Implementation of Evidence Based Practice in Human Service Organizations: Implications from Agent-Based Models
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Abstract

Much of the impact of a policy depends on how it is implemented, especially as mediated by organizations such as schools or hospitals. Here we focus on how implementation of evidence-based practices in human service organizations (e.g. schools, hospitals) is affected by intra-organizational network dynamics. In particular, we hypothesize intra-organizational behavioral divergence and network polarization are likely to occur when actors strongly identify with their organizations. Using agent-based models we find that when organizational identification is high, external change agents who attempt to direct organizations by introducing policy aligned messages (e.g., professional development emphasizing specific teaching practices) may unintentionally contribute to divergence in practice and polarization in networks, inhibiting full implementation of the desired practices as well as reducing organizational capacity to absorb new practices. Thus the external change agent should consider the interaction between the type of message and the intra-organizational network dynamics driven by organizational identification.

Keywords: implementation, evidence based practices, organizations, agent-based mode
INTRODUCTION: INTRA-ORGANIZATIONAL NETWORKS AND IMPLEMENTATION OF NEW PRACTICES

Most public policies are implemented by organizations that develop expertise and allocate internal resources to deliver services or programs (Cohen & Barnes, 1993; DeCarolis & Deeds, 1999; Cohen & Hill, 2001; Kilduff & Tsai, 2003; Werner, 2004; Kilduff et al., 2006; Scott, 2008; Weiss, Bloom & Brock, 2014). For example, educational policies are implemented by schools that reassign or replace instructional staff or choose curricular materials (Bidwell & Kasarda, 1985; DeCarolis & Deeds, 1999; Weiss, Bloom & Brock, 2014). Similarly, health policies are implemented by hospitals, insurers, and professional associations (Barley, 1990; Poon et al., 2004; Watt et al., 2005); welfare-to-work programs are implemented by program offices (Weiss, Bloom & Brock, 2014); environmental policy is implemented through NGO’s (Masuda et al., 2018), and immigration policy is implemented through law enforcement agencies (Ridgley, 2008). In this study we focus on evidence-based practices implemented by professionals in the human services. For example, consider the emphasis on basic skills instruction under No Child Left Behind (NCLB, aka the Elementary and Secondary Education Act of 2001) intended to reduce gaps in achievement in part by attending carefully to assessment in terms of standardized tests (Jorgensen & Hoffmann, 2003). As part of the institutional forces that coalesced around NCLB, the report of the National Reading Panel (2000) emphasized “the importance of applying the highest standards of scientific evidence to the research review process so that conclusions and determinations are based on findings obtained from experimental studies” (pages 1-2) but also “the importance of the role of teachers, their professional development, and their interactions and collaborations with researchers, which should be recognized and encouraged.” Similarly, in the health care professions, evidence-based practice consists of giving clinicians “strategies and tools to interpret and integrate evidence from published research in their patient care” (page 1291, Guyatt et al., 2000; Guyatt, Cook & Haynes, 2004; Labrecque & Cauchon, 2013).
Note that in the education and health examples above, the approach requires the practitioner to interpret evidence relative to their own practice and context (e.g., Lipsky, 2010). This gives the practitioner some discretion and autonomy in choosing practices to adopt. In this context, the organization (e.g., the school, hospital, or HMO), especially informal processes within the organization, affect the practitioner’s choices. Here, we focus on one key element of the organizational context, intra-organizational network dynamics – how organizational members connect with and influence each other through informal collegial networks (we will attend to networks outside the organization in the discussion). Such informal networks of colleagues convey the cultural mores, the norms of the organization, and the resources of social capital (Adler & Kwon, 2002; Bryk & Schneider, 2002; Coleman, 1988; Frank, Zhao & Borman, 2004). Correspondingly, the experience of each organizational member depends on the particular network in which that member is embedded.

Intra-organizational network dynamics have important implications for implementation of broad scale policy. Such policies are typically conveyed by change agents representing the government (e.g., state or local officials) or broad institutional norms (e.g., professional associations or the professional development industry). While change agents may adhere to the precepts of the policy, they mediate between the designers and implementers of the policy. As such, the change agents must carefully choose how they convey the policy (what we define as “messages”) to contribute to implementation of the policy.

In this study, we attend to how the change agent’s message interacts with intra-organizational network dynamics to affect the distribution of practices and network structure within the organization. Failure to account for intra-organizational network dynamics can lead to divergent practice, uncoordinated action as well as reduce the organization’s future capacity to implement new practices. For example, while NCLB policy commended basic skills instruction, professional development for literacy instruction that emphasizes only basic skills may induce network polarization (few connections between subgroups or clusters of teachers)
and divergent practices among teachers who strongly identify with their school (Penuel, Frank et al., 2013). Ultimately, this can impede the implementation of basic skills instruction.

Recognizing non-linear intra-organizational network dynamics (e.g., Anderson et al., 1999; Frank & Fahrbach, 1999), conventional techniques for characterizing the implementation process are not adequate. That is, equilibria cannot be easily predicted from initial conditions in a deterministic system. Therefore, we draw on agent based models to investigate how intra-organizational dynamics affect the implementation of policy. Specifically, we examine a system in which intra-organizational networks are driven by organizational identification (i.e. the extent to which organizational members identify with their organization). We then experiment with our system in terms of the messages conveyed by external change agents seeking to direct members of the organization to particular practices.

Anticipating one of our key results, when organizational identification is high, external change agents who introduce policy aligned messages (only supporting practices aligned with a policy) into the organization may induce divergent practices and polarization in networks. Thus, when organizational identification is high a change agent can more effectively influence the practices of organization members by conveying a message balanced between information aligned with a particular policy and information aligned with an alternative policy. Such a balanced message integrates members of potentially different predispositions, contributing to organizational coherence and collective change in practices.

