LEVERAGING SOCIAL CAPITAL IN THE VIRTUAL WORK ENVIRONMENT - KNOWLEDGE EXCHANGE THROUGH SOCIAL MEDIA PLATFORMS

Immanuel Pahlke
Goethe University Frankfurt

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LEVERAGING SOCIAL CAPITAL IN THE VIRTUAL WORK ENVIRONMENT – KNOWLEDGE EXCHANGE THROUGH SOCIAL MEDIA PLATFORMS

Pahlke, Immanuel, Frankfurt University, Grüneburgplatz 1, House of Finance, 60323 Frankfurt, Germany, pahlke@wiwi.uni-frankfurt.de

Abstract

Collaboration in information-intensive work environments is enabled through information systems that facilitate the information and knowledge exchange between collocated employees. As prior research suggests, social media platforms are a promising solution to realize electronic networks of practice bridging the gap between knowledge seeker and experts as a source of knowledge in an effective manner. To enhance the understanding of the social and structural characteristics that underlie employee’s interactions and how each individually benefit from participating in electronic networks of practice, we analyze the content of 15,505 enterprise microblogging messages created by 1,166 employees of a multi-national financial institution. Specifically, we explore how social capital is build up on an individual level and how individuals can leverage their central position with respect to knowledge improvements through faster message replies of a higher quality. Our study provides first insights on how knowledge exchange through social media is influenced by the different forms of social capital. The results stress the positive effect of social capital on individual’s information and knowledge reception as an important part of individual sensing capabilities. Thereby, we find empirical evidence that social media platforms can be utilized to facilitate collaboration and cooperative exchanges efficiently.

Keywords: Electronic Networks of Practice, Enterprise Social Media, Knowledge Exchange, Social Capital
1 Introduction

Effective knowledge exchange among employees is critical for problem solving and innovation. To address this issue, systems are needed to support the exchange of information and knowledge between distributed workers efficiently (Chiu et al., 2006). Since knowledge exchange takes place to a large extent through social interactions, spanning social networks that are enabled through electronic interactions between collocated individuals sharing a common practice have to be established. As prior research has shown, such electronic networks of practice (ENoP) make it possible to exchange knowledge quickly and globally between a large number of individuals (Wasko and Faraj 2005). In this context, social media platforms (SMP) are considered a promising solution for building ENoP (Shirky, 2009). Leveraging the connectivity of the WWW with a variety of Internet-based technologies such as wikis, blogs, and microblogging platforms, social media changes the way users collaborate and exchange knowledge through flexible relationships with collocated experts (Culnan et al., 2010). As a result, organizations have started to explore the business value of these platforms. However, while some research on social media has been conducted in the public domain, very few studies have been carried out in a corporate context (Riemer et al. 2010, Richter et al. 2011). Consequently, there have been several calls for more dedicated research on the use of social media in enterprises, specifically with respect to the question of how these technologies might be leveraged for effective knowledge exchange. What is needed is a better understanding of the social and structural characteristics that influence interactions between employees. Extant research in this field already have elaborated on individual’s knowledge contribution and knowledge sharing behavior in ENoP (Chiu et al. 2006; Wasko and Faraj 2005; Law and Chan 2008). However, it is still unclear how each individual benefits from participating in ENoP. Building upon social capital theory, comprising structural, relational, and cognitive capital (Nahapiet and Ghoshal 1998), we therefore emphasize on the following research question: How can individuals benefit from establishing social capital in social media-enabled ENoP with respect to a better knowledge reception?

We use the term knowledge reception to denote the receipt of information and/or knowledge that potentially has a positive impact on the knowledge seekers work (Levin and Cross 2004) encouraging further participation. Thereby, we explicitly focus on ENoP facilitated by SMPs residing inside organizations. In particular, we analyze the content of a huge dataset of enterprise microblogging (EMB) messages to gain insights about the quality of information and knowledge exchanged. In particular we consider initial messages from the seeker (e.g., question, comment, suggestion, status information) with the intention to sense information about current issues, get feedback to business-related suggestions, or to profit from knowledge embedded in collectives as initial act of participation. All members of the ENoP receive these messages via the underlying EMB platform and then have the opportunity to comment the suggestion, answer the question, or to provide additional information. Thus, we view each response to an initial message as a single access to information and/or knowledge.

The remainder of this paper is organized as follows. First, we provide the theoretical background. Subsequently, we conceptualize a research model to empirically discover to what extent social capital improves individual’s knowledge reception in ENoP. Next, we elaborate on the details of our empirical study, describe our research methodology and illustrate the results of our analysis. Finally, we discuss the findings and present limitations of our work as well as implications for further research.

