Identifying Key Contributors to Performance in Organizations:
The Case for Knowledge-Based Measures

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Abstract

Understanding the relative criticality of employees is important in managing turnover and security risks associated with human capital in organizations. Traditional social network analysis measures are based on static, survey-based assessments of centrality and other socio-metric aspects of organizations, limiting their effectiveness in fully evaluating human capital criticality, particularly criticality that may be "hidden" in the non-social dimensions of an organization. We introduce new task- and knowledge-based measures designed to overcome such limitations, and we apply them to a sixteen-person software development team to compare their efficacy to that of traditional social network measures of degree and betweenness centrality. Our results suggest that while each class of measures provides useful insight on criticality of organization actors, knowledge-based measures provide the most robust predictions of each actor's contribution to organizational performance.

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Identifying Key Contributors to Performance in Organizations

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Introduction

Based on how human capital is organized and managed to meet the cultural and productive needs of an organization, some individuals inevitably emerge as "key" or "critical" employees, but it is not always obvious who these important people are [Prietula & Simon, 1989]. Accordingly, it may not always be leaders and managers who are obvious key contributors, but rather those everyday actors who offer "something absolutely unique, with a special history in every respect" [Barnard, 1938]. Our objective in this study is to introduce and evaluate task- and knowledge-based measures that can be coupled with traditional social network analysis to more accurately identify hidden yet potentially valuable human resource assets.

This research makes important contributions to knowledge by offering new measures that can be used in evaluating potential human resource assets and risks. Losing such assets can be very costly in terms of both direct financial impacts and indirect effects on morale and knowledge retention. In addition, hidden "assets" can unfortunately become hidden "risks" associated with security breaches, theft of intellectual property and malicious retribution on the part of disgruntled employees [Sparrow, 1991]. A second contribution of our work is in providing measures that can be more easily calculated in realistic, evolving organization settings. Finally, our research is employs a unique and detailed combination of case study analysis, statistical techniques and multi-agent computer simulation, demonstrating how integrated empirical and theoretical methodologies may be applied in real-time human resource management applications as well as in other sociological and business research domains.

Motivation

There are numerous studies of the importance of human capital from perspectives of power, leadership, knowledge and learning, and social and human capital. However, none of these perspectives attempts to use such approaches to identify hidden human assets. Furthermore, the measurement approaches in these research domains generally focus on social network measures such as individual degree and betweenness centrality [Brass, 1984] or conceptual extensions such as Burt's [1992] structural holes and Krackhardt's [1999] Simmelian ties. While individually and collectively insightful, such measures are dependent primarily on social, friendship, communication or advice networks obtained statically through survey instruments and personal interviews, inhibiting a more comprehensive view of other critical components in the meta-network of people such as education, skill and experience.

Fortuitously, the existing literature does not rely solely on social measures in attempts to understand organization dynamics. Notably, Brass [1984] and Hinings [1974] evaluate task criticality in terms of an actor's "non-substitutability" and the number of connections the actor has to others for inputs and outputs related to the actor's task. Similar recognition of the importance of task and knowledge attributes in organization networks can be traced to Pfeffer [1981] and Mechanic [1962], with their concept of "irreplacibility." All of these measures, however, share limitations related to the potentially biased and static nature of the survey process. The primary motivation for this paper is to build on the notion of non-substitutability by proposing knowledge-based measures of human capital criticality. We then demonstrate, using an empirical case study, how to obtain and analyze relevant network data from existing information sources.

Proposed Methodology

The data we use in our study was provided by an information technology (IT) firm for a team of sixteen professionals tasked with the programming and implementation phases of a multi-phase Web site development project. The social network for the team is provided in Figure 1.

