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Information Flow Through Strong and Weak Ties in Intraorganizational Social Networks*

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Strong and weak ties are compared in terms of their contributions to information flow about the work activity of persons in intraorganizational social networks. Strong ties are more important than weak ties in promoting information flow about activities within an organizational subsystem. Weak ties are more important than strong ties in promoting information flow about activities outside an organizational subsystem. The strength of weak ties in promoting boundary-spanning information flows lies not in their individual efficiency but in their numbers. In general, production of the highest probabilities of information flow is associated with a combination of both weak and strong ties.

Introduction

There is little doubt that the diffusion of various types of information (rumor, gossip, job openings, role performance, etc.) is somehow influenced by social network structure (Coleman *et al.* 1966; Granovetter 1973; Kerckhoff *et al.* 1965). However, remarkably little is known about the manner in which network structure affects information flow. Our knowledge about the relationship between social network structure and information flow has remained at a global level because there has been a paucity of attempts to empirically address the relationship between *specific features of network structure* and information flow.

The present study is concerned with the effect of differences in the *strength* of interpersonal ties on the probability of information flow. Social networks are composed of ties that differ in their interpersonal strength, and it is natural to assume that the strong ties are more efficient contributors to information flows than the weak ties. However, since Granovetter's seminal paper (1973), the field has been more sensitive to the possible substantial contribution of weak ties to information flow. In Granovetter's work, and elsewhere, it is suggested that weak ties are important sources of

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information about activities and opportunities in distant parts of social systems (see Granovetter's 1981 review of this literature). Though weak ties may be less efficient than strong ties in promoting information flow, they may be nonetheless more important than strong ties in promoting information flow about activities outside a group.

This study compares strong and weak ties in terms of their contribution to information flow about work activities within organizations. Two types of information flow are considered: the flow of information to person u about the work of person v who is in the same subsystem of the organization, and the flow of information to person u about the work of person v who is in a different system of the organization.

Methods

The paper is based on an investigation of information flows about scientific work among faculty members in the biological, physical, and social sciences divisions of the University of Chicago and Columbia University. Virtually all the faculty members in the following disciplines were surveyed: in the biological sciences divisions, anatomy, biochemistry, biology, genetics, microbiology, pathology, pharmacology, and physiology; in the physical sciences divisions, astronomy, chemistry, geology, statistics, mathematics, and physics; in the social sciences divisions, anthropology, economics, political science, psychology, and sociology. A mailed questionnaire was used to gather the data and was sent to 851 faculty members in all. Table 1 shows the number of faculty members surveyed in each division of the two universities and the response rate in each division.[1]

Table 1. *The survey*

Network	No. of network members	No. of survey respondents	No. of respondent dyads*
The University of Chicago			
Biological Sciences Faculty	142	97 (68.3%)	9312
Physical Sciences Faculty	141	79 (56.0%)	6162
Social Sciences Faculty	153	95 (62.1%)	8930
Columbia University			
Biological Sciences Faculty	153	105 (68.6%)	10920
Physical Sciences Faculty	105	59 (56.2%)	3422
Social Sciences Faculty	157	94 (59.9%)	8742
Totals	851	529 (62.2%)	47488

*u, v dyads in which both u and v are respondents.

[1] The effects of nonresponse rates on measurement of social network structure are not well understood, though some useful work has been done on the problem (Holland and Leinhardt 1973).

The questionnaire, received by a potential respondent, named only those faculty members who were in his/her own university and academic division. For each person listed on the questionnaire, a respondent indicated whether the following statements were true:

(1) "I know something of person's current work";
(2) "I have read or heard person present his/her current work";
(3) "I have talked with the person about his/her current work".

Instructions to respondents made it plain that 'current work' refers to research a person is engaged in at the time of the survey.

Ties

A tie or a contact is anyone for whom there is some evidence that a direct discussion of current research has occurred. Thus, u is a contact of v if either u has talked to v about v's current work and/or v has talked to u about u's current work.

Tie strength

Describing the concept of tie strength, Granovetter (1937:1361) writes, "The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, and intimacy (mutual confiding), and the reciprocal services which characterize the tie". The measure of tie strength used in the present study is whether or not a discussion of current research is reciprocated or not reciprocated. Strong ties are defined as those in which both faculty members' current research has been discussed, weak ties as those in which only one of the faculty members' current research has been discussed. The measure is consistent with Granovetter (1973:1364) who treats asymmetrical contact as a weak tie and reciprocal contact as a strong tie (also see Friedkin 1980).