In the next section, we develop hypotheses in terms of the interaction between the external change agent’s message and intra-organizational network dynamics. We then describe our agent-based models, simulation methods, and present our results. We discuss our results in terms of the how the change agent’s choice of message depends on intra-organizational network dynamics, implications for different change agents, and we identify limitations.
BACKGROUND

Intra-organizational Network Dynamics

While organizations may affect members through formal decisions and hierarchical control (Weber, 1946), many of the decisions made by professionals in the human services are responsive to informal processes relating to organizational culture and norms as well as social capital (Adler & Kwon, 2002). Networks are key drivers for many of these informal processes (Adler & Kwon, 2002; Bryk & Schneider, 2002; Frank & Fahrbach, 1999). Correspondingly, intra-organizational network dynamics are defined by how organizational members interact with and influence each other through informal interactions that convey cultural mores, the norms of the organization and external institutions, and the resources of social capital. Furthermore, network dynamics include how networks themselves are constantly modified, often as a result of diffusion of information and implementation processes (Frank & Fahrbach, 1999; Xu & Frank, 2016). In this sense, an organization’s capacity to change practices is partly a function of the capacity of its network to create or sustain information flows before, during, and after the diffusion of new information or practices within the organization. That is, we define organizational capacity in network terms to complement others’ attention to organizational capacity in terms of culture or leadership (Cohen & Levinthal, 1990).

Organizational Identification as Driver of Intra-organizational Dynamics

From the economic perspective, policies are implemented by changing incentives for individuals or organizations intended to influence the behavior of organizations as corporate actors or as a collective of individuals (Schneider & Ingram, 1990; Gneezy et al., 2011). Our assumption is that the incentives associated with a policy are complex, dynamic, and context specific, and thus they are not immediately comprehensible to all of the members within the organization (Weick, 2005; Weick, Sutcliffe & Obstfeld, 2005). For example, many teachers were uncertain about the immediate implications of incentives associated with basic skills instruction associated with NCLB as well as the durability of the incentives (Frank, Penuel et al.,...
Similarly, currently teachers are uncertain about the incentives associated with the Common Core of State Standards (Coburn et al., 2016) which were developed by the Council of Chief State School Officers (CCSSO) and the National Governors Association Center for Best Practices (NGA Center) to guide schools in choosing curricula and related materials (http://www.corestandards.org/about-the-standards/).

With high uncertainty in the environment, professionals may seek information on which to base their practices (e.g., Weick, 2005). But there may also be high transaction costs/risk to access information. As a result, actors rely on members of their organizations to reduce the transaction cost/risk to access new information (Williamston, 1981). This increases the value of organizational identification, defined as “the perception of oneness with or belongingness to some human aggregate” (Ashforth & Mael, 1989, page 21).

Critically, organizational identification can alter how organization members interact with each other. In particular, we expect actors who identify strongly with their organizations to attempt to align their behaviors with others in their organizations with whom they have a network connection (Akerlof & Kranton, 2002; Xu & Frank, 2016). This is a form of the classic function of balance (Heider, 1946).

Actors can align their behaviors with others in their networks by conforming to norms in their networks. As examples, teachers and physicians can align their practices with those of their colleagues. Normative influence can be due to an actor’s shared sense of fate with others in the organization (Akerlof & Kranton, 2005; Ashforth & Mael, 1989; Portes & Sensenbrenner, 1993) or a sense of shared mission in the organization (Williamson, 1981). Normative influence can also occur as actors seek to maintain organizational membership which can be protective in uncertain conditions (Lin et al., 2001). Finally, actors may conform to norms to preserve their identities (Tajfel and Turner 1979; Shayo 2005).

Actors may also align their behaviors with those of network members by choosing to connect with others who engage in similar behaviors (McPherson et al., 2001). In particular, the theory of
value based homophily suggests that individuals seek connections with others who hold similar values or engage in similar behaviors (e.g., McPherson et al., 2001). For example, in the case of religion, the more strongly held the religious beliefs, the stronger the homophily effect (Iannaccone, 1988; Lazarsfield & Merton, 1954; McPherson et al., 2001 page 426). Furthermore, the more deeply embedded is a particular identity, the stronger is the attraction to others who hold similar values and engage in similar behaviors. Translating to our context, the stronger an actor’s organizational identification the more the actor will be attracted to others who engage in similar behaviors.

The personal motivations of normative influence and value-based homophily can be contrasted with more instrumental or opportunistic action. In particular, instead of conforming to norms of others in one’s network, one can choose behaviors instrumentally based solely on information supporting or opposing the behavior (Figlio et al., 2011). Similarly, instead of choosing to connect to others who engage in similar behaviors, one can opportunistically choose to connect with others who are likely to provide new information (e.g., Burt, 2009). In schools, such opportunistic behavior might occur when there is high turnover such that teachers are reluctant to personally invest in others who may have short tenure in the school (Ingersoll, 2001).

**Examples of Intra-Organizational Network Dynamics and the Implementation of New Practices**

In an example of how network dynamics affect the implementation of new professional practices, Frank, Penuel et al. (2013) found that the pressures and institutions associated with No Child Left behind (NCLB) contributed to divergence in instructional practices among teachers within schools. This occurred as teachers were initially affiliated with cohesive subgroups, or cliques, in which collegial relations were concentrated. Furthermore, subgroup membership aligned with receptivity to basic skills instruction associated with NCLB. Under the pressure of NCLB, subgroups with an initial predisposition towards NCLB related practices increasingly adopted those practices as their members interacted with similar others who provided expertise.
and generated norms supporting the practices. In contrast, other subgroups migrated away from basic skills instruction as they lacked expertise associated with, and orientation to, the practices. Thus, instructional practices diverged between subgroups as teachers inhabited networks aligned with their professional identities. Ironically, the national policy intended to standardize opportunity around a particular conceptualization of reading contributed to the unintended consequence of polarizing instructional staff and creating uneven instruction within schools. Such unevenness can ultimately create organizational challenges of coordination and collaboration beyond the focus of a specific intervention (Woodward, 1980; Bidwell, 1965; Thompson, 1967) and can broadly contribute to inequitable opportunities for students within schools (Frank et al., forthcoming).