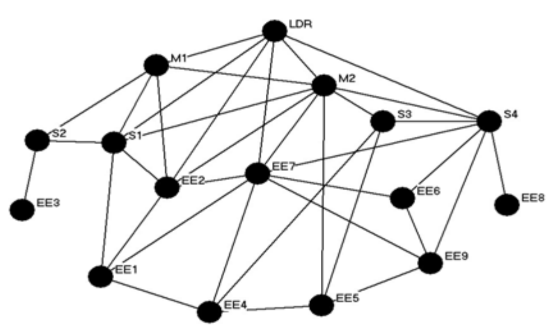

Figure 1. Team Social Network.

The phase of the software project for which we were provided data encompassed tasks associated with programming and implementation, thus the types of individuals on the software team reflect those requirements.

Building on Carley and Hill's [2001] concept of the meta-network and Krackhardt and Carley's [1998] linear algebraic framework for modeling structure in organizations, we defined the context of our analysis in terms of an organizational meta-matrix relating the following primitives: people (actors), skills (including knowledge and expertise), physical or financial resources, and tasks. The primitives are described by the following notation for each sub-matrix X_Y of the meta-matrix model:

For all X_Y :

$X_Y = X_{\hat{y}\times\hat{x}}$ ≡ matrix representing relations between each primitive *y* and *x*, where the value of matrix position $X_{yx} \in \{0, 1\}$ and is equal to 1 if a relationship holds, otherwise 0.

For $Y \neq X$:

$X_Y = X_{\hat{y}\times\hat{x}}$ ≡ Matrix *X* composed of $\hat{y}$ rows and $\hat{x}$ columns, where

$X, Y \in \{N, S, R, T\}$

$\hat{x}$ = maximum number of meta-matrix primitive *x*,

$\hat{y}$ = maximum number of meta-matrix primitive *y*, and

$(x, y) \in \{n, s, r, t\}$, $(\hat{x}, \hat{y}) \in \{\hat{n}, \hat{s}, \hat{r}, \hat{t}\}$, $y \neq x$, $\hat{y} \neq \hat{x}$

For $Y = X$:

$X = X_X$ ≡ square matrix $X_{\hat{x}\times\hat{x}}$ where $\hat{y} = \hat{x}$ indicating relationships of primitives $x \in \{n, s, r, t\}$ to all other primitives *x*.

All graphs represented by matrices are assumed to be connected, non-directional and dichotomous.

We first defined a Degree Centrality Index $CI_D(n)$ based on degree centrality [Freeman, 1979] as follows:

$$CI_D(n) = \left(\frac{1}{CI_D^{\max}}\right)\frac{\sum_{j=1}^{\hat{n}} N_{nj}}{\hat{n}-1} \tag{1}$$

This equation basically states that $CI_D(n)$ for any actor *n* is the sum of 1's across row *n* of the social network matrix N (actor *n*'s raw "degree" measure), divided by $\hat{n}$ -1 and normalized by $1/CI_D^{\max}$ (the maximum value of $CI_D(n)\ \forall\ n$).

We also defined a Betweenness Centrality Index $CI_B(n)$ [Anthonisse, 1971; Freeman, 1977] as follows:

$$CI_B(n) = \left(\frac{1}{CI_B^{\max}}\right)\frac{\sum_{j<n<k} g(j,n,k)/g(j,k)}{\left[(\hat{n}-1)(\hat{n}-2)/2\right]} \tag{2}$$

In this index calculation, the numerator represents the betweenness of actor *n* (i.e., the number of geodesics, or "shortest paths", between *j* and *k* containing *n,* divided by the total number of geodesics between *j* and *k*), which is then divided by the total number of pairs not including *n* (to compute a raw betweenness value) and normalized by multiplying the raw value by $1/CI_B^{\max}$.

