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Enterprise Social Networking Platform and Employees' Job Mobility

Mostafa Esmaeili
Information Systems & Decision Sciences, MUMA College of Business, University of South Florida, mesmaeili@usf.edu

Daniel Zantedeschi
University of South Florida, danielz@usf.edu

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Completed Research

Moe Esmaeili
Muma College of Business,
University of South Florida
4202 E Fowler Ave,
Tampa, FL 33620
mesmaeili@usf.edu

Daniel Zantedeschi
Muma College of Business,
University of South Florida
4202 E Fowler Ave,
Tampa, FL 33620
danielz@usf.edu

Abstract

We study the association between people' participation in an ESN platform and job mobility events using employees' actions on an S&P500 company's enterprise social networking (ESN) platform. Using cutting-edge text-mining algorithms, we first determine the settings in which employees use these platforms and then assess the relationship between those qualities and job mobility. According to our topic-modeling analysis, employee participation on workplace social networking platforms has multiple dimensions; nonetheless, it is mainly employed for knowledge-sharing, social networking, employee engagement, and volunteer activities. We provide empirical evidence that employees' contributions to knowledge-sharing, social networking, and organizational engagement via ESN lead to a higher likelihood of job mobility; however, a higher number of complaints, perhaps surprisingly, is associated with a higher likelihood of job mobility. We contend that better levels of knowledge-sharing, social networking, and employee engagement with less complaints can be linked to self-promotion, resulting in a higher likelihood of promotion.

Keywords: Enterprise Social Networking, Job Mobility, Promotion, Text-mining, Machine Learning

Introduction

Over the past decade, social networking platforms like Facebook, Instagram, and Twitter, have gained indisputable popularity among people for fostering and maintaining social relationships. Meanwhile, corporations and organizations have also realized the necessity of social network platforms (DiMicco et al. 2009) within their organization (van Zoonen et al. 2014; Van Zoonen et al. 2017). The heed even elevated drastically due to the potential benefits of such technologies in a corporate environment, especially for an organization with a globally distributed work mode. In such organizations identifying knowledge workers with specific skill sets is hard, and even establishing and maintaining social relationships with remotely located colleagues is a trying matter.

In other words, social media technologies revolutionized how employees communicate and interact socially within organizations, considerably impacting their careers (Correa et al. 2010; DiMicco et al. 2009; Holland

et al. 2016; Liang and Turban 2011; Moqbel et al. 2013). Hence, the primary focus of the literature in this domain was on social media usage (Drummond et al. 2020; Jiang et al. 2016; Parveen et al. 2016; Trainor et al. 2014), or on social network usage at work (van Zoonen et al. 2014; Van Zoonen et al. 2017), on the power (Charoensukmongkol 2014), or on the occurrence (Bretschneider and Parker 2016) of social media usage. Moreover, few studies examined the impact of social media usage in the workplace on the relationship between the employee and management (Tajudeen et al. 2018), knowledge sharing activities (de Zubielqui et al. 2019), employee satisfaction and performance (Parveen et al. 2015). While an abundance of research has emerged on the use of public social networking, to the best of our knowledge, less research exists on the enterprise social networking usage contexts, i.e., within the boundaries of (large) organizations, and how those attributes can impact employees' career outcomes and job mobility events.

In this research, using a unique dataset from employees' activities of an S&P500 company's enterprise social networking platform, we investigate the relationship between individuals' participation in a closed social networking platform and their job mobility and promotion events. By applying the state-of-the-art topic modeling techniques, first, we identify the contexts in which employees are currently utilizing enterprise social networking and how these applications can impact their job mobility and internal promotion moves.

Literature Review

The immediate focus of an enterprise social network (ESN) is not simply to encourage people to use the platform with a high rate of participation but to fulfill organizational objectives more effectively and successfully. This is in contrast to open social networking platforms, whose primary objective is to engage people with the medium so the technology provider company can collect user data or sell more ads. Enterprise social networking (ESN) tools like Google Workplace and Yammer are private (also referred to as closed or internal) social networking platforms that make it easy to record, manage, and organize open conversations and information sharing between specific employees or groups of employees within an organization. ESN platforms can track participants' social interactions (i.e., through a social graph) and give a customized stream (Turban et al. 2011) of updates about events or conversations to users, in addition to features that foster conversations and promote knowledge and information exchange (Von Krogh 2012). (via news feeds and activity streams). Additionally, previous research indicates that ESN platforms can play a tactical role in the IT structure and promise to improve employee performance (Dittes and Smolnik 2017). (Karoui et al. 2015). Indeed, ESN platforms can significantly help organizations with their knowledge-sharing initiatives by enhancing employee communication (Davison et al. 2014), enhancing knowledge transfer activities (Leonardi and Meyer 2015), amplifying social relations (Kline and Alex-Brown 2013), accelerating the onboarding of new employees (Leidner et al. 2010), boosting people's social capital (Riemer et al. 2015), and ultimately enhancing employee performance (Kuegler et al. 2015). Employees could use ESN to strengthen their networks of relationships and get advantages in their daily job activities, according to Mäntymäki and Riemer (2016).

Further studies suggested that ESN platforms can help businesses overcome challenges related to knowledge-sharing initiatives, such as locating and sharing subject-matter experts, exchanging information and knowledge, and establishing and maintaining social bonds with colleagues (Fulk and Yuan 2013). There is, however, a dearth of information on the connections between various ESN platform usage and career outcomes in job mobility. According to Di Maggio and Van Alstyne's (2013) research, employees are more likely to advance their careers internally if they participate in ESN platforms, gain information, and use it to solve work-related challenges. They are also more likely to improve job performance and gain gratitude. According to Huang and Zhang (2016), using ESN platforms for learning could positively impact career development by sending positive signals to potential employers or teams (internal or external) and by presenting their problem-solving skills. Building and sustaining formal and informal contacts that advance career success is an advantage of social networking relationship activities (Forret and Dougherty 2004). Previous research indicates that engaging in social networking is essential for professional success (Hoppe and Reinelt 2010). Similar research suggested that career advancement measurements such as latitude and longitude are positively influenced by social networking at work (Forret & Dougherty, 2004). According to Thompson 2005, Wolff and Moser 2009, professional networking and social networking activities are also linked to favorable performance appraisal and can be effective job search tactics (see also Wanberg et al. 2000).