2 Knowledge Exchange and Social Capital Theory

Social capital theory has been considered as an explanation for a variety of social behaviors including collective action, community involvement, as well as collaboration and knowledge contribution (see Yang et al. 2009 for an overview). While other forms of capital are based on physical assets, social capital resides in the relationships between individuals of a social network (Putnam 1993). Thus, social capital theory is rooted in the concept of social embeddedness from economic sociology which
suggests that economic behavior should not be analyzed without considering the constraints of ongoing social relations between individuals (Granovetter, 1995). However, the concept of social capital still lacks a consistent definition and common understanding (Yang et al. 2009). We adopted the definition provided by Nahapiet and Ghoshal (1998, p. 243) who define social capital as the “…sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit”. Therefore, social capital can be considered as a multi-dimensional construct comprising a structural, relational, and cognitive dimension (Nahapiet and Ghoshal 1998). The structural dimension describes whether and how people or entities are connected. Important aspects of the structural dimension are the presence or absence of network ties between people as well as corresponding network positions (i.e., centrality). The relational dimension of social capital assesses the set of personal relationships that people have developed through interactions. Thereby, the relational dimension focuses on the quality of relations resulting from, e.g., respect and friendship between people. Important aspects are trust, norms and sanctions, obligations and expectations. The cognitive dimension relates to resources providing shared interpretations and sense of meaning. Important aspects are a common understanding, common purposes, and shared narratives enabling individuals within a network to perform collective actions.

With respect to our research topic, these social capital dimensions encompass various aspects of a social context that provide the supportive conditions for knowledge exchange (Nahapiet and Ghoshal 1998). Although Nahapiet and Ghoshal’s model is conceptualized on group level to explain the creation of social capital within organizations as a prerequisite of knowledge creation in organizations, we suggest that it is also appropriate to predict individual-level knowledge exchange in ENoP. We propose that social capital can mitigate the lack of knowledge by overcoming boundaries via social relationships (Wasko and Faraj 2005). These relationships are a primary source for the generation of individual social capital, which influences how the other members provide information and share their knowledge. Accordingly, we suggest that social capital is primarily accumulated by individuals to leverage potential information and knowledge sources leading to knowledge accumulation and increased awareness of their environment (Yu et al. 2010).

3 Social Media Platforms as Facilitator of Knowledge Exchange

Based on social capital theory, we developed a research model to explore how individuals could benefit from participation in SMPs. Following Nahapiet and Ghoshal (1998), we propose that structural capital (interaction network ties and structural network ties), relational capital (trust through the norm of reciprocity and individual reputation), and cognitive capital (identification and social closeness) improve individuals’ knowledge reception in ENoP. Therefore, we take into account the role of SMPs and suggest that individuals’ participation can foster the development of social capital in intra-organizational ENoP. To investigate the linkage between SMP and social capital, we identified different functionalities supporting the formation of social capital through a literature review and a screening of SMPs deployed in a leading financial institution.

3.1 Structural Capital

The social capital theory proposes that the connections between individuals are important predictors of collective action (Burt 1992). This so-called structural capital is also relevant for examining individual actions, such as knowledge contribution within a collective (Wasko et al. 2005). Individuals who are centrally embedded in a collective are likely to benefit from their central position with respect to resource availability (Ahuja et al. 2003). Thus, an individual’s structural position in an ENoP should influence his or her possibilities of knowledge receiving.

Prior research suggests that an individual’s embeddedness in an ENoP is determined by the number of social ties the individual has with others in the network (Ahuja et al. 2003, Wasko et al. 2005). These social ties results from conversations or structural relations between individuals in a network. In this regard SMPs facilitate the building of structural capital by enabling conversations that would
otherwise be difficult or impossible to establish improving the reachability through a distant and asynchronous communication channel (Kietzmann et al. 2011). Messages can routinely reach hundreds or thousands of people and specific features help people to monitor and filter information. Accordingly, a social tie is created when one person use the SMP to send a respond to another’s posting. How many such ties an individual creates determines his or her centrality in the ENoP, which leads us to the following hypotheses: Individuals with a higher level of centrality in a SMP-enabled ENoP will receive more helpful (H1a) and faster (H1b) responses.

