (Table 2 Appendix B). The explanatory power of the structural model was assessed based on the amount of variance in the endogenous constructs for which the model could account. After computing parameter estimates for all paths in the structural model, PLS employed a bootstrap resampling technique to compute the significant level (t-values) for all paths (see Tables 1-2 Appendix B). Given that each hypothesis corresponded to a path in the structural model, support for each hypothesis could be determined based on the sign (positive or negative) and statistical
significance of its corresponding path in Tables 1-2 in Appendix B. Each table presents the results across all the three channels of knowledge. Coefficients highlighted in red represent non-significant relationships. Below we provide detailed interpretations for each channel of knowledge with respect to the relationships hypothesized. We first discuss direct effects (H1, H2, and H3), followed by mediation effects (H4 and H5).

**Direct effects.** As for H1, Table 2 Appendix B consistently shows the importance of simplicity of search functionality on knowledge application from all channels of knowledge. That is, search simplicity has a strong positive effect on knowledge application, independent whether the channel of knowledge taken into account is InfoWeb, KnowledgeBase, or workarounds. This result provides full support for H1. Relative to H2, the effect of simplicity of search functionality on work efficiency does not show a consistent pattern across the different channels of knowledge. Notably, we find support only for the positive effect in the case of InfoWeb, see Table 1 Appendix B. Interestingly, testing for H3 reveals the same pattern as for H2, in the sense that only knowledge application from InfoWeb shows a positive effect on work efficiency.

**Mediation analysis.** As regards to the mediation paths in our model, we find that satisfaction with quality of knowledge in InfoWeb partially mediates the positive relationship between simplicity of search and knowledge application. However, this pattern does not hold for either KnowledgeBase or workarounds. Thus, H5 was not supported.

A summary of all hypotheses is presented in Table 2 below. Altogether, the confirmation of H1 highlights that simplicity of search functionality is crucial for customer service specialists when deciding to use the appropriate channel of knowledge. However, when it comes to work performance, only the use of InfoWeb significantly influences work performance of customer service specialists. This highlights the key contribution of this work to the current stream of literature on workarounds: to achieve superior work performance, knowledge workers should primarily use the existing KMS, instead of attempting to employ workarounds. This means that improving the functionalities of the existing KMS should come before attempting to create workarounds. It is thus advisable for knowledge workers to cope with the existing KMS, instead of attempting to find workarounds that may represent only temporary solutions.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Evaluation InfoWeb</th>
<th>Evaluation KnowledgeBase</th>
<th>Evaluation Workarounds</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Simplicity of search functionality has a positive effect on knowledge application.</td>
<td>Supported</td>
<td>Supported</td>
<td>Supported</td>
</tr>
<tr>
<td>H2: Simplicity of search functionality has a positive effect on work efficiency.</td>
<td>Supported</td>
<td>Not supported</td>
<td>Not supported</td>
</tr>
<tr>
<td>H3: Knowledge application has a positive effect on work efficiency.</td>
<td>Supported</td>
<td>Not supported</td>
<td>Not supported</td>
</tr>
<tr>
<td>H4: Satisfaction with quality of knowledge mediates the effect of simplicity of search functionality on knowledge application.</td>
<td>Supported</td>
<td>Not supported</td>
<td>Not supported</td>
</tr>
<tr>
<td>H5: Satisfaction with quality of knowledge mediates the effect of simplicity of search functionality on work efficiency.</td>
<td>Not supported</td>
<td>Not supported</td>
<td>Not supported</td>
</tr>
</tbody>
</table>
Discussion and Conclusion

This study analyzed the impact of employing workarounds on performance in time-critical knowledge work. As hypothesized, the results highlight the importance of using the existing KMS, despite the inherent difficulties encountered in the daily knowledge work. However, the employment of workarounds has been found not to bring an improvement in the performance of knowledge work in time-critical environments. The global picture shows that knowledge workers should rather spend time on dealing with the drawbacks of the existing KMS, instead of attempting to create workarounds. It is generally advisable for knowledge workers to cope with the existing KMS, instead of attempting to find workarounds that may represent only temporary solutions.