As a second example of how intra-organizational network dynamics affect practices in the human services sector, consider the movement to evidence-based practice in medicine. There are considerable institutional norms that push for evidence-based practice, from the insurance and pharmaceutical industries to the federal government and elements of the medical profession (Guyatt, Cook & Haynes, 2004; Labrecque & Cauchon, 2013; Landry, Lamari & Amara, 2003). But some physicians may resist evidence-based practice as it may not directly translate to clinical practice (Bluhm, 2007) or it may not account for patient preferences and values (Labrecque & Cauchon, 2013). Correspondingly, implementation of evidence-based practices has the potential to spawn divergent practices among physicians within hospitals. This can occur if physicians are organized into subgroups (such as by specialty) which have differing predispositions about how to blend research findings with clinical practice (Broom, Adams & Tovey, 2009). For example, hematology oncologists are less reliant on randomized controlled trials (RCTs) and more reliant on case studies than medical oncologists (Broom, Adams & Tovey, 2009, p. 196). As physicians then are influenced by members of their subgroups, initial differences between subgroups can become accentuated when physicians are exposed to messages emphasizing a particular set of
practices, resulting in divergent practices. Not surprisingly, then, implementation guides for evidence based practice emphasize whole hospital integration and diffusion (e.g., Oman, 2010).

The External Change Agent’s Message

We now consider what happens when an external change agent seeks to direct the action of organizational members. Because the change agent is external to the organization the agent acts by delivering information, or what we will call messages, to members of the organization. In the NCLB example, the change agent might be a state level or district level policy maker who seeks to direct educational practices towards basic skills instruction. The change agent may deliver messages in the form of professional development, curricular materials, or standardized tests that encourage basic skills instruction. Our research question then is how the message of the change agent interacts with intra-organizational network dynamics, as driven by organizational identification, to affect practice.

The choice for the external change agent concerns what type of message to express. A policy aligned message encourages behavior and contains information consistent with a particular policy (e.g., basic skills for NCLB), but may create unintended consequences when interacting with intra-organizational network dynamics. We have argued that when organizational identification is high, behavior between subgroups may be prone to diverge as actors interact with and conform to norms of those already in their networks. When a policy aligned message is expressed in such a context, those most predisposed to the message may respond positively to the message, while others not predisposed to the message may resist the message or avoid exposure. As a result, a policy aligned message may accentuate existing differences between subgroups.

In contrast to a policy aligned message, a balanced message containing information supporting multiple points of view may be equally received regardless of an actor’s predisposition. Therefore, a balanced message has the potential to integrate members of different subgroups, reducing initial differences between them. But the balanced message might not be effective in changing the overall level of practice intended by the policy. This is because the balanced message
potentially exposes all members of the organization to information supporting the desired policy as well as its alternative. Therefore, the change agent must strategically choose the type of message with an eye toward the direct intended consequences for behavior, as well as toward the attendant network consequences. This choice of the change agent will be informed by the simulations we conduct in this study to explore the properties of organizations that emerge when external messages are introduced into them.

Figure 1. Interaction of the Change Agent’s Message with Intra-organizational Dynamics to Affect Practices and Intra-Organizational Networks.

The interaction between intra-organizational network dynamics and the change agent’s message is shown in Figure 1. On the left, the change agent chooses a message to convey an external policy to the organization. Upon permeating the organizational boundary, the message will interact with the intra-organizational network dynamics. According to our theory, the interaction between the change agent’s message and the intra-organizational dynamics can affect the overall practices, divergence or convergence of practices between subgroups, and polarization or integration of the network. Note also that within the organization, the intra-organizational dynamics are themselves a function of organizational identification as the stronger the identification the stronger the desire to connect with others based on personal attributes rather than for instrumental purposes. Correspondingly, the change agent should be aware of how organizational identification affects intra-organizational network dynamics. It is these dynamics
that can interact with the change agent’s messages to contribute to divergent practices and network polarization as well as to the intended behavior.

**Hypotheses**

Based on our theory and figure we generate two hypotheses. First, we consider conventional thinking about how to shift organizational behavior by introducing direct and policy-aligned messages. For example, if one wants teachers to adopt new practices one introduces professional development endorsing those practices (Garet et al., 2001; Desimone et al., 2002; Weiss, Bloom & Brock, 2014). The same holds for any form of professional development such as in a hospital concerning evidence-based practice. But, our theory raises the possibility that a policy aligned message may differentiate and polarize an organization when members identify strongly with their organizations. This can impede the implementation of a new practice. Therefore policy-aligned messages may be most powerful primarily when actors do not strongly identify with their organizations. This leads to our first hypothesis:

H1) external change agents should introduce new practices through policy-aligned messages when organization members do not strongly identify with their organizations.

When organization members do strongly identify with their organizations, a balanced message may integrate members of the organization, ultimately allowing them to respond more comprehensively to integrate the desired practices into their work. For example, a balanced message in the NCLB context could be professional development that places equal emphasis on basic skills and whole language instruction. That is, the balanced message communicates the potential legitimacy of two different sets of practices, even though basic skills are emphasized in the policy. This leads to our second hypothesis:

H2) external change agents should introduce new practices through balanced messages when actors strongly identify with their organizations.
Thus, drawing on intra-organizational network dynamics, we hypothesize that the effect of a policy aligned or balanced message depends on how strongly organization members identify with their organization. In the next Section, we turn to formal models of intra-organizational network dynamics so that we may simulate how these dynamics affect systemic responses to exogenous messages.

SIMULATION MODELS

In this section, we illustrate the basic models we used for agent-based simulations to study the distribution of practices and evolution of the intra-organizational network emerging from individual behavior (Wilensky & Rand, 2015). In particular, we consider how actors in the organization deliberately seek information and choose their behavior relative to information and norms in their networks (influence process) and with whom they connect (selection process). We conceptualize that actors make these choices based on their organizational identification. When organizational identification is high, actors respond to personal characteristics of others in the organization, adopting norms of those with whom they connect and seeking connections with others with whom they have commonality. In contrast, when organizational identification is low, actors opportunistically engage in behaviors based on information to which they have been exposed and seek connections with others who potentially can provide new information to help accomplish primary goals. We then initiate our simulations by assigning actors to two subgroups with different behaviors (representing baseline differentiation within most organizations – an assumption we check in the results and technical appendix A). Finally, we experiment to learn which types of strategies enacted by change agents exert the most leverage on the organization given the intra-organizational network dynamics (all Netlogo code is available at https://msu.edu/~kenfrank/create%20events%20with%20example.nlogo).