Study	Method	Data	Horizon
(Forret and Dougherty 2004)	Regression and Correlation Models	Survey, Case Study	The authors identified the type of social networking behaviors that impact job mobility outcomes. Moreover, they argue that gender does impact networking behavior which is a proxy for a career enhancement strategy.
(Hoppe and Reinelt 2010; Nikitkov and Sainty 2014)	Regression Models	Archival data of social media usage	The result of this study indicated that an individual's professional social networking (e.g., Linkedin) presence has positively associated with career success. A similar relationship was not found with other non-professional sites (e.g., Twitter)
(Skoric et al. 2015)	Path Analysis	Survey	The authors proposed that social networking activities are positively associated with bonding and bridging social capital.
(Kwahk and Park 2016; Oostervink et al. 2016)	Structural equation model	Survey	The authors proposed that social networking activities can significantly impact knowledge-sharing, influencing individual job performance.
(Lu and Pan 2019)	Regression Models	Corporate Data, Correlation Analysis	The authors found that information-seeking behaviors on ESM positively affect job performance, but information-sharing behaviors on ESM negatively affect job performance.
(Yingjie et al. 2019)	Correlation analysis	Case Study	The authors argue that even though pleasurable use of ESN is positively associated with employee turnover, ESN usage is negatively associated with employee turnover,
(Luqman et al. 2021)	Structural Equation Modeling	Survey	The study proposed that mental overload can mediate the association of ESM usage with enervation and innovation.
(Moqbel et al. 2020)	Structural Equation Modeling	Survey	The authors proposed that the successful adoption of ESN platforms within organizations can increase employee integration at the workplace, decrease turnover intention, elevate employee satisfaction, and reduce employee strain.
(Bulgurcu et al. 2018)	Regression Models	Corporate Archival Data	The authors proposed that identifying the patterns of employees' contribution is the primary factor in understanding participation in social networking communities
(Oksa et al. 2021)	a sequential exploratory strategy, mixed-method study	Interview, Survey	The authors proposed that employees' intention to fulfill the needs for "autonomy, competence, and relatedness" is the key to utilizing social media more.
(Ma et al. 2021)	Descriptive Statistics	Interview	The authors proposed that ESN usage at the workplace impacts employee performance via work efficiency and emotional maintenance. They also proposed that frequency of usage and individual characteristics can moderate this process
(Liang et al. 2020)	structural equation modeling	Survey	The authors proposed that if ESN platforms are used for social networking, they can benefit employee satisfaction and, if used for work-related reasons, enhance employee efficiency.

Table 1 : Literature Review

An ESN encourages communication and collaboration among employee silos, resulting to better employee engagement and more inventive ideas (Sharma and Bhatnagar 2016). Monitoring other employees' social networking activities can help rookies understand the company's values and culture and give them a platform for sharing thoughts and engaging with coworkers. ESN allows individuals to connect, discuss, participate, speak up, and indicate their expertise to other teams or sectors within the same organization. Individuals and teams found cooperating and sharing knowledge easier with ESN platforms, according to Wehner et al. (2017). ESN systems reportedly help employees make faster decisions, create more original ideas, and become more engaged at work. Employee involvement can boost corporate performance and success. Less dynamic work settings induce job discontent, turnover, or intent to leave the team or company (Daileyl and Kirk 1992). High-engagement employees are less likely to quit than disengaged ones. Corporate volunteerism is one of the ways that organizations and their employees can give back to their community; in this regard, ESNs made it easier for the corporation to promote such behaviors. Such activities can assist employers in elevating their reputation and placing them in a competitive position map for those individuals seeking positions in determined corporations. Literature also proposed that workplace

volunteering can boost employee engagement and job satisfaction leading to more productivity (Boccalandro 2018). Further research also provides empirical evidence that individuals who often participate in their company's volunteering activities are more likely to feel very devoted to their organization. That can signify employee retention and less likelihood of job mobility (Valéau et al. 2013).

ESN allows businesses to gain direct insights into employees' worries and struggles, yet they fear losing employee productivity if the platform triggers confidentiality breaches and employees share too much of their complaints there (Hedley 2015). An empirical study on job discontent and career mobility (primarily turnover) indicated substantial connections, although not direct. Employees who complain less are happier, more driven, and less inclined to switch professions or teams, according to Hogan et al. (2013). Lee and Mowday (1987) suggested that employees who spend time and energy changing undesirable work environments might otherwise resign. Employees who thrive in changing difficult work situations reduce their discontent, change their intention to quit into an intention to stay, and are more likely to stay with their employers. ESNs let businesses and teams gather direct information like employee complaints, recommendations, and visions to help leaders and decision-makers improve the team and organizational performance. Using text mining, we identify the varied usage of ESN platforms and evaluate how they affect employee job mobility.

Data

We collected a unique dataset including enterprise social networking activities for randomly selected 92 employees from a large US Fortune 500 financial company where the platform has been adopted for more than eight years. The dataset consists of 31944 activities (posts and comments) from these employees between 2014 to 2019. Besides, we also collected Human Resource information (HR feed) that includes employees' job mobility and promotion events during the same time span, plus their gender information, title level, employee sector, joined date, and their latest attained education. In the next section, we first apply topic modeling on social networking content from these employees to identify the contexts in which these employees were using this platform, and we will define our variables of interest. Our modeling framework is presented in Figure 1.

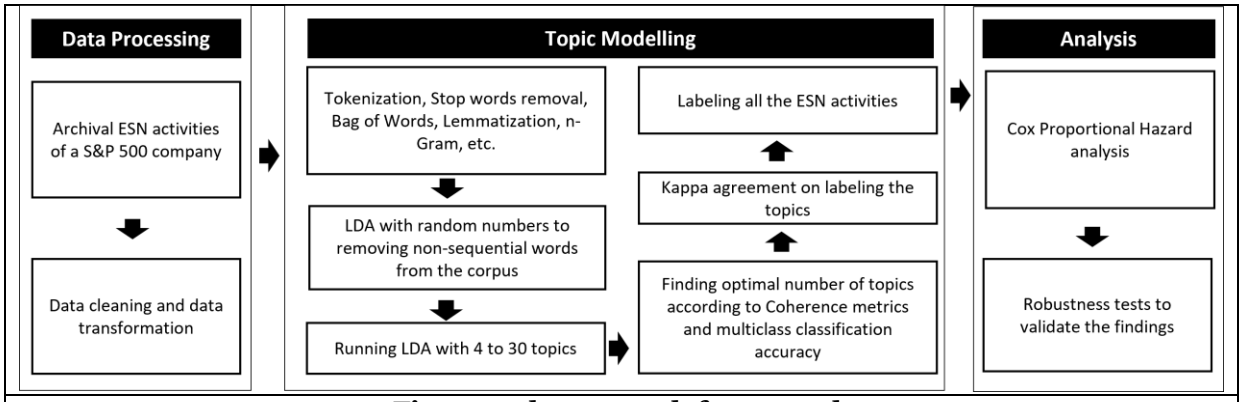

Figure 1: the research framework

Topic Modelling

To better understand the theme of social networking activities among individuals and capture important topics embedded in their posts and conversations on the platform, we used one of the most well-known topic modeling techniques, Latent Dirichlet Allocation (LDA), introduced by Blei et al. (2003). LDA is a statistical approach that extracts cohesive clusters of contents (topics) from a collection of documents and assigns each content a membership probability. Like other topic modeling techniques, LDA assumes each corpus comprises several clusters named topics, and each topic is a collection of words. LDA can infer the topics from a given content collection without supervisory or prior knowledge. However, the quality of the outputs is impacted by the input data quality, which emphasizes the importance of data cleaning and text preprocessing. Therefore, we applied a series of text preprocessing steps, including stop-word removal,