Information flow

If a faculty member u has not been in contact with faculty member v, has not read about the current work of v, and has not heard a presentation of the current work of v, then u's awareness of v's current work is likely to be based on a flow of information from contacts who are informed about v's work (hereafter, these contacts are referred to as the informed contacts of u). Screening out possible alternative sources of knowledge is a method of isolating the occurrence of an awareness of current work that is based on the flow of information through contacts.

The method is a good one to the extent that it isolates *only* those cases in which u's awareness of v's work is based on information flow from the contacts of u. Confidence in the method rests on logical grounds: u is most likely to have learned about v's current work from an acquaintance if u has not read about the work, heard a presentation of the work, or talked to v

about the work. It is sufficient for the purposes of the analysis that this assumption holds in a large majority, if not all, of the cases. The advantage of the method is that it provides a large number of likely instances of information flow for analysis and permits a multivariate investigation of factors that might influence the probability of information flow.[2]

Units of analysis

The measure of information flow depends on the selection of dyads in which u's awareness of v's current work is most likely to have occurred on the basis of contacts who are informed about v's work. Accordingly, the analysis focuses on dyads u,v:

(1) in which both u and v are survey respondents,
(2) in which there is no evidence of contact,
(3) in which u has not read about v's current work, and
(4) in which u has not heard a presentation of v's current work.

Dyads in which u and v are in the same department and dyads in which u and v are in different departments are examined. Given the requirement of no contact between u and v, it is likely that the persons who are involved in the intradepartmental dyads work in different specialities of a particular discipline (Friedkin 1978). To the extent that this is the case, even the intradepartmental information flows may be interpreted as boundary-spanning.

Results

Information flow and the number of potential informants

Within the six faculties of science, the probability that information flows to faculty member u about faculty member v's current work is a function of the number of u's contacts who are informed about v's work (the strength of u's ties with the contacts is ignored for the moment):

$$L = 1 - C(1 - P)^X \tag{1}$$

where L is the probability that u is informed about the current work of v; P is the probability that a single informed contact of u will transmit information to u about v; X is the number of informed contacts of u; and C is the probability that u is unaware of v's work when u has no informed contacts (C should equal or be close to 1.0 in the dyads examined).

If P is the probability that a single informed contact of u will transmit information to u about v, then $1 - P$ is the probability that such transmission will not occur and $(1 - P)^X$ is the probability that not one of the X informed contacts of u will transmit information to u about v. Therefore, the probability (L) that at least one of u's informed contacts will transmit information is

[2] At this point, I wish to acknowledge and again thank James Coleman, who was of great assistance to me in the development of this measure of information flow.

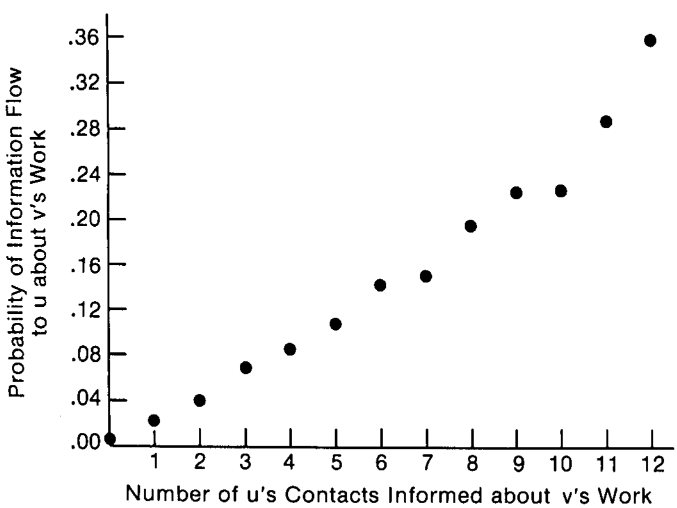
$$1 - C(1 - P)^X$$

where C is equal to 1.0 if no other factors affect the probability of u's being aware of v's current work.

The model assumes that P and C are constants; in fact, both are likely to be affected by a variety of factors and vary across individuals. The model also assumes that the informed contacts of u make independent contributions to the probability that u is informed about the current work of v. Finally, the model assumes that if u knows of v's work, after alternative sources of information have been screened out, it is primarily as a result of information flow from people u knows who know of v's work, and that these people are among the ones named by u in the survey. The adequacy of these simplifying assumptions, for the present purposes of prediction, must be assessed on the basis of the degree of fit of the model to the data.