3.2 Relational Capital

Following the explanations of Nahapiet and Ghoshal (1998), we propose that a participant’s knowledge reception is not only facilitated by the quantity of social ties but also by the quality of these relations. Individuals establish relational capital if other participants trust and accept them as a part of the collective facilitating the access to resources and expanding their action repertoire (Putnam 1993). We examine two dimensions of relational capital which prior research is indicating as relevant to ENoP: individual reputation and norm of reciprocity.

Reputation is an important asset that an individual can leverage to achieve and maintain information and knowledge provision (Jones et al. 1997). This can be explained by the social exchange theory (Blau 1964) which proposes that individuals engage in social interaction based on an expectation of social rewards such as status, trust, and respect. In a social media setting, reputation can be seen as the extent to which users can identify the standing of others based on certain features which automatically aggregate user-generated information to determine trustworthiness. For instance, the number of followers on a microblogging platform attests reputations as boundary spanner and expert (Kietzmann et al. 2011). Being a follower on the investigated EMB platform specifically means that a user receives all the messages from those he follows with a higher priority. Moreover, informal and self-regulated feedback mechanism can be used to describe past experiences with specific community members. These mechanisms are usually based on peer evaluations, reviews, and ratings. By capturing the overall reputation of the community participants, the feedback mechanism gives people a self-reference on what constitutes appropriate conduct, and provides incentives not to engage in opportunistic behavior (Ba and Pavlou 2002). Accordingly, reputation can be seen as a future option of an individual to be engaged in future activities and knowledge exchange processes within the ENoP. Hence, we hypothesize: Individuals with a high reputation realized through SMP-enabled ENoP will receive more helpful (H2a) and faster (H2b) responses.

However, relational capital is sometimes not motivated by reputation but by norms of reciprocity (Blau 1964; Putnam 1993). According to the social exchange theory, reciprocity implies “... actions that are contingent on rewarding reactions from others and that cease when these expected reactions are not forthcoming” (Blau 1964, p. 6). In brief, Putnam (1993) describes reciprocity as a rational motivation that follows the mutual exchange: “I’ll do this for you now, knowing that somewhere down the road you’ll do something for me” (Putnam 1993, pp. 183). Reciprocity thereby resolves problems of collective action and stabilizes social interaction. Accordingly, individuals participate in ENoP due to a perceived moral obligation to give something back to the collective. This also explains why people who regularly helped others seemed to receive help more quickly when they ask for it (Rheingold 2000). According we hypothesize: Individuals with a higher level of reciprocal relations realized through SMP-enabled ENoP will receive more helpful (H3a) and faster (H3b) responses.

3.3 Cognitive Capital

In addition to structural and relational capital, Nahapiet and Ghoshal’s (1998) conceptual model examines an organization’s cognitive capital as social identification and common understanding among individuals which enhance the creation of knowledge and innovations. In this regard, identification refers to the degree to which individuals perceive themselves similar to others in the network. For improving individuals’ identification and common understanding with others, ENoP can
leverage group functionalities of SMPs which allow users to organize themselves in specific interest groups. According to social identity theory, these groups support individual’s sense of affiliation to the same collective and the creation of a high level of shared understanding (Hogg and Abrams 1988). As previous studies have demonstrated this mutual understanding help removing rigidities and barriers of knowledge flow (Law and Chang 2008). Consistent with our focus on the individual level, we examine how an individual’s cognitive capital affects the speed and quality of received replies in an ENoP. Therefore, we refer to the work of Granovetter (1985) and Coleman (1986) who emphasize the positive effect of cohesive ties on the formation of social norms and a shared identity which both facilitate trust and cooperative behavior. Accordingly, we define the amount of cognitive capital available to an actor as a function of the closure of the network (i.e., cohesiveness) surrounding that actor; and hypothesize: Individuals within groups of higher cohesion on SMP-enabled ENoP will receive more helpful (H4a) and faster (H4b) responses.

Referring to the work of Smith et al. (2009), we further consider individuals as actors characterized by a wide range of social attributes (e.g., interests, preferences, occupation) and let social relationships emerge naturally as a result of commonalities across these social attributes. The social identity theory posits that people categorize themselves and others to derive their social identities (Turner 1987). In this self-categorization process, people evaluate the perceived similarities between the self and other group members based on any traits and social cues they can observe from others. The traits and social cues can be anything like attitudes, beliefs and values, or behavioral norms. In a social media setting people utilize profiling functionalities to reveal their identities by disclosing personal information, e.g., gender, profession, personal interests, or experiences. This self-disclosure provides opportunities for building up relationships among individuals (Collins and Miller 1994). Unlike the structural relationship-centric perspective (i.e., structural capital) where ties represent explicit relationships, ties according to this individual-centric perspective are based on inherent similarities among the actors which create implicit and multi-faceted relationships (i.e., the sharing of characteristics induces some level of similarity or affinity among actors) (Smith et al. 2009). Accordingly, we hypothesize: Individuals with a high social affinity to the collective in the SMP-enabled ENoP will receive more helpful (H5a) and faster (H5b) responses.