stemming, lemmatizing, tokenization, and identifying n-gram (Inzalkar and Sharma 2015) procedures using Python packages, such as the Natural Language Toolkit (NLTK) (Wallach 2006), and other data cleaning approaches such as lowercase conversion and punctuation elimination. The stop-words are those common words in every language, such as articles and prepositions, that do not add much information to the text. The purpose of stemming and lemmatization is to convert words to their meaningful base forms. Tokenization is used for splitting phrases, sentences, and texts into smaller units, individual words, or terms. These preprocessing steps are delivered in Stanford's NLTK Library (Kolini and Janczewski 2017). Next, we ran the LDA model several times with a different random number of topics to find non-sequential words from the generated topics and then remove them from the main corpus.

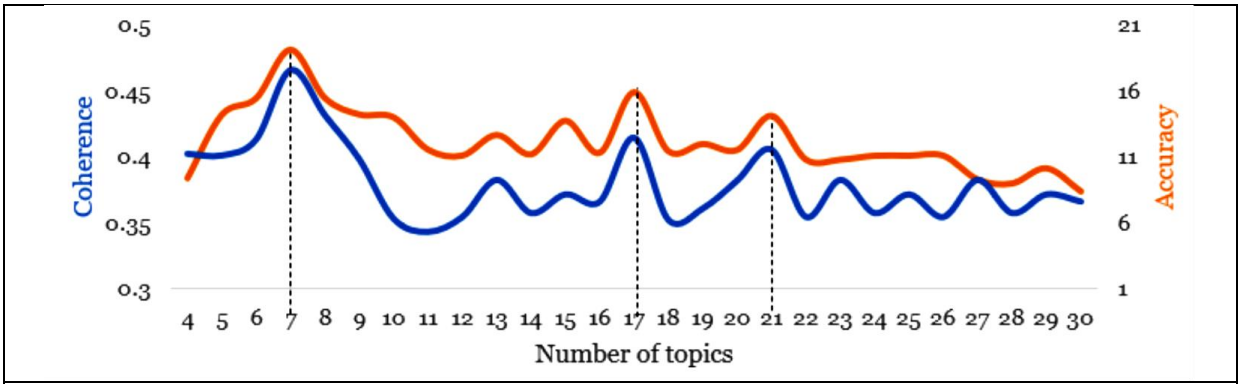

Figure 2: coherence and accuracy values of LDA models with different num of topics

Once the data preprocessing phase is completed, we run the LDA model on the final corpus to determine the optimal number of topics. It is worth noting that no structured framework exists for picking an optimal LDA model for a specified problem. However, we adopted a two-factor approach to finding an optimal LDA in this study: Coherence factor and Usability factor (accuracy in our context) text classification. Topic Coherence metric (Röder et al. 2015) determines the level of semantic similarity among words with the highest rank in the topic. The assessment assists in separating topics that can be interpreted semantically from the ones that are artifacts of statistical inferences. In this paper, we measured the topic coherence by applying a four-phase coherence approach: Segmentation, Probability Calculation, Confirmation Measure, and Aggregation (Röder et al. 2015). We ran LDA with a different number of topics and measured the coherence metric. The result indicates that the optimal number of topics can be 7 or 17 and even 21, as shown in Figure 2 (highest Coherence measures compared to the rest). Then, we measure the accuracy of naïve multiclass classification for each possible candidate (topic number). That means we calculate the accuracy of naïve multiclass classification where the content (posts or comments) is equally allocated to the number of classes that are the same as the topics' number. For example, according to Table 2, LDA(17) has a coherence value of 0.448 and achieves the naïve multiclass classification accuracy of 12.43 %.

# Topics	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
CV	0.48	0.44	0.43	0.43	0.41	0.40	0.42	0.40	0.43	0.40	0.45	0.40	0.41	0.42	0.40
Accuracy(%)	17.51	14,12	10,82	6.35	5.36	6.48	9.26	6.77	8.18	7.63	12.43	6.25	7.12	9.22	13.53

Table 2: Coherence value and accuracy measure for different LDA

In the classification context, topics with the highest quality turn into the primary element in classification decisions as an alternative to the most coherent topics (O'callaghan et al. 2015). According to the results from Table 2, LDA(7) becomes the final choice for topic modeling as LDA (7) provides the highest classification accuracy of 17.51 % along with the highest coherence value of 0.48 (also shown in Figure 2.

For clarity and better interpretability, we labeled the topics generated by LDA (7). Three meetings were held to understand the research project scope on the research to build a labeling (coding) book. We followed the labeling (coding) steps suggested by Krippendorf (1980) and Landis and Koch (1977). One of the authors, two master's students, and an expert in the domain were part of the labeling process to assign each topic a name separately. Neither hypotheses nor research questions, nor measurement models are shared with individuals in charge of labeling, and they are asked not to communicate with each other during the coding process. We also performed pilot topic labeling (coding) in three rounds for the topics generated by LDA (7) with a different number of keywords (10, 20, and 30 keywords). Our primary goal was to replicate

the labeling process and improve the labeling (coding) book until independent coding results achieved the kappa value greater than .70. The kappa value indicates the degree (percentage) of agreement among coders, which is substantially higher (>.7) than what can be achieved by chance (Krippendorf 1980; Landis and Koch1977). Finally, by examining those topics manually, we noticed that the majority of the LDA(7) topics produce comparatively more interpretability, as presented in Table 2.