We propose three new task- and knowledge-based measures, the first of which is a Task Exclusivity Index (TEI), defined as

$$TEI_n = \tfrac{1}{TEI^{\max}} \sum_{t=1}^{\hat{t}} \alpha_t T_{N_{nt}} e^{(1-\overline{T}_{N_t})} \tag{3}$$

where $\overline{T}_{N_t} = \sum_{n=1}^{\hat{n}} \frac{1}{\beta_n} T_{N_{nt}}$ and $TEI^{\max}$ is the largest observed value of TEI_i; α_t and β_n are weighting factors for each task *t* and individual *n*, respectively, where $\alpha_t > 0$ and $0 < \beta_n \leq 1$. The TEI essentially measures the extent to which each actor is the only one who can do certain tasks. The TEI is weighted toward unity for individuals who have one or more unique task assignments, with values associated with individuals with fewer unique tasks declining exponentially.

Our second proposed measure is similar in scope to the TEI, but focuses on the knowledge dimension rather than task. The Knowledge Exclusivity Index (KEI) is defined as

$$KEI_n = \tfrac{1}{KEI^{\max}} \sum_{s=1}^{\hat{s}} \alpha_s S_{N_{ns}} e^{(1-\overline{S}_{N_s})} \tag{4}$$

where $\overline{S}_{N_s} = \sum_{n=1}^{\hat{n}} \frac{1}{\beta_n} S_{N_{ns}}$; $KEI^{\max}$ is the largest observed value of KEI_n; and α_s is a weighting factor for skill *s*. As in the TEI, the KEI measures the extent to which each actor is the only one who possesses certain skills, knowledge or expertise. Also similar to the TEI, the KEI is weighted toward unity for individuals who possess one or more unique skill or knowledge elements, with values associated with individuals with fewer unique skills declining exponentially.

Extending Brass's notion of access exclusivity and Blau and Alba's [1982] suggestion that "communication access" to key individuals increases actor criticality, our next proposed measure is the Knowledge Access Index (KAI). Unlike the TEI and KEI, which are values between 0 and 1, the KAI is binary and is defined as follows:

Definition: $KAI_n = 1$ iff $\exists$ skill *s* for individual *n* | $\overline{S}_{N_s} = 1$ and (5)

$\overline{N}_n = \sum_{j=1}^{\hat{n}} N_{nj} = 1$; $KAI_i = 0$ otherwise.

Furthermore, if $KAI_n = 1$, then $KAI_j = 1$ for the value of *j*

where $N_{nj} = 1$.

The KAI calculation first identifies an actor who is the only actor possessing certain knowledge. If this actor is tied to only one other actor in the social network matrix *N*, then both the person with the unique knowledge (or skill or expertise) and the actor to whom this person is uniquely tied are considered potentially critical employees and are assigned KAI values of 1.

Our final proposed measure is a Composite Criticality Measure (CCM), defined as

$$CCM_n \equiv f(CI_D(n)) + f(CI_B(n)) + f(TEI_n) + f(KEI_n) + f(KAI_n) \quad (6)$$

where $f(Index_n) = 1$ iff $Index_n$ is in the critical cluster of *Index*, and 0 otherwise. We determine critical clusters based on agglomerative hierarchical clustering analysis. For purposes of our analysis, we assume that a higher value for any index indicates an actor with a higher level of criticality with respect to that index. In addition, without loss of generality, we set parameters α and β to 1.

Another important component of our approach involves establishing a benchmark for comparing and validating our proposed measures versus traditional network measures. The benchmark we use to measure an actor's criticality is performance impact as defined through successive simulations of the software team with and without each actor. Accordingly, we define a *key* or *critical employee* as an individual whose absence or loss will result in a greater decrease in organizational performance relative to other individuals in the same organization. Since it is impossible to obtain empirical studies examining team performance with and without each actor, simulation proves to be an excellent means of estimating baseline performance values for each individual on the team. The computer simulation model we employ is an adaptation of the Construct model originally developed by Kaufer & Carley [1993] and validated in studies by Carley & Krackhardt [1996] and Carley & Hill [2001].