Overview of Agent-Based Processes
Agent-based models simulate the simultaneous operations and interactions of multiple agents in an attempt to re-create and predict the appearance of complex phenomena. In agent-based modeling (ABM), a system is modeled as a collection of autonomous decision-making entities which we refer to as actors to reflect our focus on human systems. In each time step, each actor assesses its situation and makes decisions on the basis of a set of rules, and thus updates its own attributes as well as its relationship with other actors (Bonabeau, 2002). This type of model can generate emergent and complex phenomenon on the macro level from micro behavior (Wilensky & Rand, 2015), which are difficult to capture with conventional linear models or macro level system dynamics.

In our model, the system is an organization, and each actor represents a member of the organization. Each actor possesses three dynamic attributes, namely behavior (y), information (I), and network connections (w). Behavior (y) is a positive continuous measure representing levels of implementation of a policy. For example, for a given educational policy with multiple elements, a teacher with behavior 12 implements 12 elements associated with the policy per week. Information is a discrete variable, representing the sum of unique pieces of information possessed by the actor. The information can be consistent (positive) or inconsistent (negative) with the intended policy. For example, information about the benefits of phonics instruction would be positive for supporting basic skills instruction and information about the benefits of whole language would be negative for a policy supporting basic skills instruction. If teacher A is exposed to three pieces of information supporting phonics and one supporting whole language then teacher A’s net exposure would be 3-1=2. Network connection (w) is directional (A->B is different from B->A) and can be represented as a simple indicator, with 1 representing there is a connection from agent A to agent B, 0 representing there is none.

The models include two parameters, organizational identification ($\alpha$) and strength of normative influence relative to selection (k). Organizational identification ($\alpha$) is continuous ranging from 0 (low organizational identity) to 1 (high organizational identity). Strength of
normative influence \((k)\) is also continuous ranging from 0 to 1. The parameters are constant across actors and over time steps within a simulation round.

The rules for agents to update their attributes are as follows: in each time step, (1) agents seek information from whom they have a connection as described in the information seeking process; (2) if actors receive new information from their network connections, actors adjust their behaviors based on information and norms as described in the influence process; (3) actors decide whether to maintain current network connections as described in the selection process – maintaining old connections; (4) if actors decide to dissolve a current connection, they form new connections as described in the selection process – initiating new connections.\(^1\) Next, we define and explain each process.

**Information Seeking Process**

Each time step begins with each actor seeking information from others with whom they have a network connection. Each member of an actor’s network randomly provides one piece of information in their possession to the actor. If the information is new to the actor, then the actor will add this piece of information to its own information list; if the information is redundant, then it will not go into the actor’s information list. Consider actor A who has 3 unique pieces of information, and who seeks information from B, C, and D with whom actor A has network connections. Actor A receives one piece of information from each of the three connections, but the piece of information received from B is redundant with what actor A already has. As a result, actor A now has 5 unique pieces of information, two of which are new.

**Influence Process**

In each time step, actors choose their behavior according to their previous behavior, new information they receive, as well as the behaviors of their network members. Formally, we employ a variation of Friedkin and Johnsen’s (1990) influence model:

\(^1\) See also Fig. F1 in appendix F for a visualization of the simulation process.
\[ y_{it} = (1 - \alpha)y_{it-1}I_{it-1} + \alpha \sum f_{ijt-1}w_{ijt-1}y_{jt-1} \]

(1)

Where \( y_{it} \) represents the behavior of actor \( i \) at time \( t \), and \( y_{it-1} \) represents actor \( i \)'s behavior at time \( t-1 \).

The term \( I_{it-1} \) represents new information possess by an actor. Given our focus on changes in professional practices within organizations, here we consider information concerning knowledge and practice that is conveyed by a deep exchange (Coburn & Russell, 2008; Centola, 2010; Hansen, 1999; Szulanski, 1996). That is, the information is more than what can be uttered in a quick hallway conversation. The information provides an anchor to behavior that prevents the system from exploding to extreme behavioral equilibria (Frank & Fahrbach, 1999).

Formally, the value of the term \( I_{it-1} \) is proportional to the total new information to which an actor is exposed that supports a behavior. For each piece of positive information we assume a 5% increase in behavior, and for each piece of negative information we assume a 5% decrease in behavior. In particular, \( I_{it-1} = 1 + 0.05\sum_{z} \text{information}_{iz} \) where \( \text{information}_{iz} \) is a binary variable (1 if positive, -1 if negative) representing the \( z \)th piece of information to which actor \( i \) is exposed. For example, if an actor receives 2 new pieces of positive information and 1 new piece of negative information at time \( t-1 \), the overall effect of information \( I_{it-1} \) is calculated as \( 1 + (0.05\times2 - 0.05) = 1.05 \).

The term \( I_{it-1} \) is then used as a multiplier for \( y_{it-1} \) in Eq. [1], modifying the effect of an actors’ prior behavior on the new behavior. For example if Actor A engages in behavior at a level of 10 and is exposed to new information summing to 4 then the new behavior would be \( (1-\alpha)10(1+0.05\times4) = (1-\alpha)12 \). By implication, previous information to which an actor was exposed is represented via an actor’s prior behaviors \( y_{it-1} \) in Eq. [1] (Frank & Fahrbach, 1999).

The term \( \sum f_{ijt-1}w_{ijt-1}y_{jt-1} \) represents the mean behavior of actor \( i \)’s network connections who provided information at time \( t-1 \). The term \( w_{ijt-1} = 1 \) if actor \( i \) is connected to actor \( j \) at time \( t-1 \), 0 otherwise and the term \( f_{ijt-1} \) takes a value of 1 if actor \( j \) provided new information to actor \( i \) at \( t-1 \), 0 otherwise. Thus actors respond to the mean behavior or norms only of those who provided new
information in the previous time point. This is an example of a social capital exchange (Frank, Zhao & Borman, 2004) in which actors exchange conformity of behavior for new information (the social capital exchange is especially relevant for novices who rely extensively on others for local knowledge and information).

Consider actor A who has network connections with B, C and D who engaged in behaviors at time 2 at levels of 9, 5, and 10 respectively. But only C and D provided new information to A at time 2. Correspondingly, actor A is exposed to mean behavior of 7.5 ([5+10]/2=7.5) through network connections C and D that provided new information at time 2. Note also that in our model, actors respond to norms of those from whom they received new information, even if they subsequently sever the connection.

Given the model in Eq. [1], $\alpha$ represents the strength of organizational identification, with $0 \leq \alpha \leq 1$. For a high value of organizational identification, actors respond strongly to the mean behavior of their network connections. This is distinctive from the information actors obtain as a result of interacting with organization members – high organizational identity generates a normative effect of others in the organization.