Topic #	LDA keywords	Topic
1	0.021*team, 0.014*work, 0.013*share, 0.011*link, 0.010*file, 0.010*confluence, 0.009*support, 0.009*supervisor, 0.008*partner, 0.008*page, 0.007*document, 0.006*approach, 0.005*article, 0.004*framework, 0.004*doc	Knowledge Sharing
2	0.007*events, 0.006*expo, 0.006*work, 0.006*coffee, 0.005*time, 0.005*voice, 0.005*employee, 0.005*value, 0.005*gather, 0.004*support, 0.004*game, 0.004*sharing, 0.003*hike, 0.003*food, 0.003*bike	Social Networking Activity
3	0.011*challenge, 0.009*development, 0.009*value, 0.007*VOE, 0.007*workshop, 0.006*advance, 0.005*action, 0.006*career, 0.006*work, 0.006*support, 0.006*commitment, 0.005*culture, 0.004*work, 0.004*vision, 0.004*celebrate	Employee Engagement
4	0.021*deadline, 0.018*exhaust, 0.015*dedication, 0.013*lack, 0.013*complaint, 0.013*best, 0.009*vigor, 0.006*cynic, 0.006*support, 0.005*stress, 0.005*job, 0.004*due, 0.004*project, 0.003*manager, 0.002*evaluation	Employee Complain and Suggestions
5	0.020*charity, 0.019*society, 0.014*voice, 0.011*local, 0.008*volunteer, 0.006*work, 0.006*build, 0.006*value, 0.005*public, 0.005*support, 0.005*hike, 0.004*outreach, 0.004*team, 0.004*culture, 0.003*expo	Volunteer Activity
6	0.024*information, 0.018*online, 0.017*ticket, 0.014*access, 0.012*internet, 0.010*tools, 0.008*mobile, 0.008*support, 0.008*INC, 0.005*employee, 0.004*Lo, 0.003*IThelp, 0.003*Ops, 0.003*contact, 0.002*issue	ICT and IT Help Desk
7	0.016*retirement, 0.016*benefit, 0.013*description, 0.009*compensation, 0.008*insurance, 0.008*team, 0.008*time, 0.007*handbook, 0.006*training, 0.005*career, 0.004*manual, 0.004*employee, 0.003*contact, 0.003*support, 0.002*onboarding	Employee Onboarding/ HR

Table 3: List of topics and their corresponding keywords

After further investigation of the topics, we found the content of two of the topics were mainly related to the HR department (such as onboarding, initial training, etc.) and IT Help-Desk (such as incidents raised for software issues on employees' computers) and provided no relevant information for our study. As a result, all 2,746 observations were discarded.

Topic	min	max	mean	STD.DEV	Total
Social Networking	1818	2279	2040.857	172.071	14286
Knowledge Sharing	1108	1434	1303.429	113.816	9124
Complains	69	101	89	12.7410	623
Engagement Activities	433	599	516	59.7271	3612
Volunteer Activities	190	252	221.857	21.605	1553

Table 4: Summary Statistics of the topic modeling over the data

The final dataset includes 29,198 posts and comments. Table 4 provides a summary statistic of the data. Grouping contents calculate these statistics based on their creation date (year basis). The number of activities shows the average number of posts and comments which were created per year for each topic. As can be seen, the data includes an average of 2,040 Social comments and posts per year, having the largest share of content, followed by Knowledge-sharing content and Engagement activities. Topic 1, which includes social networking activities, shows the highest level of variation across different years, as indicated by its significant standard deviation.

Variables

Using topic modeling and then labeling each activity, we formed a panel dataset where every row in the dataset includes the individuals' yearly count of enterprise social networking activities for different categories (topic) of interest. In each row, employees' job mobility is also included.

Dependent Variables

In our analysis, the first primary dependent variable is Job Mobility. In this study, we consider Job Mobility as employees changing their position to another position within the current team or a position in another team. Job mobility, also referred to as career mobility (or job change or job switch), is the movement of employees across positions or grades and can be any move in one's career, including both lateral and vertical. The Job Mobility variable is denoted by $Job\ Mobility_{it}$, which is set to 1 if a member i changes his/her job at the time (year) t and 0, otherwise. The other dependent variable is Promotion. Promotion can be defined as switching positions to higher-level positions (within the current team or in another team). The Promotion variable is denoted by $Promotion_{it}$, which is set to 1 if a member i switches to a higher-level position at the time (year) t and 0, otherwise. Moreover, We define the dependent variable Promotion Within Team, $Promotion_{it}^{within}$ as a position move, where the individual switches to a higher-level position within the current team (i.e., contributes to the team's employee retention event). Similarly, $Promotion_{it}^{within}$ is set to 1 if a member i changes his/her job at year t within the current team, and 0, otherwise. We also define Promotion between Teams ($Promotion_{it}^{between}$) as a position move, in which the individual switches to a higher-level position with a new team (i.e., contributes to the teams' employee turnover event). Similarly, $Promotion_{it}^{between}$ is set to 1 if a member i changes his/her job at year t and moves to another employer, and 0, otherwise.

Independent Variables

This section introduces the independent variables and provides a detailed procedure to obtain information about them. The first independent variable is $Social\ Networking$. $Social\ Networking_{it}$ is the number of social networking activities (posts and comments) member i contributed on the enterprise social networking platform at year t. Similarly, we define $Knowledge\ Sharing_{it}$, $Engagement_{it}$, $Volunteer_{it}$ and $Complaint_{it}$ as total number of contributions in knowledge-sharing, employee engagement, volunteer, and complaints an employee i made on organization social networking platform at year t.

Control Variables

Based on attributes available in the dataset, we defined a couple of control variables in our model. Specifically, using the education information obtained from the HR feed dataset, we create a control variable for different levels of educational attainment completed by an employee, including bachelor's degree, master's degree, and doctoral degree. Another control variable is employee gender, where 1 represents male employees, and 0 represents females. Moreover, using the employee's join date, we create a control variable for different levels of work experience for employees inside the corporation, including Junior(0-3 years), Intermediate (3-7 years), and Senior (7+ years). Another control variable is also created for Sectors (seven levels: Bank, Compliance, Finance, HR, Client, Risk, and Technology) to which these employees belong. Another control variable is included to capture the level of employees' position with four levels: C14 (Senior Vice President), C13 (Vice President), C12 (Assistant Vice President), and C11 (Analyst).