Figure 1 shows that the probability that u has received information about v's current work is 0.005 when u has no contacts who are informed about v's work and that this probability rises steadily as the number of u's informed contacts increases.

Figure 1. *The probability of information flow to u about v's work increases with the number of u's contacts who are informed about v's work.*



Our interest is in the parameter P, i.e., the contribution of a single informed contact to information flow. Let L' equal the probability that u is not aware of v's current work:

$$L' = 1 - L$$

Then,

$$\log L' = X \log(1 - P) + \log C$$

With this equation, which is of the form

$$y = bx + c$$

ordinary least squares regression can be used to estimate the parameter P.

The slope of the regression line through the points in Fig. 1 is -0.01402; hence, $P = 0.032$. The analysis suggests that the contribution of a single informed contact to the likelihood of u's being aware of v's work is low and that multiple informed contacts make an independent contribution to the probability of u's being informed ($r^2 = 0.94$, Table 2).

Table 2. *Computing a regression line for the points in Figure 1*

No. of informed contacts of u x	Observed proportion of us who are aware of v's current work* p	$100(1 - p)$ y	$\log[(1 - p)\,100]$ $\log y$
0	105/21116	99.5	1.9978
1	172/7942	97.8	1.9903
2	162/4100	96.0	1.9823
3	199/2842	93.0	1.9685
4	149/1753	91.5	1.9614
5	128/1191	89.3	1.9508
6	109/765	85.8	1.9335
7	73/491	85.1	1.9299
8	57/294	80.6	1.9063
9	39/175	77.7	1.8904
10	28/125	77.6	1.8899
11	16/56	71.4	1.8537
12	16/45	64.4	1.8089

OLS regression: $\log y = x \log(1 - P) + \log C$
$r^2 = 0.94$
$\log(1 - P) = -0.01402$
$\log C = 2.012$

*Only observed proportions with a base of 30 cases or more are reported.

Contributions of strong and weak ties

The same procedure may be used to disentangle the relative contributions of the strong and weak informed contacts of u to u's likelihood of being informed about v:

$$L = 1 - C(1 - P_1)^{X_1}(1 - P_2)^{X_2} \qquad (2)$$

Here, L and C have the same interpretation as in eqn. (1); X_1 is the number of u's informed weak contacts: P_1 is the probability that an informed weak contact of u will transmit information to u about v; X_2 is the number of u's informed strong contacts; and P_2 is the probability that an informed strong contact of u will transmit information to u about v.

The model fits the data well ($R^2 = 0.93$, Table 3).[3] Weak ties are less efficient contributors to the probability of information flow than strong

Table 3. *Relative effect of strong and weak ties on information flow*

No. of weak ties informed about v's work x_1	No. of strong ties informed about u's work x_2	Observed proportion of *us* who are aware of v's work* p	$100(1-p)$ y	$\log[(1-p)\,100]$ $\log y$
0	0	105/21116	99.5	1.9978
1	0	108/5866	98.2	1.9921
2	0	64/2081	96.9	1.9863
3	0	60/1027	94.2	1.9740
4	0	33/480	93.1	1.9689
5	0	24/222	89.2	1.9504
0	1	64/2080	96.9	1.9863
1	1	71/1581	95.5	1.9800
2	1	63/1071	94.1	1.9736
3	1	53/619	91.4	1.9609
4	1	25/336	92.6	1.9666
5	1	19/152	87.5	1.9420
0	2	27/438	93.8	1.9722
1	2	64/627	89.8	1.9533
2	2	33/434	92.4	1.9657
3	2	41/348	88.2	1.9455
4	2	24/183	86.9	1.9390
5	2	17/106	84.0	1.9243
0	3	12/117	89.8	1.9533
1	3	25/194	87.1	1.9400
2	3	26/190	86.3	1.9360
3	3	34/179	81.0	1.9085
4	3	15/115	87.0	1.9395
5	3	17/83	79.5	1.9004
1	4	12/87	86.2	1.9355
2	4	16/94	83.0	1.9191
3	4	14/77	81.8	1.9128
4	4	10/49	79.6	1.9009
5	4	8/38	79.0	1.8976

$r_{12} = -0.0769$ OLS regression: $\log y = x_1 \log(1-P_1) + x_2 \log(1-P_2) + \log C$

$R^2 = 0.93$

$r_{y_1} = -0.5656$ $\log(1-P_1) = -0.00858$

$\log(1-P_2) = -0.01605$

$r_{y_2} = -0.8234$ $\log C = 2.0022$

*Observed proportions with a base of 30 cases or more.