The findings of this study have to be viewed in light of several limitations. With regard to the research setting, the study is employed in one large traditional organization. We acknowledge that this may generate a bias in our results. Indeed, it would be worthwhile to complement the results of this study with insights on workaround practices from other companies, and, if possible, from other industries. Of particular interest would be to compare our results with the potential effect of workarounds on work performance in time non-critical work environments. A further limitation of this study is the lack of objective data, which is due to the fact that objective data on work performance is difficult to obtain because of confidentiality issues. Indeed, for this investigation, we have primarily used self-reported data from surveys and interviews. We acknowledge that this study could be complemented with the analysis of more objective data. Given the difficulty to obtain performance data, we have devoted special attention to ensure content validity and avoid potential biases.

Nonetheless, by examining the workaround practices in knowledge application in a time-critical environment, this study has important implications for both knowledge management as well as information systems literature. Relative to the knowledge management literature, this is one of the few studies to analyze the direct link between knowledge application and work performance. This was possible due to the setting of the study; that is, in a time-intensive environment, such is the case of this study, there is very little time between using the KMS and closing a customer case. Notably, most of the knowledge management studies in conventional settings (i.e., time non-critical work environments) that analyze system use do not go further into assessing work performance, as the theoretical link is not very direct such as in the case of time-critical contexts. Thus, in our study, we are able to capture the direct effect of knowledge application on work performance with little or no noise. With respect to the contribution to the information systems literature, this research is one of the first studies to look at computer workarounds in knowledge application. The study thus constitutes a response to recent calls to produce more consistent IS research into post-adoption behaviors, see (Lapointe and Rivard, 2007). Additionally, the study extends recent post-adoption research on motivation for differences in technology use in an enterprise context (Li et al., 2013). By studying workarounds, our study regards the whole spectrum of technologies used by the customer service department, instead of focusing on the use of a particular technology.
Appendix A: Construct operational definitions and scales

<table>
<thead>
<tr>
<th>Name of construct</th>
<th>Operational definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>System quality</td>
<td>System quality refers to the desirable characteristics of an information system (Petter et al., 2008). Among them, system features has been developed and validated as a dimension of system quality construct in the IS success model (Petter et al., 2008). For our research setting, according to the insights gathered during interviews, we focus our investigation on the most prevalent system feature used by customer support specialists, namely the simplicity of the search functionality. We propose to measure simplicity of search functionality relative to each channel of knowledge used by customer service specialists using the following item: Searching for content in [channel of knowledge] is simple.</td>
</tr>
<tr>
<td>Satisfaction with the quality of knowledge</td>
<td>Satisfaction with the quality of knowledge has been overly used in the previous IS literature, see (Durcikova and Gray, 2009; Rai et al., 2002). In this study, we are focused on satisfaction with the quality of knowledge as indicator for the choice of a channel of knowledge as support in the knowledge application process. We measure the satisfaction with the quality of knowledge in each channel of knowledge using the following standard items: (1) The content in [channel of knowledge] meets my needs; (2) I am satisfied with the content in [channel of knowledge]; (3) The overall quality of content in [channel of knowledge] is high.</td>
</tr>
<tr>
<td>Knowledge application</td>
<td>Knowledge application is &quot;the phase in which existing knowledge is brought to bear on the problem at hand&quot; in order to support organization's processes, products or services (Alavi and Tiwana, 2002). Empirical studies have adopted several measures of knowledge application, the most commonly hand in order to support organization's processes, products or services (Alavi and Tiwana, 2002). We use an adaptation of this self-reported measure in which existing knowledge is brought to bear on the problem at hand. Knowledge application is measured through the following items: (1) To what extent do you use knowledge from [channel of knowledge] when solving a customer case? (2) When working on a customer case, to what extent do you look in [channel of knowledge] for support?</td>
</tr>
</tbody>
</table>
There are several ways to measure work performance, the most encountered are in terms of work efficiency and work effectiveness at the individual level. As stretched by Petter et al. (2008), a key point to consider when measuring organizational benefits is that researchers must ensure that the person self-reporting organizational benefits is indeed in the position to offer accurate information on work performance. In our research setting, customer service specialists are confronted on a daily basis with up-to-date summaries of their performance from the previous day and of the overall week; the interviews revealed that they are aware of how they perform during each day. In service industries, such as the present case, the primary need for knowledge management systems is to reduce variation in organizational processes, thereby increasing efficiency; as customer support specialists have clear time targets that need to be achieved, they have to stay effective over their work (Schmenner, 2009). In this context, time becomes a key parameter for performance measurement, thus time efficiency. We thus measure work performance by time efficiency using the following item (Bstieler, 2005; Bstieler and Hemmert, 2010):