Methodology

Hazard models, a.k.a as; survival analysis, are a statistical approach to measuring the likelihood that a subject experiences an event within a particular time period, given that the individual was subject to the possibility that the event might take place. Hazard models do not rely on the normality assumption of the residuals that exists in linear regression approaches (Allison 2010); most notably, multiple hazard events are also allowed in these models (e.g., an employee may change jobs or get promotions more than once during the sample period). Due to their flexibility and capabilities, hazard models have been widely adopted in the literature, including the IS domain (Huang and Zhang, 2016). Consistently with the dichotomous nature of the dependent variable, we implement the Hazard model to analyze how employees' participation in organizational social networking platforms can impact their job mobility events, including promotions. Especially in this study, we chose the Cox proportional hazard model, a semi-parametric approach that assumes no baseline hazard parameterization. The hazard rate for i th subject at time t is specified as: $h_i(t|\mathbf{x}_{i,t}) = h_0(t)\exp(\mathbf{x}_{i,t}\,\beta)$, where:

$$\boldsymbol{x}_{i,t}\beta = \beta_0\, Knowledge\ Sharing_{\ i,t} + \beta_1\, Social\ Networking + \beta_2\, Engagement$$
$$+ \beta_3\, Complaint + \beta_4\, Volunteer_{\ i,t} + \theta C_i + \Omega Z_{\ i,t}$$

and C_i represents a set of time-invariant control variables such as an academic degree, and $Z_{i,t}$ represents a set of time-variant control variables such as work experience.

Results

The Cox proportional hazard model results are presented in Table 5. We find empirical evidence that activities such as knowledge-sharing, social networking, and employee engagement are positively associated with a greater likelihood of job mobility. The estimated coefficient in Table 5 suggests that a 1 percent increase in knowledge sharing is associated with a 4.1 percent increase in the hazard ratio of job mobility. Similarly, a 1 percent increase in social networking activities is associated with a 35 percent increase in the hazard ratio of job mobility. In comparison and not surprising, complaining on the enterprise social networking platform is also positively associated with job mobility events, i.e., a 1 percent increase in complaints is associated with a 13 percent increase in the hazard ratio of job mobility. Although we posited volunteer activities should positively impact the likelihood of job mobility, it has a negative impact. According to the result, a 1 percent increase in volunteer activity is associated with a 6 percent decrease in the hazard ratio of job mobility. Interestingly, according to the results, employees from HR, ICG, and Risk sectors do more job mobility compared to other employees from other sectors. Moreover, Senior employees tend to have less job mobility compared to other types of employees.

Variables	COEF	Exp	SE
Knowledge Sharing	0.041 ***	1.041	0.012
Social Networking	0.359 ***	1.431	0.099
Engagement	0.207 *	1.230	0.082
Complain	0.133 *	1.142	0.053
Volunteer	-0.067 *	0.935	0.027
Gender	0.025	1.026	0.183
Education - MS	-0.265	0.767	0.172
Education - PHD	-0.184	0.832	0.415
Position level - C12	-0.134	0.875	0.263
Position level - C13	-0.049	0.952	0.246
Position level - C14	0.281	1.325	0.236
Sector - Compliance	0.406	1.501	0.414
Sector - Finance	0.034	1.035	0.489
Sector - HR	0.785 .	2.193	0.398
Sector - Client	0.683 .	1.979	0.349
Sector - Risk	0.780 .	2.182	0.386
Sector - Technology	0.436	1.547	0.359
Experience level - MID	-0.088	0.916	0.188
Experience level - SEN	-0.502 .	0.605	0.291
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

Table 5: Result of Hazard model for Job Mobility

The Cox proportional hazard model results for promotion are presented in Table 6. The results provide empirical evidence that knowledge-sharing and social networking activities are positively associated with the greater likelihood of getting a promotion. The estimated coefficient in Table 6 suggests that a 1 percent increase in knowledge sharing is associated with a 9.2 percent increase in the hazard ratio of getting a promotion. Similarly, a 1 percent increase in social networking activities is associated with a 63 percent increase, and a 1 percent increase in engagement activities is associated with a 22 percent increase in the hazard ratio of promotion. In contrast, complaint and volunteer activities in the enterprise social networking platform are negatively associated with promotion events, i.e., a 1 percent increase in

complaints is associated with a 60 percent decrease, and a 1 percent increase in volunteer activities is associated with an 9 percent decrease in the hazard ratio of promotion.

Variables	COEF	Exp	SE
Knowledge Sharing	0.092***	1.096	0.019
Social Networking	0.631***	1.880	0.130
Engagement	0.223 .	1.250	0.118
Complain	-0.606 *	0.545	0.239
Volunteer	-0.094 .	0.911	0.041
Gender	-0.558 .	0.572	0.270
Education - MS	0.018	1.018	0.247
Education - PHD	0.384	1.468	0.521
Position level - C12	-0.665	0.514	0.395
Position level - C13	-0.137	0.872	0.347
Position level - C14	-0.180	0.835	0.350
Sector - Compliance	-0.354	0.702	0.489
Sector - Finance	-0.526	0.591	0.606
Sector - HR	-0.421	0.657	0.484
Sector - Client	-0.552	0.576	0.432
Sector - Risk	0.183	1.201	0.481
Sector - Technology	-0.590	0.554	0.434
Experience level - MID	-0.234	0.792	0.284
Experience level - SEN	-0.575	0.563	0.432
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

Table 6: Result of Hazard model for Promotion

	Promotion within the current team			Promotion with alternative team		
	COEF	**Exp**	**SE**	**COEF**	**Exp**	**SE**
Knowledge Sharing	0.131***	1.140	0.031	0.065***	1.068	0.025
Social Networking	0.365*	1.440	0.199	0.749***	2.114	0.172
Engagement	0.206	1.229	0.184	0.223	1.250	0.158
Complain	-1.252**	0.286	0.452	-0.333	0.717	0.247
Volunteer	-0.093	0.911	0.064	-0.087	0.917	0.055
Gender	-0.310	0.733	0.402	-0.749 .	0.473	0.365
Education - MS	0.042	1.043	0.400	-0.084	0.920	0.325
Education - PHD	0.884	2.420	0.715	-0.061	0.940	0.790
Position level - C12	-1.206	0.299	0.578	-0.060	0.942	0.573
Position level - C13	-0.599	0.550	0.496	0.359	1.432	0.507
Position level - C14	-0.745	0.475	0.500	0.356	1.428	0.519
Sector - Compliance	-0.453	0.636	0.765	-0.434	0.648	0.646
Sector - Finance	0.069	1.072	0.859	-1.146	0.318	0.896
Sector - HR	-0.608	0.544	0.802	-0.415	0.660	0.616
Sector - Client	-0.529	0.589	0.688	-0.719	0.487	0.572
Sector - Risk	-0.256	0.774	0.823	0.274	1.315	0.613
Sector - Technology	-0.310	0.734	0.650	-0.910	0.403	0.598
Experience level - MID	-0.088	0.916	0.414	-0.366	0.693	0.406
Experience level - SEN	-1.380 .	0.252	0.833	-0.039	0.962	0.540
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table 7: Result of Hazard model for promotion within the team or with alternative team

We also ran the Cox proportional hazard model results for cases where promotion happens within the current team and another team. According to the results presented in Table 7, knowledge-sharing is positively associated with promotion within the current team, and in contrast, complaints harm the likelihood of getting a promotion within the current team. The estimated coefficient in Table 7 suggests that a 1 percent increase in knowledge sharing is associated with a 13.1 percent increase in the hazard ratio of obtaining a promotion within a team, and also a 1 percent increase in the complaint is associated with a 125 percent decrease in the hazard ratio of getting a promotion within a team. On the other side, knowledge-sharing and social networking are positively associated with the promotion with the alternative teams and increase the likelihood of getting a promotion within an alternative team. In addition, according to the results, senior employees are less likely to obtain promotion with the current team compared to other types of employees.