[3]Equation (1) fits the data slightly better than eqn. (2). Equation (2) does not include the variable found in eqn. (1); it is a wholly different model. For this reason, one would not necessarily expect a higher R^2 in eqn. (2) than in eqn. (1).

Table 4. *Relative effect of strong and weak ties on information flow about the work of a person in a different department of the university*

No. of weak ties informed about v's work x_1	No. of strong ties informed about v's work x_2	Observed proportion of us who are aware of v's work* p	$100(1-p)$ y	$\log[(1-p)\,100]$ $\log y$
0	0	91/20460	99.6	1.9982
1	0	74/5411	98.6	1.9939
2	0	42/1868	97.8	1.9903
3	0	27/802	96.6	1.9850
4	0	13/348	96.3	1.9836
5	0	9/145	93.8	1.9722
0	1	44/1907	97.7	1.9899
1	1	51/1370	96.3	1.9836
2	1	38/852	95.5	1.9800
3	1	25/448	94.4	1.9750
4	1	12/225	94.7	1.9764
5	1	12/96	87.5	1.9420
0	2	17/373	99.4	1.9974
1	2	32/490	93.5	1.9708
2	2	16/340	95.3	1.9791
3	2	18/231	92.2	1.9647
4	2	11/119	90.8	1.9581
5	2	9/69	87.0	1.9395
0	3	7/84	91.7	1.9624
1	3	7/123	94.3	1.9745
2	3	13/134	90.3	1.9557
3	3	12/120	90.0	1.9542
4	3	9/83	89.2	1.9504
5	3	9/55	83.6	1.9222
1	4	4/55	92.7	1.9671
2	4	6/64	90.6	1.9571
3	4	6/48	87.5	1.9420

$r_{12} = -0.0572$ OLS regression: $\log y = x_1 \log(1-P_1) + x_2 \log(1-P_2) + \log C$**

$r_{y_1} = -0.6271$ $R^2 = 0.84$

$\log(1-P_1) = -0.00772$

$r_{y_2} = -0.6315$ $\log(1-P_2) = -0.00970$

$\log C = 2.0052$

*Observed proportions with a base of 30 cases or more.

**Using the subset of observed proportions with a base of 100 cases or more:

$R^2 = 0.84$

$\log(1-P_1) = -0.0057$, $P_1 = 0.013$

$\log(1-P_2) = -0.0090$, $P_2 = 0.020$

$\log C = 2.0017$

ties ($P_1 = 0.020$ and $P_2 = 0.036$). The relative strengths of these effects suggest that it requires approximately twice as many weak ties to obtain the equivalent effect of a given number of strong ties: a 0.20 probability of information flow may be obtained on the basis of approximately 10 weak ties or 5 strong ties; a 0.30 probability may be obtained on the basis of approximately 16 weak ties or 8 strong ties, etc.

Information flow about research inside and outside the departments

Ties may be informed about members of *u*'s department or about members of departments other than *u*'s own. The model (eqn. (2)) fits the data concerning information flows about activity in other departments better ($R^2 = 0.84$, Table 4) than the data concerning information flows about activities in the same department ($R^2 = 0.60$, Table 5).[4]

The relative contributions of weak and strong ties are as follows:

Concerning the work of a person in another department	Concerning the work of a person in the same department
$P_1 = 0.018$	$P_1 = 0.018$
$P_2 = 0.022$	$P_2 = 0.057$

Strong ties are more efficient conduits of information flow than weak ties, whether the information is concerned with a fellow department member's work or with the work of a member of a different department.[5]

Individual efficiency and total impact of ties

While weak ties are less efficient than strong ties, they may be an important basis of information flow about activities outside a department if persons maintain many more weak than strong ties who are informed about activities in other departments. A direct test of this proposition involves separating, for each dyad, the total contributions of weak and strong ties to the probability of information flow to *u*.