As the first step in our research approach, we determined which members of the software team are critical employees based on their performance impact using the Construct simulation engine. We accomplished this by running a base case with all employees and then modifying Construct to permit the selective deletion of any actor. Based on the incremental difference in performance associated with the removal of each actor, we defined a benchmark measure of each actor's relative criticality as the absolute value of the mean percentage decrease in organization performance resulting from the deletion of that actor, *ceteris paribus*. To confirm effect sizes, we conducted statistical testing on the performance differences to examine significance of actor impacts and performed clustering analysis to identify the baseline group of "critical" actors. Then, for all actors, we calculated and compared the traditional and proposed new measures using hierarchical clustering analysis.

Results

For the base case (that is, for the complete team of 16 people) and for each of the 16 cases representing incremental removal of an actor on the software team, we executed 100 monte carlo simulations using Construct. Besides establishing a baseline for further comparison, this result confirms our intuition that each actor on a well-formed team with no slack resources will have measurable impact on the team's overall performance. In Figure 2, we show the actors ranked by performance impact and grouped into two clusters based on a hierarchical similarity analysis that minimizes average Euclidian distance differences between clusters. Based on statistical analysis, the differences in impacts are generally significant. The *z* values for a hierarchical, two-tailed Wilcoxon signed rank test of the difference in performance distributions between each actor and the next-lower ranked actor show significance at $p<0.05$ for 11 out of the 15 differences; values exhibiting the least significance ($0.0910<p<0.7114$) are consistent with the results of our clustering analysis. Figure 3 shows a relative comparison of all normalized index values for each actor on the software team.

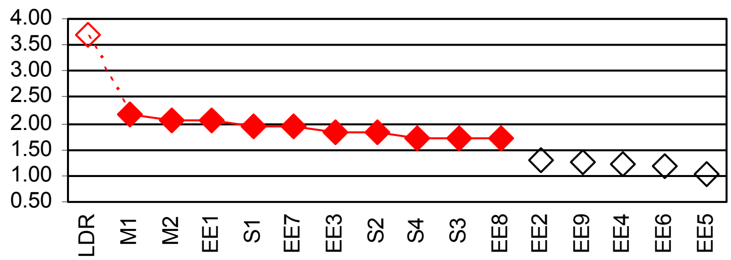

Figure 2. Determination of Critical Employee Cluster.

Results in Figure 3 are non-linear across measures but consistent in many respects with expectations based on traditional social network analysis. Despite a few exceptions (e.g., LDR, S3 and EE2), degree and betweenness measures appear to be correlated. In addition, the leaders of the team (LDR, M1, M2, and S1-S4) have generally higher degree and betweenness centrality measures compared to the employee group (EE1 through EE9). Notable exceptions are employees 7 and 9, both of whom exhibit centrality measures similar to the leadership group. Upon further inspection, however, Figure 3 indicates clear inconsistencies between traditional and proposed measures. For example, while employees EE1, EE3 and EE8 have relatively low degree and betweenness centrality measures, they score among the highest in terms of task exclusivity for EE1 and EE8 and in terms of knowledge exclusivity for EE3. While not always the case, actors with low centrality measures may be more introverted "experts," so the fact that EE3 and EE8 are near-isolates is not inconsistent with such tendencies.

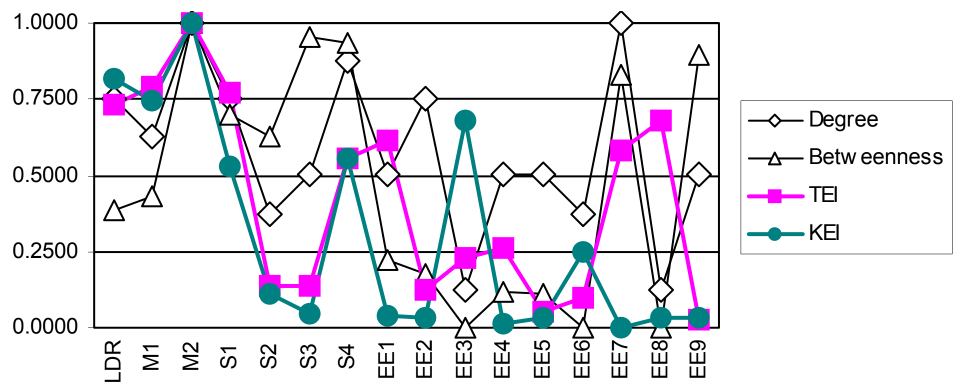

Figure 3. Measures Results for All Team Members.