Robustness Analyses

A series of robust checks were performed in order to address the concerns over the reliability of our findings. First, we ran a few models using alternative samples regarding the corporate social networking members to see whether their social networking involvement behavior can be responsible for potential estimation bias impacting the ultimate findings. For example, the findings' consistency was tested by running models using sample data that included high contributors (more active members) or low contributors (less active members). High contributors are the ones who contribute to ESN more often (posts, comments) compared to others on a yearly basis. We calculated the average number of ESN activities (number of posts and comments) by these employees annually, and if an employee contributes to ESN more than average, we labeled her/him as a "high contributor" in that year; otherwise, "low contributor". Results are presented in Table 8, confirming that both the findings' directionality and statistical significance still hold.

	Job Mobility						**Promotion**					
	High Contributor			**Low Contributor**			**High Contributor**			**Low Contributor**		
	COEF	**Exp**	**SE**	**COEF**	**Exp**	**SE**	**COEF**	**Exp**	**SE**	**COEF**	**Exp**	**SE**
KNWL Sha.	0.021*	1.021	0.018	0.052*	1.053	0.028	0.049**	1.050	0.026	1.143**	3.137	0.841
Social Net.	0.386***	1.471	0.120	0.342*	1.408	0.215	0.637***	1.892	0.146	-1.176 .	0.309	2.644
Engagement	0.200 .	1.221	0.108	0.234 .	1.264	0.161	0.155	1.168	0.128	-6.889	0.001	4.928
Complain	-0.352 .	0.703	0.225	0.202***	1.223	0.058	-0.491	0.612	0.292	-3.597*	0.027	2.444
Volunteer	-0.069	0.933	0.037	-0.087*	0.916	0.045	-0.064	0.938	0.044	0.706	2.026	0.759
Gender FEM	-0.193	0.824	0.243	0.166	1.180	0.302	-0.653*	0.521	0.294	5.031*	153.043	4.238
Edu. MS	-0.131	0.878	0.231	-0.312	0.732	0.282	0.164	1.179	0.272	2.431	11.371	2.507
Edu. PHD	0.148	1.159	0.507	-0.804	0.448	0.772	0.344	1.410	0.587	-14.194	0.000	13.887
Position C12	-0.421	0.656	0.365	0.129	1.138	0.416	-0.904*	0.405	0.451	-1.211	0.298	3.798
Position C13	-0.096	0.908	0.325	0.032	1.032	0.397	-0.111	0.895	0.373	-7.177	0.001	5.358
Position C14	0.011	1.012	0.311	0.664 .	1.943	0.392	-0.347	0.707	0.381	9.672*	15866.404	5.057
Sector COM	-0.009	0.991	0.491	1.009	2.742	0.858	-0.451	0.637	0.531	-5.798	0.003	4.846
Sector FIN	-0.227	0.797	0.573	0.407	1.503	1.034	-0.670	0.512	0.661	-1.417	0.243	5.419
Sector HR	-0.158	0.854	0.511	1.982 .	7.257	0.797	-0.808	0.446	0.540	11.644	113970.204	7.706
Sector CON	0.161	1.175	0.408	1.498 .	4.471	0.771	-0.626	0.535	0.464	-9.616	0.000	5.588
Sector RISK	0.571	1.769	0.476	1.388 .	4.005	0.803	0.081	1.084	0.515	5.618	275.262	4.666
Sector TCH	-0.112	0.894	0.427	1.429 .	4.175	0.768	-0.685	0.504	0.461	-3.911	0.020	3.907
Exp. MID	-0.431	0.650	0.266	0.146	1.157	0.307	-0.409	0.664	0.330	-2.771	0.063	2.031
Exp. SEN	-0.485	0.616	0.376	-0.755	0.470	0.498	-0.661	0.516	0.470	-7.995	0.000	5.193
Signif. Codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1												

Table 8: Result of Hazard model for Job Mobility and Promotion in case of High and Low contributor employees

Second, the involvement of full-time employees (FTE) in the sample might cause estimation bias because one may assume that these employees systematically act differently in ESN compared to other employees.

i.e., they may make substantial contributions compared to consultants. We reran the primary model using an alternative sample that excluded all full-time corporate employees (i.e., only full-time consultants remained in the sample) and presented the results in Table 9. We find our results still hold.