$$L_{\mathrm{TOT}} = 1 - C(1 - P_1)^{X_1}(1 - P_2)^{X_2}$$

gives an estimate of the probability that information will flow to *u* about *v* for each dyad, while

$$L_{\mathrm{WEAK}} = 1 - C(1 - P_1)^{X_1}$$

[4]Each of the models has a proportion as its dependent variable. The average number of cases (i.e., base) upon which the proportions are calculated differs in the various models. For example, the proportions used to estimate eqn. (1) have a smaller base, on average, than the proportions used to estimate the contribution of strong and weak ties among the intradepartmental dyads (cf. Tables 2 and 5). The greater the size of the bases of the proportions used to estimate a model, the larger a model's R^2. This suggests that greater instabilities associated with smaller bases account for differences in the R^2 values. However, note that the reanalysis of the data in Tables 4 and 5, using only the proportions with a base of 100 or more cases, does not substantially improve the fits. It may be that very high R^2 values emerge only with very large bases.

[5]Reanalysis of these data using only the proportions with a base of 100 gave the following results: for the intradepartmental information flows, the values of P_1 and P_2 do not change; for the interdepartmental information flows, the values of P_1 and P_2 are more divergent than they were in the full sample. In subsequent analysis, I use the more conservative, i.e., less divergent, estimates of these effects.

Table 5. *Relative effect of strong and weak ties on information flow about the work of a person in the same academic department*

No. of weak ties informed about v's work x_1	No. of strong ties informed about v's work x_2	Observed proportion of us who are aware of v's work* p	$100(1-p)$ y	$\log[(1-p)\,100]$ $\log y$
0	0	14/656	97.9	1.9908
1	0	34/455	92.5	1.9661
2	0	22/213	89.7	1.9528
3	0	33/225	85.3	1.9309
4	0	20/132	84.8	1.9284
5	0	15/77	80.5	1.9058
0	1	20/173	88.4	1.9464
1	1	20/211	90.5	1.9566
2	1	25/219	88.6	1.9474
3	1	28/171	83.6	1.9222
4	1	13/111	88.3	1.9460
5	1	7/56	87.5	1.9420
0	2	10/65	84.6	1.9274
1	2	32/137	76.6	1.8842
2	2	17/94	81.9	1.9133
3	2	23/117	80.4	1.9052
4	2	13/64	79.7	1.9014
5	2	8/37	78.4	1.8943
0	3	5/33	84.8	1.9284
1	3	18/72	75.0	1.8751
2	3	13/56	76.8	1.8854
3	3	22/59	62.7	1.7973
4	3	6/32	81.2	1.9010

$r_{12} = -0.0934$ OLS regression: $\log y = x_1 \log(1-P_1) + x_2 \log(1-P_2) + \log C$**

$R^2 = 0.60$

$r_{y_1} = -0.2783$ $\log(1-P_1) = -0.00798$

$r_{y_2} = -0.6920$ $\log(1-P_2) = -0.0253$

$\log C = 1.9750$

*Observed proportions with a base of 30 cases or more.

**Using the subset of observed proportions with a base of 100 cases or more:

$R^2 = 0.63$

$\log(1-P_1) = -0.0079,\quad P_1 = 0.018$

$\log(1-P_2) = -0.0256,\quad P_2 = 0.057$

$\log C = 1.9748$

gives an estimate of the probability that information will flow to u about v based on the weak ties of u exclusively.[6]

Our interest is in the distribution of

$$W = L_{\text{WEAK}}/L_{\text{TOT}}$$

[6]Similarly,

$$L_{\text{STRONG}} = 1 - C(1-P_2)^{X_2}$$

In terms of these two components $L_{\text{TOT}} = L_{\text{WEAK}} + L_{\text{STRONG}} - (L_{\text{WEAK}})(L_{\text{STRONG}})$

To the extent that weak ties are an important component of the total probability of information flow, the value of W will be close to 1.0. If strong ties are more central to intradepartmental information flow while weak ties are more central to interdepartmental information flow, the distribution of W among the interdepartmental dyads will tend to differ from the distribution of W among the intradepartmental dyads. Table 6 indicates that this is the case ($\chi^2 = 1061.99$, d.f. = 4).