To what extent are you able to operate efficiently when solving customer cases?

Likert: 1=Strongly Disagree, 6=Strongly Agree

<table>
<thead>
<tr>
<th>Experience in the current position (expposition)</th>
<th>Dummy: current position</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=less than 6 months, 2=range of 6 months</td>
<td></td>
</tr>
<tr>
<td>3=range of 6 months, 4=range of 1 to 2 years</td>
<td></td>
</tr>
<tr>
<td>5=range of 1 to 2 years, 6=more than 10 years</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Work expertise (Expertise)</th>
<th>How long have you been working in customer service? (workexperience)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=less than 6 months, 2=range of 6 months</td>
<td></td>
</tr>
<tr>
<td>3=range of 6 months, 4=range of 1 to 2 years</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender (Gender)</th>
<th>What is your gender?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=female, 2=male</td>
<td></td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Age (age)</th>
<th>What is your age range?</th>
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</thead>
<tbody>
<tr>
<td>1=21 and under; 2=22 to 34; 3=35 to 44; 4=45 to 54; 5=55 to 64; 6=65 and over</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender (Gender)</th>
<th>What is your gender?</th>
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</thead>
<tbody>
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<td></td>
</tr>
</tbody>
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<tr>
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<th>What is your age range?</th>
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<tbody>
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<td>3=range of 6 months, 4=range of 1 to 2 years</td>
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</tr>
<tr>
<td>5=range of 1 to 2 years, 6=more than 10 years</td>
<td></td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Work expertise (Expertise)</th>
<th>How long have you been working in customer service? (workexperience)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=less than 6 months, 2=range of 6 months</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>5=range of 1 to 2 years, 6=more than 10 years</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
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<th>What is your gender?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=female, 2=male</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age (age)</th>
<th>What is your age range?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=21 and under; 2=22 to 34; 3=35 to 44; 4=45 to 54; 5=55 to 64; 6=65 and over</td>
<td></td>
</tr>
</tbody>
</table>
Job stress level (JobStressLevel) was operationalized as in (Shigemi et al., 2000), using the following items:

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Too much trouble at work</td>
</tr>
<tr>
<td>2</td>
<td>Too much work to handle</td>
</tr>
<tr>
<td>3</td>
<td>Pressure on SD employees</td>
</tr>
</tbody>
</table>

Training (Training) was operationalized as in (Chen and Huang, 2009), using the following items:

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Never</td>
</tr>
<tr>
<td>6</td>
<td>Very frequently</td>
</tr>
</tbody>
</table>

Sourcing form (SourcingColleagues) of knowledge refers to the extent to which you communicate with your colleagues when you need assistance or information.