	Job Mobility						Promotion					
	FTE			Consultant			FTE			Consultant		
	COEF	Exp	SE	COEF	Exp	SE	COEF	Exp	SE	COEF	Exp	SE
KNWL Sha.	0.036***	1.036	0.013	0.357*	1.429	0.151	0.086***	1.090	0.021	0.357*	1.429	0.151
Social Net.	0.302***	1.353	0.109	0.563 .	1.755	0.582	0.711***	2.036	0.148	0.563 .	1.755	0.582
Engagement	0.137	1.147	0.088	2.043 ***	7.713	0.710	0.041	1.042	0.137	2.043 **	7.713	0.710
Complain	0.150***	1.162	0.054	-3.042 *	0.048	1.440	-0.532*	0.587	0.274	-3.042*	0.048	1.440
Volunteer	-0.045	0.956	0.029	-0.709 **	0.492	0.252	-0.035	0.966	0.046	-0.709**	0.492	0.252
Gender FEM	-0.127	0.881	0.192	3.704 **	40.609	1.377	-0.631*	0.532	0.310	3.704**	40.609	1.377
Edu. MS	-0.210	0.810	0.184	-4.936 **	0.007	1.803	0.199	1.220	0.305	-4.936**	0.007	1.803
Edu. PHD	-0.091	0.913	0.503	-2.269	0.103	1.956	0.321	1.378	0.734	-2.269	0.103	1.956
Position C12	-0.060	0.941	0.275	3.595	36.401	2.709	-0.781 .	0.458	0.438	3.595	36.401	2.709
Position C13	-0.118	0.889	0.275	2.879	17.798	2.709	-0.325	0.722	0.406	2.879	17.798	2.709
Position C14	0.426 .	1.531	0.249	2.516	12.376	2.151	-0.059	0.943	0.380	2.516	12.376	2.151
Sector COM	0.314	1.369	0.462	2.393	10.947	2.825	-0.766	0.465	0.631	2.393	10.947	2.825
Sector FIN	-0.001	0.999	0.542	7.509 *	1824.952	3.856	-0.801	0.449	0.745	7.509 .	1824.952	3.856
Sector HR	0.795 *	2.214	0.418	6.942 *	1035.067	3.215	-0.363	0.696	0.556	6.942 *	1035.067	3.215
Sector CON	0.583	1.792	0.361	-0.150	0.860	7833.395	-0.654	0.520	0.449	-0.150	0.860	7833.395
Sector RISK	0.907	2.478	0.407	4.257	70.615	2.724	-0.081	0.922	0.559	4.257	70.615	2.724
Sector TCH	0.405	1.499	0.375	2.639	13.997	2.266	-0.752	0.471	0.459	2.639	13.997	2.266
Exp. MID	-0.064	0.938	0.196	-2.400	0.091	1.728	-0.284	0.753	0.314	-2.400	0.091	1.728
Exp. SEN	-0.572 *	0.564	0.311	0.370	1.447	2.260	-0.908	0.403	0.517	0.370	1.447	2.260
Signif. Codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1												

Table 9: Result of Hazard model for Job Mobility and Promotion in case of FTE and Consultant type of employees

	Exponential Model			
	Job Mobility		Promotion	
	COEF	STD ERR	COEF	STD ERR
Intercept	-4.210 ***	0.487	3.811 ***	0.745
Knowledge Sharing	0.044***	0.012	0.095 ***	0.018
Social Networking	0.268***	0.099	0.453 ***	0.125
Engagement	0.181*	0.080	0.224 *	0.113
Complain	-0.130 *	0.052	-0.545 *	0.225
Volunteer	0.059	0.026	0.091*	0.039
Gender	-0.032	0.181	-0.377	0.255
Education - MS	0.206	0.170	-0.049	0.241
Education - PHD	0.221	0.414	-0.275	0.513
Position level - C12	0.056	0.260	0.421	0.379
Position level - C13	0.052	0.2454	0.087	0.340
Position level - C14	-0.283	0.235	0.096	0.344
Sector - Compliance	-0.374	0.411	0.260	0.477
Sector - Finance	0.068	0.485	0.685	0.591
Sector - HR	-0.726 .	0.394	0.287	0.464
Sector - Client	-0.620 .	0.347	0.527	0.426
Sector - Risk	-0.785 .	0.382	-0.226	0.465
Sector - Technology	-0.384	0.357	0.583	0.421
Experience level - MID	0.093	0.187	0.265	0.273
Experience level - SEN	0.458	0.288	0.583	0.427
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Table 10: Result of Exponential model for job mobility and promotion

Third, the Cox proportional hazards model is considered to be a semi-parametric approach. In such models, researchers do not assume the shape of the baseline hazard function. There are, however, other assumptions to make, such as independence and changes in predictors, that make corresponding alterations in the hazard. However, other regression models are used in survival analysis that assumes particular hazard times distributions, such as the Exponential distribution. Even though the Cox proportional hazard model has been widely adopted in the literature (due to its flexibility and ease of implementation), the model's results are sometimes inefficient compared to full parametric models (Cameron and Trivedi 2005). Thus, we examine an alternative parametric hazard model using the well-known Exponential hazard function. The results for the exponential model are presented in Table 10, confirming our findings are robust to different model assumptions.

Forth, we also ran Random Effect models to control for unobserved heterogeneity when this is constant over time and uncorrelated with the observed variables (Mithas, 2022). It is worth noting that if the unobserved variables across employees are random, estimates from the random-effects model are consistent. According to the result in Table 11, our findings are both directionally and statistically consistent.

	Random Effect Model			
	Job Mobility		**Promotion**	
	COEF	**STD ERR**	**COEF**	**STD ERR**
Intercept	-2.417 ***	0.631	-0.912	0.576
Knowledge Sharing	0.050 ***	0.012	0.067 ***	0.014
Social Networking	0.438 ***	0.111	0.532***	0.115
Engagement	0.173 *	0.072	0.238*	0.096
Complain	0.113 *	0.046	-0.515**	0.193
Volunteer	-0.064 **	0.024	-0.100**	0.032
Gender	-0.005	0.296	-0.423*	0.210
Education - MS	-0.161	0.279	0.180	0.197
Education - PHD	-0.412	0.630	0.331	0.436
Position level - C12	0.099	0.403	-0.182	0.305
Position level - C13	0.130	0.376	0.063	0.280
Position level - C14	0.422	0.385	-0.060	0.277
Sector - Compliance	0.425	0.601	-0.168	0.404
Sector - Finance	-0.205	0.650	-0.860 .	0.462
Sector - HR	0.719	0.592	-0.221	0.399
Sector - Client	0.664	0.503	-0.490	0.355
Sector - Risk	0.927	0.572	0.478	0.405
Sector - Technology	0.397	0.510	-0.656 .	0.358
Experience level - MID	-0.206	0.303	-0.384 .	0.216
Experience level - SEN	-0.557	0.438	-0.655	0.325
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Table 11: Result of Random Effect Model model for job mobility and promotion

Discussion and Conclusion

While social networking platforms have grown in popularity for establishing and sustaining social relationships, corporations recognized the value of such platforms within their organizations. Although there has been a wealth of research on the usage context of public social networking at the workplace and its impact on employee job mobility events, little research exists on the enterprise social networking usage contexts, i.e., within the boundaries of organizations, and how those attributes can impact employees' career outcomes and job mobility. To the best of our knowledge, this is the first study that uses a unique dataset from employees' activities on an S&P500 company's enterprise social networking platform to investigate the relationship between individuals' participation in a closed social networking platform and their job mobility events. We identified the situations in which employees are now adopting workplace social networking using cutting-edge topic modeling approaches, and then we analyzed the influence of those applications on employees' career mobility and promotion events. According to our topic modeling findings, employees mostly use ESN platforms for knowledge sharing, social networking, participation,

volunteering, and even complaining. According to the preliminary results (Tabe 4), employee social networking activities have the highest proportion of usage, followed by knowledge-sharing content and engagement activities. As previously stated, we contend that by utilizing ESN platforms, employees can identify knowledge workers, create and sustain social interactions, become more connected with their colleagues, and identify with the corporate's core values. Employees can even make their thoughts known by leadership by using the platform. Without taking into account the recommendations and criticisms of all individuals at all levels, the company's executives may be acting without a clear vision of the entire environment. This lack of insights and information exposes firms (and their shareholders) to an untold number of potentially unpleasant shocks in today's modern business environment, where microscopic errors can have enormous effects. We believe that ESPs enable organizations and teams to use direct evidence such as employee complaints, ideas, and visions to assist high-level decision-makers in addressing such concerns and making organizational changes to improve both team and organizational performance.