4 Empirical Study – Enterprise Microblogging

While we believe that there are other technologies worth to be analyzed with respect to our research questions, EMB is considered as one of the most pervasive forms of SMPs (Riemer et al. 2010), and as such, a promising platform to improve knowledge exchange in organizations. Accordingly, we suggest that EMB platforms are utilized to realize an ENoP among large numbers of people regardless of the physical location.

To validate our hypotheses, we collected data from a leading multi-national financial services provider that implemented an EMB platform to support communication and collaborative activities among employees in different departments, countries, and time zones. While participation in the network was limited to employees only, access to the platform was possible via a web frontend, a desktop application, or mobile devices. Similar to Twitter, users voluntarily posted short messages that appeared in a chronological stream on the user’s EMB interface. When a message is posted all users of the platform are able to read it. By option, the sender of a message can tag the post with custom keywords or predefined group names. Based on these keywords, other users can then automatically filter all messages posted on the platform to reduce the risk of information overload. Furthermore, customizing of incoming message streams was enabled by a ‘follower-feature’ which means that each user had the opportunity to define specific “followers” and was subsequently able to restrict incoming messages only to them. Since participation was non-anonymous, each person’s name and picture was visible as part of the message header. The maximum length of each post was restricted to 300 characters. We gathered data consisting of all messages sent during the second half of 2010. Since the EMB platform had already been implemented in the second quarter of 2009, we assume that the initial
stages of assimilation, which are often characterized by use lags and unstable utilization, had already been overcome. The dataset comprises 9,164 conversations (threads including an initial message and all of its replies), 15,505 message postings by 1,166 unique users. Moreover, the total amount of messages is differentiated in 9,123 initial messages (also including status messages) and 6,382 replies.

4.1 Model Operationalizations

Whenever possible, we adapted existing measures and proxies from previous empirical studies. To further ensure the content validity of our measures, we asked a panel of two practitioners and two academic judges to review them. All measures were aggregated on the individual level and therefore were calculated for each member of the EMB-enabled ENoP when possible.

<table>
<thead>
<tr>
<th>Type</th>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Helpful</td>
<td>5</td>
<td>Provides helpful information in the form of a valuable comment. Moreover, the reply is positively marked with a „win“-tag that can be set by the user to demonstrate the usefulness of this reply.</td>
</tr>
<tr>
<td>Helpful</td>
<td>4</td>
<td>Provides helpful information or complements the initial request with useful information. The seeker has to confirm this helpfulness by a thankful respond.</td>
</tr>
<tr>
<td>Somewhat Helpful</td>
<td>3</td>
<td>Answers the question posted at least partially or provides a valuable insight into how the issue was resolved elsewhere, and/or contains relevant information.</td>
</tr>
<tr>
<td>Indirect Helpful</td>
<td>2</td>
<td>Does not directly provide helpful information but contains a link to a potential information source or gives feedback information.</td>
</tr>
<tr>
<td>Not Helpful</td>
<td>1</td>
<td>Reply message was not helpful for the information seeker. The recipient has to indicate this meaninglessness with a corresponding answer.</td>
</tr>
</tbody>
</table>

Table 1. Reply Quality – Coding Schema

We examined two independent measures based on the received responses to operationalize knowledge reception on an individual level: 1) the helpfulness of corresponding posts (reply quality), and 2) the reply time. For measuring quality of responses (R\textsubscript{qual}), we conducted a manual content analysis as a technique for making systematic, replicable, and valid inferences from data to the context (Morris, 1994). In a first step, we chose single messages as the appropriate unit of analysis as these are objectively identifiable by independent coders (Harwood and Garry 2003). Based on the work of Wasko and Faraj (2005), we then derived the coding schema for the quality of replies. To ensure validity, the quality categories have been subject to several revisions until reaching the final version (see Table 1). According to Morris' procedure we started an iterative process of sample coding on reliability samples of 200 messages. In each iteration two researchers independently assigned all posts in the corresponding sample to the quality categories, discrepancies between the coders were discussed, and the coding schema was revised accordingly (Morris 1994). The whole process was repeated twice until Krippendorff's alpha and Cohen's kappa reached a threshold value of more than .70 as evidence for the intercoder reliability of our measures (Dewever et al. 2006). Once reliability of the coding scheme was approved, one researcher processed all remaining replies in our dataset. Then, we calculated the average quality of all incoming replies during the investigation period for each member of the EMB-enabled ENoP. Thereby, we only considered those members who sent less than five posts during the whole period of investigation as all other participants were identified as “passive”. Consequently, we were able to assess the average quality score for 372 members of the EMB-enabled ENoP ranging from 1 to 5 (mean value: 3.17, median: 3, standard deviation: 1.57).