Task analyzability (Analyzability) refers to the extent to which there is already an acceptable solution to a given task, or the extent to which tasks can be managed by a clear set of procedures as opposed to requiring sophisticated judgment (Perrow, 1967). Less analyzable tasks are subject to causal ambiguity with respect to their performance implications. We measure task analyzability as a function of the characteristics of each task and the experience of the task performer.
Analyzability using the following items which were adapted from Adler’s (1995) and Nidumolu’s (1995)

<table>
<thead>
<tr>
<th>Construct and Measurement Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are there common practices to work on customer cases?</td>
</tr>
<tr>
<td>Are there precise instructions that can be followed when solving customer cases?</td>
</tr>
<tr>
<td>To what extent is there a clearly known way to solve a customer case?</td>
</tr>
</tbody>
</table>

Table 1: Construct and Measurement Summary
Appendix B: Results

<table>
<thead>
<tr>
<th>Work Efficiency</th>
<th>InfoWeb</th>
<th>KnowledgeBase</th>
<th>Workarounds</th>
<th>InfoWeb</th>
<th>KnowledgeBase</th>
<th>Workarounds</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M1-Controls</td>
<td>M2-Controls+Predictors</td>
<td>M1-Controls</td>
<td>M2-Controls+Predictors</td>
<td>M1-Controls</td>
<td>M2-Controls+Predictors</td>
</tr>
<tr>
<td></td>
<td>T- Coef. score</td>
<td>T- Coef. score</td>
<td>T- Coef. score</td>
<td>T- Coef. score</td>
<td>T- Coef. score</td>
<td>T- Coef. score</td>
</tr>
<tr>
<td>Controls</td>
<td>Age</td>
<td>0.04 n.s.</td>
<td>0.00 n.s.</td>
<td>0.04 n.s.</td>
<td>0.05 n.s.</td>
<td>0.04 n.s.</td>
</tr>
<tr>
<td></td>
<td>Gender</td>
<td>0.06 n.s.</td>
<td>0.06 n.s.</td>
<td>0.06 n.s.</td>
<td>0.07 n.s.</td>
<td>0.06 n.s.</td>
</tr>
<tr>
<td></td>
<td>ExpPosition</td>
<td>0.06 n.s.</td>
<td>0.04 n.s.</td>
<td>0.06 n.s.</td>
<td>0.06 n.s.</td>
<td>0.06 n.s.</td>
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<tr>
<td></td>
<td>WorkExpertise</td>
<td>0.15 n.s.</td>
<td>0.17 2.08</td>
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<td>0.17 n.s.</td>
<td>0.16 n.s.</td>
</tr>
<tr>
<td></td>
<td>JobStressLevel</td>
<td>-0.14 n.s.</td>
<td>-0.11 n.s.</td>
<td>-0.15 n.s.</td>
<td>-1.97</td>
<td>-0.14 2.00</td>
</tr>
<tr>
<td></td>
<td>Training</td>
<td>0.06 n.s.</td>
<td>0.01 n.s.</td>
<td>0.06 n.s.</td>
<td>0.07 n.s.</td>
<td>0.06 n.s.</td>
</tr>
<tr>
<td></td>
<td>SourcingColleagues</td>
<td>0.03 n.s.</td>
<td>-0.03 n.s.</td>
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Table 1: Results for work efficiency for InfoWeb, KnowledgeBase, and workarounds

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Table 2: Results for knowledge application for InfoWeb, KnowledgeBase, and workarounds
### Appendix C: Descriptive Statistics and Correlations

#### Table 1: Descriptive statistics and correlations for InfoWeb.

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<th>Correlation with other variables</th>
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Note: Diagonal elements represent the square root of the AVE. Off diagonal elements are the correlations.
Table 2: Descriptive statistics and correlations for KnowledgeBase. Diagonal elements represent the square root of the AVE. Off-diagonal elements are the correlations.

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Note: Mean = 5.2, SD = 2.8
Table 3: Descriptive statistics and correlations for workarounds. Diagonal elements represent the square root of the AVE. Off-diagonal elements are the correlations.

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### Appendix D: Cross-loadings

#### InfoWeb

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#### Table 1: Cross-loadings for InfoWeb

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- Cross-loadings for InfoWeb
- Table 1: Cross-loadings for InfoWeb
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Table 2: Cross-loadings for KnowledgeBase

Table 3: Cross-loadings for workarounds
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