**Selection Process**

*Maintaining Old Connections.* At each time step actors decide whether to maintain each network connection. Assuming actors are motivated to seek at least some new information to respond to external uncertainties even when organizational identification is high, we specify that when actors fail to access new information from a network connection, there is higher probability that the actor will dissolve the network connection. Formally, the decision to maintain the connection is a function of how many consecutive times an actor is exposed to redundant information from the network connection:

$$P_{ijt} = \lambda^x,$$

where $P_{ijt}$ is the probability that actor $i$ will maintain the network connection with $j$ at time $t$, $\lambda$ is a constant between 0 and 1, and $x$ is an integer between 0 and $+\infty$ that indicates how many consecutive times actor $i$ is exposed to redundant information from $j$. If actor $i$ accesses new
information from $j$, $x$ is set to 0 and the probability that $i$ will maintain a network connection with $j$ at time $t$ is 1. The first time actor $i$ is exposed to redundant information from $j$, $x$ will be 1 and the probability to maintain the connection at time $t$ becomes $\lambda$. For example, if $\lambda = 0.8$, the first time $i$ receives a piece of redundant information from $j$ the probability to maintain the connection becomes 0.8. Then if $i$ receives a piece of redundant information from $j$ again, the probability to maintain the connection becomes $0.8^2 = 0.64$. If actor $i$ continues to be exposed redundant to information from $j$, $x$ will increase by 1 each time until the connection is discontinued or actor $j$ provides new information to actor $i$, in which case the probability is reset to 1.

We then compare the probability on the left side of Eq. [2] with a number randomly drawn from a uniform distribution over the range 0 to 1 to evaluate whether a particular connection persists. In the example above, if the random number is smaller than 0.64, $i$ maintains the connection to $j$. Note that even if the connection is discontinued, it may be reinitiated depending on organizational identification ($\alpha$) and the similarity of behaviors between actors $i$ and $j$ as in the next subsection.

*Initiating New Connections*

In each time step, each actor calculates its utility to connect with every other actor in the organization. Then when an actor decides to establish a new connection, the actor chooses to connect with those with highest utility, while keeping its out-degree (total number of connections an actor initiates) constant as is likely for deep exchanges (Blau, 1977). In our model, we assume actors prefer to connect with others of similar behavior when they have a strong identification with the organization. In this sense, we assume that the behaviors of others are known. When an actor does not identify strongly with the organization, the actor seeks merely to connect with others who can instrumentally shorten their path lengths to potentially new information (Frank & Fahrbach, 1999).

Formally, the utility for actor $i$ to choose $j$ is:

$$U_{ijt}(mp_{ijt-1}, y_{ijt-1}, y_{j-1}) = (1-\alpha)(mp_{ijt-1}) - \alpha |y_{ijt-1} - y_{j-1}|,$$

(3)
where the term \(|y_{it-1} - y_{jt-1}|\), the absolute difference between actor \(i\)'s and actor \(j\)'s behaviors at time \(t-1\). This is the standard homophily term in network selection models – birds of a feather flock together (McPherson et al., 2001). The counterbalance to homophily in Eq. [3] is the term \(m_{ijt-1}\) which represents the path length, or number of intermediaries between \(i\) and \(j\) at \(t-1\).\(^2\) For example, if \(i\) does not connect directly with \(j\) but both connect with \(k\) then the path length between \(i\) and \(j\) is 2: \(i \rightarrow k \rightarrow j\). By comparison, if the path length between \(i\) and \(g\) is 3 (\(m_{ig}=3\)), then \(i\) will gain more utility by connecting to \(g\) instead of \(j\), because \(g\) is more likely to have new information for \(i\) (Frank & Fahrbach, 1999; Granovetter, 1973). Note that the maximal path aspect of the utility does not assume knowledge of others’ possession of information, only potential to access new information based on their relative locations in the network structure (Arrow 1979; Frank & Fahrbach, 1999).

As in Eq. [1], organizational identification is represented by \(\alpha\) in Eq. [3]. When organizational identification is high, the more similar the behavior of two actors, the more likely they are to connect because of the personal motivation of homophily. The lower the organizational identification, the more actors instrumentally seek new information to inform their practice by initiating connections with others who are at greater network path length. Combining with the influence process in Eq. [1], when organizational identification (\(\alpha\)) is high actors typically form subgroups in which connections are concentrated, with homogeneous practices within the subgroup and heterogeneous practices between subgroups.

*The Strength of Normative Influence (k)*

Note that in the influence and selection processes, we use the same parameter \(\alpha\) to represent organizational identification. That is, organizational identification can be manifest through either the influence or selection process. However, the strength of normative influence relative to selection can vary. For example, normative influence would be stronger relative to selection if actors fully adopt the behaviors of network connections but make few changes in network

\(^2\) The network distance between two actors is infinity if they belong to different components (no path between them). In this case we set their network distance to be 5, one step further than the longest network distance between any two nodes in the initial setup of the simulation, which is typically 4 for most set-ups.
connections based on homophily. We express the strength of normative influence relative to that of selection using \( k (0 \leq k \leq 1) \) in the influence process:  

\[
y_{it} = (1 - k\alpha)y_{it-1}I_{it-1} + k\alpha \sum f_{jt-1}w_{jt-1}y_{jt-1} \sum f_{jt-1}w_{jt-1}. \tag{4}
\]

Generally, when \( k \to 0 \) actors retain their previous behaviors modified only by information – normative influence is weak relative to selection; as \( k \) increases the process of influence is stronger relative to selection, and when \( k \to 1 \) normative influence is as strong as selection.\(^4\) Note that by setting \( 0 < k < 1 \) we assume the extent to which networks change (selection) is always larger than that of behavioral change (normative influence), consistent with literature showing that behavior is more stable than networks (Engels et al., 1997; Mercken et al., 2010; see technical appendix B for how we empirically anchored the ranges for \( \alpha \) and \( k \)). Ultimately, our models allow us to express the system in terms of the interplay between influence and selection using two parameters: organizational identification (\( \alpha \)) and the strength of normative influence relative to selection (\( k \)).