According to the Cox proportional hazard analyses, for employees who participate in enterprise social networking platforms, while volunteer activities ($P<0.05$) are moderately significant and negatively associated with the likelihood of job mobility, knowledge sharing ($P<0.0001$), social networking ($P<0.0001$), complaint ($P<0.01$), and engagement ($P<0.05$) activities are statistically significant and positively associated with the likelihood of job mobility. These findings require contextual interpretation in light of job mobility and people' uses of workplace social networking platforms.

Regarding the findings, whether making a lateral shift or getting a promotion, knowledge-sharing and social networking activities play critical roles in forecasting employee job mobility events. This is consistent with the literature, which shows that participating in ESN platforms during knowledge-sharing actions and creating social links and knowledge networks positively help job mobility by sending good signals to potential teams by displaying their skill set. Furthermore, it has been proposed that enhanced work performance as a result of information sharing may lead to job mobility within the firm, hence contributing to employee retention. Excessive effort in contributing and marketing oneself as a field expert, on the other hand, can indicate one's expertise to other teams, resulting in the team's loss of talent and knowledge. Managers may be unable to control employees' excessive knowledge contributions to these valuable ESN platforms; however, efforts can be made to develop incentive programs that encourage employees to promote and gain specific knowledge and skills required within the team, particularly for solving existing work-related problems.

Despite the fact that knowledge-sharing and social networking activities benefit employees' job mobility, the complaint plays a variety of roles in job mobility events once they are identified as promotional. According to the findings, complaining on the enterprise social networking platform is also positively associated with job mobility events, with a 1% increase in complaints associated with a 13% increase in the job mobility hazard ratio. Employees who send an unhappy message (for whatever reason) have higher career mobility, team turnover, and organizational turnover than employees who complain less. On the other hand, complaining on the ESN platform is negatively associated with promotion events; a 1% increase in complaints is associated with a 60% decrease in the promotion hazard ratio. Complaints can indicate high staff turnover, a greater possibility of career mobility, and a lower chance of promotion. According to Table 7, complaining is associated with a lower likelihood of advancement within the current team. There could be a variety of reasons for this, but it is clear that disgruntled or unhappy employees are looking for opportunities with other teams or companies. Managers may decide not to advance such individuals or provide them with the "option" to examine different teams or organizations rather than keep them due to job, team culture, or performance-related factors.

As previously indicated, there are strong links between complaining and job mobility. Employees who understand the team and the organization, according to Smith (2010), complain less, are happier, more driven, and are less inclined to quit jobs or teams. We contend that motivated and team players are those who make efforts to improve dissatisfying work settings rather than leaving the team (or leave the organization). Furthermore, employees who thrive in changing difficult work situations will lower their unhappiness level, converting their intention to quit into an intention to stay, increasing the possibility that

these employees would finally stay with their employers. We believe that leaders and managers should not overlook such commendable initiatives. Volunteering is regularly encouraged by executives as a strategy to assist organizations in improving their reputation. As volunteering can increase employee engagement, research shows that individuals who participate in their business's volunteering activities are more likely to feel strongly loyal to their organization and are less likely to move professions. Even at the organizational level, we see that volunteering has a detrimental influence on job mobility, with a 1% increase in volunteer activity resulting in a 6% fall in the hazard ratio of job mobility. Similar to work mobility, but interestingly, despite our expectations that volunteering would positively affect promotion events, it is inversely related to promotion events, and we found no significant impact of volunteering on promotion events within or with other alternative teams.

In summary, we suggest that employees can foster a balanced atmosphere for creating relationships and collaborative work in an organizational context where ESN technology is adequately utilized. Once socially networked, the larger the density of the network, the better the task performance and the likelihood of receiving a promotion. As a result, employees who frequently collaborate develop a strong bond due to shared knowledge and beliefs. As a social networking tool, ESN creates an environment that encourages such activities. As a social networking and knowledge-sharing medium, ESN platforms represent informal relationships and promote approachability among colleagues, provide employees with needed breaks when the workplace becomes an intense work setting, and even offer ways to distinguish colleagues' successes and connect individuals professionally and socially.

With the increasing number of communication methods used by enterprises, it is critical to understand the factors that influence individual and organizational success. Furthermore, we underline the importance of social networking and knowledge sharing for such planned achievements. According to the literature, socially connected personnel can profit from a harmonious environment for collaborative work. More crucially, a social connection can improve knowledge-sharing and teamwork experience, allowing team members to obtain better job outcomes by improving individual and organizational performance. As a result, the connection between employees in a network can improve cooperation, boosting individual, team, and organizational performance.

Additionally, we contend that ESN allows companies to gain firsthand knowledge of their employees' worries and perspectives and hear their voices. It is critical to understand that by failing to consider the recommendations and concerns of all individuals at all levels, the company's executives are acting without a clear view of the entire environment. Furthermore, ESN provides a unique chance for an employer to promote the company's fundamental values and culture while also adjusting their plan based on employee reactions.

Based on our analyses, ESN platforms are used for a variety of objectives, including knowledge sharing, social networking, engagement, volunteer activities, and complaints and concerns. ESN technology suppliers should improve the features and capabilities of their products to facilitate and encourage such behavior. For example, employees' actions on such a platform include knowledge sharing. It should be simple to share and locate knowledge that people want to share and find. It should provide a method for users to see knowledge and content in a more organized manner without losing its social networking nature. ESN technologies should be configured in such a way that they drive social networking activities while also providing businesses with features that engage employees with their fundamental values.

This study backs up and expands on previous research by recognizing that ESN platforms are excellent channels for employees to obtain and share knowledge, create and maintain social links with coworkers, engage with other employees and corporate core values, and get their views heard by leadership. Interestingly, our findings show that knowledge sharing and social networking activities in ESN platforms increase the likelihood of promotion, possibly due to improved job performance, increased visibility within the organization, and sending positive signals to potential teams by presenting skillsets in recognizing and formulating complex problems.

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