Obtaining replies timely is likely to increase the value of knowledge reception for an individual member of the EMB-enabled ENoP. The rationale behind this is that the task for which the knowledge is needed may be completed faster and thus an employee can dedicate more time and energy towards other activities. Accordingly, we included reply time (R\textsubscript{time}) which is calculated as the difference of the timestamps (logged by the EMB tool) of every initial message and the timestamps of the corresponding replies in our model. Once this delay of each reply was assessed, an average reply time score of all incoming replies was calculated at the individual level. Accordingly, we were able to calculate an average reply time score for 404 members of the EMB-enabled ENoP as all other
participants did not receive a reply so that the average reply time could not be calculated. The observations of the reply time variable ranged from 1 to 991 minutes with a mean value of 226.7 (median: 114.5) and a standard deviation of 250.7 minutes.

As far as the independent variables are concerned, structural capital was assessed by determining each individual’s degree of centrality (DoC) based on dyadic interactions. In ENoP, a dyadic interaction is created when an actor responds to another’s posting (Ahuja et al. 2003). Such interactions form a social network that comprises all conversations between participants realized via the EMB platform. For this purpose, a network matrix was computed which allowed us to determine the number of unique members of the ENoP a specific individual had interacted with in the past, independent of the total number of interactions (Ahuja et al. 2003). For example, an individual who interacts 30 times with 20 unique individuals has a degree centrality of 20.

With regard to individual’s relational capital, members of the ENoP build up reputations of trustworthiness that are likely to become important information for other actors in the network. Especially, an individual’s reputation may become visible to other members of the network through features which automatically aggregate information about an individual’s past behavior. Thus, in our case, we decided to assess an individual’s reputation in the social network based on the quality of contributions in the past. Since answers of low quality are also likely to negatively influence an individual’s reputation (Rep), we computed the average quality score of all replied messages sent by a specific member of the ENoP as a measure for reputation. Moreover, we count the number of followers for each member (Fol) as an alternative measure (Kietzmann et al. 2011). However, trustworthiness is also built upon norms of reciprocity (Blau 1964; Tsai and Ghoshal 1998), which in turn is of central importance for social exchange relationships. To measure for reciprocity, we utilized an individual-centered proxy which counts all reciprocal interactions (Rec) an individual member of the ENoP is involved in (Izquierdo and Hanneman 2006). In this context, a reciprocal interaction between two members A and B occurs if actor A had posted a message that was replied by actor B, and then B posted a message that was answered by actor A.

With an increase in the study of social network analysis, social network density was employed as a measure of social cohesion (e.g., Yang and Tang 2004). We describe network density (De) as the overall level of dyadic interactions of network members within predefined social boundaries. According to Reagans and McEvily (2003), group-level boundaries are appropriate for our investigations. Thus, we refer to the group functionality provided by the investigated EMB which allows users to organize themselves in specific interest groups (e.g., “application designing”, “security processing”). Based on the corresponding group boundaries, we compute the density of the emerging network for each group as the number of existing relations divided by the number of all possible interaction opportunities (Wasserman and Faust 1995). To aggregate the results at the individual level we average all density values for each group an individual member of the ENoP participates in. As explained above, we furthermore identified social affinity (SA) of a member to all other members of the ENoP as an important factor of cognitive capital. Therefore, we use a social affinity score to define the weights of the (implicit) relations between members of the ENoP based on individual’s social attributes (Smith et al. 2009). In particular, we refer to the EMB platform’s grouping functionality enabling the formation of user-defined groups. Each group membership captures some personal information, such as occupations (e.g., “IT architects”), hobbies (e.g., “private pilots”), interests (e.g., “Apple products”). Based on this information, we computed affinity scores that correspond to the amount of overlapping group memberships between two individuals. Finally, we calculate the overall social affinity of a member by taking the average of the pairwise social affinity scores to all other members of the ENoP.