**SIMULATION DESIGN**

We initiate our simulations with connections concentrated within two subgroups and behaviors differentiated between the two subgroups. This is consistent with the organizational literature that describes an internal differentiation of connections and behaviors (e.g., Frank & Fahrbach, 1999; Selznick, 1948; Simon, 1962; Weber, 1946). For example, in the health care profession, connections and behavior may align with job description (e.g., doctors, nurses, technicians) or specialty (e.g., surgery, medicine, oncology). Similarly, teachers tend to connect with others in the same grade (Spillane, Kim & Frank, 2012; Wilhelm et al., 2016) as well as share teaching practices with those in the same grade (Penuel, Frank et al., 2013). Nonetheless, we

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\(^3\) Alternatively, we can substitute \( \alpha k \) with \( \gamma \), a term that is different from \( \alpha \), representing that influence and selection are two separable processes as in Frank and Fahrbach (1999). However, here we recognize that influence and selection are driven by the same underlying motivation – organizational identification (Frank, Kim & Belman, 2010; Xu & Frank, 2016), so we link the two processes through \( \alpha \).

\(^4\) If selection does not occur at all the network does not change, and the system behavior converges to a single steady state for \( 0 < k < 1 \) (Frank & Fahrbach, 1999).
evaluate the sensitivity of our interpretations to the assignment of actors to subgroups at baseline in the results and technical appendix A.

After establishing baseline conditions we experiment using the simulation model to learn which types of messages conveyed by change agents exert the most leverage on the system depending on organizational identification and the strength of normative influence relative to selection. We assume a change agent can only change organizational members’ behavior via a message. Organization members can then select to connect with the message (based on Eq. [2] and [3]) and be influenced by the message (based on Eq. [4]) just as they do with network members. In this sense messages are passive actors, as others can connect to messages and be influenced by them, but messages do not initiate connections or change their own behavior.

**Experiment Conditions**

*Baseline*

In the baseline condition there are 20 actors, with 10 actors assigned to each of two subgroups. Network connections are randomly assigned to actors such that connections are more concentrated within subgroups (density=.4) than between (density=.02), where density is defined by the proportion of possible connections that are realized. For example, among a set of 10 actors there are 90 possible connections (10x9, assuming asymmetry). If 36 are realized the density is 36/90=.4.

We generate behaviors within subgroups from normal distributions with standard deviation 1; for the positive subgroup the mean behavior is 12, and for the negative subgroup the mean behavior is 8. The difference between the two subgroups might represent the differences in the frequency with which the members of each subgroup, as teachers, implement elements of a given educational policy (with the positive subgroup implementing 12 elements per week and the

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5 See also Fig. F1 for the visualization of the initial setup of the simulation.
6 Behavior of the agents are strictly positive, given the normal distribution and our parameter range most initial behavior ranges from 6 to 14.
negative subgroup implementing 8 elements per week). While the differences between subgroups relative to the standard deviation are guided by empirical studies, the specific numerical values (e.g., 12 and 8 for the subgroup means) are not explicitly empirically determined.

Actors in the positive subgroup are initialized with 3 random pieces of positive information and 2 random pieces of negative information. The pieces of information are randomly drawn from a total of 15 pieces of positive information and 15 pieces of negative information. Each actor in the negative subgroup is initialized with 2 random pieces of positive information and 3 random pieces of negative information. In this way information is aligned with subgroup membership.

A round of simulations is generated by the actors’ decisions according to Eq. [2] through Eq. [4] over a series of time steps. We stop a round of simulation when every actor obtains all pieces of information in the system, or after 600 time steps. We set the baseline parameter to maintain connections \((\lambda)\) to be 0.8, and we vary organizational identification \((\alpha)\) from 0.3 to 1 by intervals of 0.05 (total of 15 intervals), and choose the relative rate of influence \((k)\) to be 0.1 or 0.5 (total of 2 states). In each configuration (baseline, policy aligned message, balanced message) we simulated 200 rounds, with a total of 200*15*2=6000 rounds.

**Experiment: The Change Agent’s Message**

We initiate each round of the experiment with 30 time steps for the given baseline condition, with all set-ups, parameter ranges and stopping ranges the same as for the baseline condition. At time step 30 we then introduce a message from the change agent. The policy aligned message presents a behavioral level of 13, one standard deviation above the initial mean behavior of the positive subgroup. The policy aligned message also contains 3 pieces of positive information that are new to the organization (and no negative information), representing external information.

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7 We stop at 600 time steps because in a baseline experiment where we start from random networks, in most simulation rounds actors obtain all pieces of information in the system within 500 time steps.

8 As a robustness test we also simulate the scenario where \(k=1\). Results are consistent with the main findings, except that when organizational identification is very high \((\alpha \geq .95)\) even a balanced message cannot create full information diffusion, as the networks polarize before the introduction of the message.
introduced by change agents to support a policy goal.9 The message is inserted to the system as an actor that does not initiate connections or change behaviors but that can attract connections with other actors as in Eq. 3 and in so doing shares information and presents norms that can influence behaviors as in Eq. 4. Following the baseline parameter set-up, we simulate 6000 rounds in which policy aligned messages are introduced into the system.

In contrast to the positive message, the balanced message is assigned a behavior equal to the mean behavior of all actors at time 30. Furthermore, the balanced message includes 10 pieces of positive information and 10 pieces of negative information already in the system. In this sense the change agent expressing a balanced message functions in part by redistributing information in the system. To avoid singularities and trivial solutions in which the system precariously balances between two evenly weighted subgroups of opposite behavior (Frank & Fahrbach, 1999) we shift the balanced message slightly by including 3 extra pieces of new positive information; the balanced message contains a total 13 pieces of positive information (10 from within the system and 3 new) and 10 pieces of negative information (from within the system). Following the baseline set-up, we simulate 6000 rounds in which balanced messages are introduced into the system.