Table 6. *Weak ties have a larger role in the probability of interdepartmental information flows than intradeparmental information flows**

Fraction of the probability of information flow based on weak ties	Intradepartmental information flows		Interdepartmental information flows	
0 - 0.19	20.3%	(670)	14.9%	(2466)
0.20 - 0.39	19.3%	(637)	5.8%	(965)
0.40 - 0.59	20.2%	(667)	14.2%	(2348)
0.60 - 0.79	3.4%	(112)	11.2%	(1863)
0.80 - 1.0	36.8%	(1215)	53.8%	(8905)
Totals	100.0%	(3301)	99.9%	(16547)

*$\chi^2 = 1061.99$, d.f. = 4.

Weak ties are more important than strong ties in the probabilities of information flow concerning research activities of other departments; conversely, strong ties are more important than weak ties in the probabilities of information flow concerning the work of fellow department members. But even with respect to information flow about fellow department members, the contribution of weak ties is impressive. This result is not surprising when it is recalled that these intradepartmental dyads are ones in which u and v have not been in direct contact about current work and, therefore, are most likely to be in different fields of a discipline.

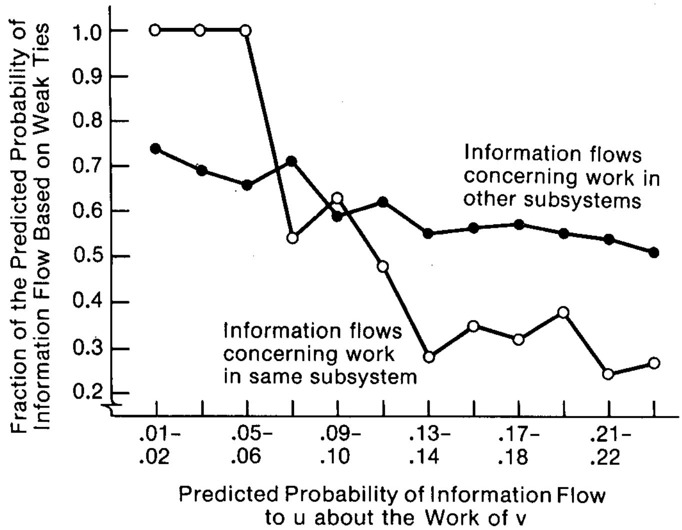
We have seen that the total impact of weak ties on the probabilities of information flow is impressive. This total impact diminishes as we move into the higher part of the range of information flow probabilities. Figure 2 shows the average contribution of weak ties for a given value of L_{TOT_j}, that is,

$$\overline{W}_j = \left(\sum_{i=1}^{n_j} \frac{L_{\mathrm{WEAK}_{ij}}}{L_{\mathrm{TOT}_j}} \right) \Big/ n_j$$

as a function of the estimated likelihood of information flow, L_{TOT}.

As L_{TOT} increases, strong ties make an increasingly important contribution to the estimated likelihood of information flow. This tendency is more pronounced with regard to information flows concerning activity within the

Figure 2. *The higher the probability of information flow, the smaller the relative contribution of weak ties.*



same department than concerning activity in other departments. The *highest* probabilities of information flow tend to be based on a *combination* of weak and strong ties.

Discussion

This analysis has shown that while weak ties are generally less efficient contributors to information flow than strong ties, weak ties may make an important contribution to the probability of information flow by virtue of their numbers. The total contribution of strong and weak ties to the probability of an information flow depends on the relative number of each type of tie. While strong ties tend to be more central than weak ties in accounting for information flow about activities within an organizational subsystem, weak ties are more central than strong ties in accounting for information flow about activities outside an organizational subsystem. In both types of information flow, the contribution of weak ties is impressive since persons tend to maintain more weak than strong ties. At the same time, attainment of the highest probabilities of information flow is associated with an increasingly important role for strong ties. One does not tend to find high probabilities of information flow based on weak ties alone.

These findings enlighten the theoretical viewpoints of Granovetter (1973) and Blau (1974:623) who have stressed the importance of weak ties in promoting the macro-level integration of complex systems. Informal contacts, strong or weak, are generally inefficient transmitters of information. However, weak ties have an important impact on intraorganizational information flows when they occur in sufficient numbers. The strength of weak ties lies not in their individual efficiency but in their numbers.

While it is plain that weak ties are a major basis of intergroup connectivity (Granovetter 1981), we must not be led into the synecdochic fallacy of believing that strong ties have no part in intergroup cohesion (Hirschi and Selvin 1967:260). If the present findings are generally applicable to intergroup information flows, we should expect to find that strong ties are an important factor in the production of the highest probabilities of information flow between the informal groups and formal subsystems of organizations.

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