4.2 Empirical Analysis

To test our hypotheses, we performed several multiple regressions with Rqual and Rtime as measures for individual’s knowledge reception using the statistical software package Stata 10. To secure an
unbiased and reliable estimation as well as an adequate interpretation of the empirical results, we graphically (QQ-plots, histograms, boxplots) and empirically (Chi-square tests) analyzed the distributions of the dependent variables in a pre-analysis phase. The results show that the dependent variable Rtime is positively skewed (i.e., the median is much smaller than the mean). Moreover, extant studies in sensory and cognitive psychology as well as studies in IS research verify that variables of response latency often follow a gamma, Weibull, Poisson or negative binominal distribution (e.g., (Kalman et al. 2006, Schnipke and Scrams 2002). Accordingly, we used generalized linear models (GLM) as a flexible generalization of the OLS (McCullagh and Nelder 1989) for our empirical investigation. Based on the analysis of histograms and the fact of high overdispersion of Rtime, we decided to apply GLMs with a negative binominal and a gamma variance function. In contrast, the results of our pre-analysis indicate that Rqual is only slightly skewed. Based on the results of Χ² tests and graphical analysis, we suggest that Rqual follows a normal distribution. Accordingly, we performed a normal OLS regression as well as a GLM estimation with the Gaussian variance function. However, the investigation of different transformation functions showed that the squared transformation of the Rqual would help to make it more normally distributed (Χ² = 2.53, p-value = 0.28). Therefore, we also performed a GLM estimation with the Gaussian variance function and a squared link function to check for robustness of our results.

Due to the concern of variance inflation and estimation sensitivity, we tested all regression models for multicollinearity. Thereby, we first analyzed the correlations between the independent variables. The significant (p < 0.01) Pearson correlations between almost all independent variables are below 0.6. However, the correlation analysis points out that Fol is highly correlated DoC. Accordingly, we conducted separate estimations for these variables. In a second step, we performed a comprehensive collinearity diagnostic based on tolerance values, variance inflation factors (VIFs), and conditional indices (Belsley 1991). The tolerance values are greater than 0.1, VIF values less than 10, and all conditional indices are below 15. Therefore, no indications for multicollinearity were found.

<table>
<thead>
<tr>
<th></th>
<th>Rqual (quality score)</th>
<th>Rtime (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model1 GLM-GAU</td>
<td>Model2 GLM-GAU</td>
</tr>
<tr>
<td>_cons</td>
<td>2.60***</td>
<td>2.28***</td>
</tr>
<tr>
<td>GC</td>
<td>0.03***</td>
<td>0.03*</td>
</tr>
<tr>
<td>GS</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Dy &lt;sub&gt;eng&lt;/sub&gt;</td>
<td>0.12</td>
<td>0.06</td>
</tr>
<tr>
<td>H1: DoC</td>
<td>0.06*</td>
<td>-1.83*</td>
</tr>
<tr>
<td>H2: Fol Rep</td>
<td>0.19***</td>
<td>0.19***</td>
</tr>
<tr>
<td>H3: Rec</td>
<td>0.68***</td>
<td>0.69***</td>
</tr>
<tr>
<td>H4: De</td>
<td>6.24***</td>
<td>7.07***</td>
</tr>
<tr>
<td>H5: SA</td>
<td>0.94**</td>
<td>0.92*</td>
</tr>
<tr>
<td>Df</td>
<td>371</td>
<td>368</td>
</tr>
<tr>
<td>Deviance</td>
<td>299</td>
<td>277</td>
</tr>
<tr>
<td>Pearson X²</td>
<td>299</td>
<td>277</td>
</tr>
<tr>
<td>AIC</td>
<td>2.63</td>
<td>2.56</td>
</tr>
<tr>
<td>BIC</td>
<td>-1897</td>
<td>-1901</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

- _p-values_: *** p < 0.01; ** p < 0.05; * p < 0.1 (two-tailed significance test)
- Variance functions: GAU = Gaussian/normal; NB = negative binominal; GA = gamma
- The estimations of Rqual are based on a dataset including 372 individuals (as descript in the measurement section)
- The estimations of Rtime are based on a dataset including 404 individuals (as descript in the measurement section)