Outcome Measures at Steady State (i.e., at Equilibrium)

Our first measure is the mean of behavior for each subgroup at the end of a round, averaged across rounds for a given set of parameters (e.g., \( \alpha = 0.4 \) and \( k = 0.5 \)). These averages represent the extent to which (1) actors have adopted specific practices, (2) there is divergence in behavior between subgroups within the organization. Our second outcome measure is the probability of full information diffusion (Rogers, 2010). It is calculated as the percentage of the total rounds for a given parameter set in which all actors obtain all pieces of information in the system. This represents the extent to which actors have acquired all the information to evaluate the incentives for adopting practices associated with a given policy. We compare these outcome measures for

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9 When a message is first introduced it does not have any connection with the actors in the system. The initial path length between the message and any other actor is set to 5, one step further than the longest path lengths realized between any two actors in the initial setups of the simulations.
baseline and policy aligned versus balanced messages to determine the effectiveness of different messages.

SIMULATION RESULTS

Steady State Subgroup Behavior

We present our main results when influence is strong (k=.5) and then support with complementary results when influence is weak (k=.1). Figure 2 shows how subgroup behaviors are affected by organizational identification ($\alpha$) as well as different messages delivered by a change agent. Green (or light gray in gray scale) shows the positive subgroup and red (or dark gray in gray scale) shows the negative subgroup. In the baseline condition (represented by the solid lines) the difference in mean behavior between the subgroups is small for low to moderate levels of organizational identification ($\alpha<.45$). When organizational identification is low to moderate actors connect with others outside their subgroups in search of information and adopt behaviors based on the shared information as well as network norms.

![Figure 2](image)

**Figure 2.** Mean Behaviors for Each Subgroup at Steady State (End of Simulations) when Influence is Strong (k=.5). Red lines (dark gray in gray scale) indicate mean behaviors for the
negative subgroup, green lines (light gray in gray scale) indicate behavior for the positive subgroup.

When organizational identification is high ($\alpha > .45$), actors increasingly select connections with members of their subgroups with whom they already share behavioral similarity. Furthermore, they respond strongly to the behavioral norms (average behaviors) of network connections. These two forces combine to create a divergence in behavior between the members of the positive and negative subgroups. See also Figure C1 in the appendix C, where network polarization occurs as the connections between subgroups are reduced as organizational identification increases.

The effects of the messages of change agents on behavior are shown with the dotted (policy aligned message) and dashed (balanced message) lines in Figure 2. For low levels of organization identification ($\alpha < .45$) the members of each subgroup respond to the intended message of the change agent. As a result, a policy aligned message of the change agent generates the largest increase in the overall level of behavior, supporting hypothesis 1.

But when organizational identification increases (.45 < $\alpha < 1.0$), the dotted lines show that when the change agent introduces a policy aligned message, the positive subgroup ultimately adopts slightly more positive behaviors and the negative subgroup ultimately adopts extremely negative behaviors. This also creates greater average path lengths between the positive and negative subgroups (in Appendix C). As a result there is little counterbalance to the normative pressures within the subgroups and the subgroups adopt divergent behaviors in the final steady state.

Note that the divergence between subgroups is less extreme when change agents introduce a balanced message. The balanced message attracts connections from members of both subgroups, providing opportunities for sharing information and bridging (see also Figure C1 in appendix C, where the probability of factions emerging and network modularity when a policy aligned message is introduced are much higher than for balanced messages, especially when organizational identification is high). The balanced message mitigates the tendencies for connections to become
purely homophilous or for behavior to be purely driven by norms. As a result, when organizational identification is high, a change agent can more effectively alter the behaviors with a balanced message than with a policy aligned message. This is consistent with our second hypothesis.

Figure 3. Example of Final Steady States for Simulations Initiated with Two Subgroups when a Message is Introduced and Organizational Identification is High ($\alpha = 0.9$) and Strength of Influence is High ($k = 0.5$). The larger the node the more positive the actor’s behavior. Numbers indicate the number of pieces of information each actor possess. Red circles (dark gray in gray scale) represent members of the negative subgroup; green circles (light gray in gray scale) represent members of the positive subgroup; squares represent messages. Figure 3a shows differentiated exposure to information and network polarization in response to a policy aligned messaged. Figure 3b shows homogeneous access to information and an integrated network for a balanced message.

Examples of the final steady states (equilibria) for high organizational identification ($\alpha = .9$) and strong influence ($k = .5$) for the different messages of the change agent are shown in Figure 3. Figure 3A includes a change agent with a policy aligned message that becomes integrated into the subgroup with positive behaviors. As a result, the positive subgroup diverges in behavior.
from the negative subgroup. Correspondingly, the steady state network is polarized and the change agent’s information does not completely diffuse to the negative subgroup. Furthermore, information does not fully circulate, as the red (dark gray in gray scale) subgroup possesses only 20 pieces of information at equilibrium relative to the 28 pieces possessed by the green (light gray in gray scale) subgroup. See also appendix C for the general trend of polarization. Figure 3B shows a more integrated system as a result of a balanced message. The balanced message attracts actors from each of the two subgroups. This allows for information and norms to flow between the subgroups (all actors possess 32 pieces of information at equilibrium), more closely aligning behaviors between the two subgroups.

**Diffusion of Information**

![Graph showing probability of full information diffusion](image)

**Figure 4.** Probability of Full Information Diffusion for Simulations Initiated with Two Subgroups when Influence is Strong (k=.5). Probability of full information diffusion decreases with organizational identification (α), with more dramatic decrease when change agents convey a policy aligned message.
The pursuit and spread of information is one of the key drivers of our system (equations 2-4). Correspondingly, in Figure 4 we show the diffusion of information under the two types of messages delivered by the change agent relative to the level of organizational identification. In the baseline condition (solid lines), for low values of organizational identification ($\alpha$) actors establish an integrated network of connections with others of similar or different behaviors, thus allowing the diffusion of information across the system. For high values of organizational identification there are few conduits for information to flow between subgroups, slowing down the ultimate rate of the diffusion of information.

Turning to the effects of the change agent’s message, for low levels of identification all information diffuses regardless of the strength of the message. As organizational identification ($\alpha$) increases, the dotted line shows a significantly sharper decrease (relative to the baseline solid line) in the probability of full information diffusion when a change agent delivers a policy aligned message for moderate to high organizational identification ($\alpha > .45$), with the probability decreasing to near zero when organizational identification is high ($\alpha > .8$). On the other hand, the system is more able to diffuse full information when a change agent delivers a balanced message (the dashed line in Figure 4).\footnote{For organizational identification $> .9$ the equilibria when a balanced message is introduced are comparable to those for the baseline because the balanced messages cannot compensate for the effects of homophily for extremely high organizational identification.} This is consistent with the example equilibria in Figure 3b, and therefore with hypothesis 2.