Results of hierarchical clustering performed on all measures are shown in Table 1, indicating that there is a "core" of three critical actors identified by all four indexes – M2, S1 and S4. However, the traditional network measures of degree and betweenness identify certain actors who are not deemed critical by the proposed measures. In one case, for example, the traditional measures correctly identify actor S3 as critical when the proposed measures do not. In other instances (e.g., EE2 and EE9), the traditional measures ascribe criticality erroneously. In Table 1, rather than using numerical values, we indicate criticality of an actor for any given index with the letter "C." In the "Traditional" and "Knowledge" columns, we provide a heuristic measure denoting an individual as critical ("C") if the union of the respective traditional or proposed measures yields a "C". False negatives and false positives versus the base case for each index are flagged with a "-" or "+" sign, respectively. For example, the "C+" for employee EE2's degree index ($CI_D(n)$) indicates that the degree index measure identified EE2 as critical, but the "+" indicates that this result was a false positive. Likewise, the "-" shown for employee M1's betweenness index ($CI_B(n)$) indicates that M1 was *not* identified as critical according to the cluster analysis of betweenness results, but the "-" means this is a false negative (i.e., M1 should have been identified as critical).

Based on these results, we can further compare the social network versus knowledge-based measures. Since indexes $CI_D(n)$ and $CI_B(n)$ as well as the $CI_D(n) \cup CI_B(n)$ relation ("Traditional Heuristic" result) all display instances of false negatives and false positives, it is clear that social network measures alone cannot be used to identify all critical actors and that such measures may in fact identify actors as critical when they are not. Complementarily, since the TEI_n identifies EE1 and EE8 as critical, the proposed knowledge-based measures can be used to identify critical human assets that may be overlooked by traditional measures. Interestingly, even our proposed measures exhibited a false negative, since TEI_n, KEI_n, KAI_n, and CCM_n all omit S3 as critical compared to the base case. However, we find no evidence that the knowledge-based measures result in false positives. Our proposed composite measure, CCM_n, was slightly more robust than the social network measures alone, but still exhibited several false negatives (S3, EE1 and EE8).

	Base Case	*$CI_D(n)$*	*$CI_B(n)$*	*TEI_n*	*KEI_n*	*KAI_n*	*CCM_n*	*Traditional Heuristic*	*Knowledge Heuristic*
LDR	C	C	-	C	C	-	C	C	C
M1	C	C	-	C	C	-	C	C	C
M2	C	C	C	C	C	-	C	C	C
S1	C	C	C	C	C	-	C	C	C
S2	C	-	C	-	-	C	C	C	C
S3	C	-	C	-	-	-	-	C	-
S4	C	C	C	C	C	-	C	C	C
EE1	C	-	-	C	-	-	-	-	C
EE2		C+						C+	
EE3	C	-		-	C	C	C	-	C
EE4									
EE5									
EE6									
EE7	C	C	C	C	-	-	C	C	C
EE8	C	-	-	C	-	-	-	-	C
EE9			C+					C+	

Table 1. Critical Employee Groups as Determined by Clustering Analysis of Index Results.

Our results confirm that traditional social network measures are generally correlated with employee criticality, but they do not always identify critical employees when task assignment and knowledge are taken into account. We proposed new task- and knowledge-based measures that substantially improve the robustness of analyzing criticality of employees based on their relative impact on organizational performance, and we validated their effectiveness by applying them to a sixteen-person software engineering team. We find that no single measure or class of measures perfectly identifies all critical employees, but that a heuristic application of the proposed knowledge-based measures results in the highest overall accuracy.

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