Table 2. Regression results
To check the robustness of our results, we compared three models for each dependent variable. Model 1 as a baseline model included a random intercept only. Model 2 included the number of groups (GC) an individual participates in and the average group size (GS) as control variables (Oh et al. 2004, Reagans and McEvily 2003). Moreover, individuals whose native language is not English may be restricted in their ability to participate. Thus, we also controlled for this effect by including a dummy variable (Dyeng) that is equal to ‘1’ for individuals from an English-speaking country and ‘0’ otherwise. In Model 3 individuals’ knowledge reception was regressed on the identified measures of individual social capital to test our hypotheses. These models are fully nested so that the difference in fit-measures provides a valid model comparison. The results are shown in Table 2. We used maximum likelihood approaches to estimate the coefficients and z-tests to check for statistical significance. Moreover, we evaluated the GLMs to their goodness of fit based on the deviance and Pearson $\chi^2$ statistics. Both are score test statistics that compare the hypothesized model to the saturated model, which have one parameter for each observation that imply a perfect fit of the data (McCullagh and Nelder 1989). We also deployed the more recent Akaike (AIC, Box et al. 1994) and Bayesian (BIC, Schwarz 1978) information criterion statistics as goodness-of-fit measures.

4.3 Discussion of Empirical Results

The empirical results provide support for most of our hypothesized relations. The decreasing goodness-of-fit measures confirm the validity of our proposed model (Model3) in comparison to the baseline (Model1) and the control models (Model2), especially since the goodness-of-fit measures (i.e., AIC and BIS) do not only consider the accuracy but also the model complexity. Moreover, the variability in the data that is accounted for our research model of $R_{qual}$ (quantified by the $R^2$ and adj. $R^2$ measures) indicates a reasonable predictive power (see, e.g., Wasko and Faraj 2005).

In particular the results indicate that structural capital is a significant predictor for individual’s knowledge reception. Accordingly, H1a and H1b are supported with regard to the positive and significant effects of DoC on $R_{qual}$ and the negative and significant effect of DoC on $R_{time}$. Accordingly, and consistent with the theory of collective action, members who are central in an ENoP interacting with a large number of other participants are more likely to receive more helpful information and faster responses from the collective (Burt 1992). In particular, our results confirm that structural social capital could be built up through interaction in SMPs improving individual’s knowledge reception and resolving problems of collective action and stabilizing social interaction.

In addition, we find evidence for the important role of relational capital developed in SMP-enabled ENoP. In this respect, the results indicate that the reputational effect of high social status through a higher level of followers results in faster response reception. However, the high correlation of Fol and DoC indicates that the follower network can also be considered as an important part of structural capital. In this context, participants structurally confirm social ties by listing each other as contacts (i.e., followers), automatically sharing objectives (i.e., messages), and actually spending less time directly interacting with each other. However, in social media, reputation refers also to the quality of participant’s contribution, which is often evaluated by using content voting systems (Kietzmann et al. 2011). Accordingly, the positive and significant coefficients of the Rep variable in the $R_{qual}$ model point out that an employee can leverage personal reputational status as a long-term measure of the quality of one’s contribution. In this regard, EMPs allow individuals to express their expertise to a broad audience at a low cost. Once employees are identified as experts, they may receive indirect incentives, such as higher quality of knowledge provision. In sum, the results confirm that reputation can be seen as an option of an individual to be engaged in future activities and effective information sharing processes within the ENoP (H2a and H2b are supported). Moreover, the coefficients of Rec show the expected and significant effects in the $R_{qual}$ and $R_{time}$ model suggesting a higher quality as well as a lower reply time through a higher proportion of reciprocal ties as an indication for the formation of norms of reciprocity. Thus, H3a and H3b are supported.
The results also provide clear indication that cognitive capital plays a vital role in developing “knowledge reception” capabilities. The high and significant coefficients of $De$, as a proxy for cohesiveness, verify that the available cognitive capital is positively related to the quality of knowledge provided to a member. Even the $De$ values are relatively small (0.01-0.12), this result stresses the positive effect of cohesive social ties on the formation of social norms in ENoP facilitating efficient collaboration. Moreover, the negative and statistically significant coefficient in the $R_time$ model provides evidence for the positive effect through shorter response times. Consequently, $H4a$ and $H4b$ are fully supported. Finally, the results indicate that a higher social closeness leads to a provision of knowledge that is of higher quality (support for $H5a$ only). In combination with the identified effects of cohesiveness ($De$), these results indicate the establishment of ‘strong’ social ties in SMP-enabled ENoP that binds members in social sub-structures (e.g., group, project team) enabling effective information sharing and knowledge integration. One possible explanation may be that a higher social closeness implies a higher (situational) awareness (due to the sharing of social characteristics, activities, and an equal context), eventually leading to a more suitable knowledge provision. However, one must consider that the SA values show relatively small values (0-1.52). Combined with the relatively small coefficient in the $R_qual$ and the insignificant effect in the $R_time$ model our findings also seem to be reconciling with the argument that in ENoP the lack of shared history, co-presence, and social affinity is a subordinate issue (Cohen and Prusak 2001).

5 Conclusion, Limitations, and Future Research

This study shed initial light on the effects of social capital on knowledge reception of employees in virtual and distributed work environments by analyzing an ENoP realized through an EMB platform. The empirical results confirm distinct influences of the different forms of social capital on individuals’ knowledge reception in terms of reply quality and reply latency. Prior to the discussion of the implications of our study, we note that our findings should be interpreted in the light of its limitations requiring further research. First, the theoretical insights about the nature of individuals’ knowledge reception may be restricted since we focused on a single SMP in a specific organizational context. In this regard, future studies may replicate this study in different departments or industries to ascertain the generalizability and robustness of our findings. In particular, the present study analyzed an EMB platform that was primarily used by employees of the financial institution’s internal departments (e.g., IT and operations) characterized by a relatively open culture of information sharing and problem solving. It would be interesting to investigate the knowledge exchange behaviour via SMP in a more competitive environment as it is expected in departments that are closer to the market (e.g., investment banking department). Moreover, it would be worth to investigate the participation behaviour of SMPs with a higher amount of users. Intuitively, the implementation of SMPs seems to be most beneficial for large and globally operating firms, where employees are dispersed across many locations. The rationale for this is that it is difficult - even for long-lasting employees - to be aware of each colleague’s knowledge in such companies. However, future studies are needed to analyse the trade of between a higher amount of knowledge resources (i.e., participating employees) and negative effects resulting from, e.g., information overload. Second, our empirical investigation is restricted to objective archival data enriched by qualitative information. In this regard, the data set could be augmented by applying additional research methods, such as participant surveys, which might help to deepen our understanding about variations attributed to the participant’s knowledge reception in ESM-enabled ENoP. Moreover, our measurement model suffers from potential issues resulting from the aggregation of data residing at the message level to the individual level. Thereby, we exclude meaningful variations resulting for example from averaging the quality and reply time of all incoming replies an individual member of the ENoP receives. Thus, the knowledge reception of a member who receive only one message with a reply quality of 3 within 10 minutes is assessed equally to the knowledge reception of another member who receive three messages with qualities of 3, 2, 4 and reply times of 5, 10, 15 minutes. Accordingly, further research should elaborate on more appropriate measures considering the microfoundations of knowledge exchange on the message level.
However, since the role of social capital with respect to individuals’ knowledge reception in ENoP has been widely neglected so far, our study serves as a starting point to the extant literature in this context. On the one hand, we contribute to the social capital theory by investigating the role of social capital in SMP-enabled ENoP. While public online communities of practice (e.g., Law and Chang 2008), and collaboration in open source communities (Wang et al. 2008) has been analyzed already, research on enterprise-wide internal SMPs is still in its infancy. In this regard, we demonstrated 1) how individuals can establish social capital through SMPs, and 2) how this capital shapes individuals’ knowledge reception in an organizational context. On the other hand, we contribute to the emerging literature of knowledge management through ENoP within enterprises. Previous research in this field mainly focused on individuals’ knowledge contribution behavior (Wasko and Faraj, 2005) or knowledge sharing as well as collaboration in general (Law and Chang 2008). We add to this research focusing on the role of social capital and investigate which benefits (i.e., improved individuals’ access to knowledge) arise for a focal employee participating in an ENoP.

Moreover, our results exhibit implications for practitioners that regard SMPs as a possible solution for improving knowledge management in organizations. Participating in an SMP-enabled ENoP, members have the opportunity to build up reputation and to become core in a large social network with dispersed and diverse knowledge sources. Disallowing such participation may cut off valuable organizational information and knowledge flows, decrease situational awareness and eventually reduce employees’ efficiency. Managers interested in developing and sustaining enterprise-internal SMPs should focus on encouraging employees to create relationships between different professions, hierarchies, and locations to ensure access to heterogeneous information, knowledge, and ideas from across the organization. However, there is also a need for creating ‘strong’ social ties within subnetworks (of groups or teams) so that they become cohesive social units in which an effective and efficient sharing of work-related information and accumulation of knowledge is possible. This may be realized through enhanced group functionalities, like the formation of private groups, group chats, and the integration of collaborative virtual workspaces. Moreover, the results clearly indicate that reputation is a key factor to enhance knowledge reception through ENoP. Accordingly, managers should promote individual participation by leveraging techniques that help to uncover an individual’s reputation, e.g., by reputation scores visible to other members of the social network platform.

**Literature**