**Varying the Strength of Influence Relative to Selection ($k$)**

Eq. (4) includes the parameter ($k$) representing strength of influence relative to that of selection. Correspondingly, in Figure 5 we present changes in subgroup behaviors when influence is weak ($k=.1$, compared with strong influence for $k=.5$ in Figures 2 through 4). In Figure 5 we observe the same trends as in Figure 2, except that (1) the transition to divergent behaviors as organizational identification increases is more gradual in Figure 5 (for organizational
identification .5 to .9) than in Figure 2 (from organizational identification of .5 to .7);\(^{11}\) (2) the distinction between the effects of change agents with different messages is smaller in Figure 5 than in Figure 2, especially when organizational identification is high (see also appendix C). Correspondingly, we interpret that the interaction between the change agents’ message and organizational identification is stronger when influence is strong.

**Figure 5.** Mean Behaviors for Each Subgroup at Steady State When Influence is Weak (k=.1).

**Summary of Results**

Across our results the effect of the change agent’s message depends on the level of organizational identification. When organizational identity is low (\(\alpha < .5\)) an external change agent conveying a policy aligned message can shift the overall level of behavior of the organization without inducing divergence in behavior or polarization in the network. Therefore, consistent with our first hypothesis, external change agents can encourage new practices through policy aligned messages when organizational members do not strongly identify with their organizations.

On the other hand, when organizational identification is high (\(\alpha > .5\)) a policy aligned message contributes to divergence in behavior within the organization, ultimately inhibiting the diffusion of information.

\(^{11}\) The probability of information diffusion relative to organizational identification when influence is weak is also similar to that when influence is strong.
information and constraining overall change in behavior (increases in the behavior of one subgroup are offset by decreases in the behavior of the other). In contrast, a balanced message can shift the overall level of behavior of the organization to some extent, while not inducing divergence in behavior or polarization in the network. Consistent with our second hypothesis, external change agents can encourage new practices through balanced messages when actors strongly identify with their organizations. Thus the effectiveness of the change agent depends on the interaction between the type of message with the level of organizational identification.

**Table 1.** Interaction between the Message of the Change Agent and Organizational Identification

<table>
<thead>
<tr>
<th>Message</th>
<th>Organizational identification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Policy aligned</td>
<td>Convergent subgroups;</td>
</tr>
<tr>
<td></td>
<td>large changes in mean behavior</td>
</tr>
<tr>
<td>Balanced</td>
<td>Convergent subgroups;</td>
</tr>
<tr>
<td></td>
<td>small changes in mean behavior</td>
</tr>
</tbody>
</table>

Our results are synthesized in Table 1 which highlights that the effect of the change agent’s message is contingent on the identification of organizational members. When organizational identification is high, those predisposed to a policy aligned message will engage the message and one another, becoming more extreme in their behaviors. Others not predisposed to the message will divert away from the message. This produces a divergence of behavior based on predisposition and little overall change (as in the upper right hand corner of Table 1). Divergence does not occur even when organizational identification is high for a balanced message which provides opportunities for actors to integrate as in the bottom right of Table 1. The trade-off is that the balanced message does not generate as large changes in average behavior as does the policy aligned message when organizational identification is low (as in the left side of Table 1). Thus
when organizational identification is low a balanced message may be a missed opportunity to shape behavior.

**Specification Checks**

*The Emergence of Subgroups*

Our analyses assume the existence of informal subgroups within the organization. In appendix A, we explore the emergence of the subgroups from the fundamental network dynamics as given by equations [2] through [4]. Results show that subgroups emerge from random networks under most conditions except the extreme condition when organizational identification is low ($\alpha = .3$). But this represents a situation in which actors are almost indifferent to the organizational boundary that is critical to our premise.

*Messages Conveyed by Members of the Organization Instead of External Change Agents*

We have focused on the action of the external change agent to represent how innovations or policies outside an organization become integrated into an organization. Alternatively, we can consider scenarios in which the policy is championed by a member of the organization who has connections with members of the organization at the time the message is introduced. In particular, we consider messages conveyed by leaders of subgroups (those with the most connections within their subgroups). That is, instead of inserting information through a new message we provide a subgroup leader already in the system with new information. A key difference is that the subgroup leader can initiate and sever connections and change behavior whereas the message conveyed by the external agent cannot. Other actors can then access this information as buffered by leaders (c.f., Honig & Hatch, 2004). The results of this alternative scenario are reported in technical appendix D including examples of final equilibria. The direction of the effects of messages conveyed by leaders are consistent with the effects of messages conveyed by external change agents, but the magnitudes of the effects of messages delivered by subgroup leaders are smaller than when conveyed by external change agents.
Implications of Messages Conveyed at Different Time Steps in the Simulation

In our primary analyses, external change agents delivered their messages at time step 30, at which point the network structure has already begun to emerge. Alternatively, we can consider scenarios in which external agents deliver their messages earlier in the evolution of the organization’s behavioral and network patterns. The results of these alternative scenarios are reported in technical appendix E. The direction of the effects of introducing messages earlier in the time steps are consistent with the effects presented in the main experiment, but the effects are slightly stronger, especially when organizational identification is moderate to high. That is, a policy aligned (balanced) message is more likely to polarize (integrate) the organization if introduced earlier. These results suggest that network leverage might be greater when exerted before the emergence of subgroups within organizations. However, the effects of messages do not vary greatly with the time point of introduction.

DISCUSSION

We seek to inform those external to human service organizations who intend to change practices within the organizations. As examples, we considered efforts to encourage educational or health care professionals to adopt evidence based practices. We make what we believe to be an authentic definition of one who is truly external to the organization, and therefore must exert leverage by expressing messages supporting the intended change. But ultimately agency lies in the members of the organization to adopt the practices desired by the change agent. Moreover, the members of the organization can influence one another through informal networks. In this context, we use agent-based models to investigate how the message of the change agent interacts with organizational identification as mediated by intra-organizational networks.

We start by assuming that there exist at least modest divisions within the organization such as by formal departments or informal cliques. Given the existence of these divisions, our dynamic analysis shows there is a tendency for divergence of behavior and polarization of the network
when actors strongly identify with their organizations. In this sense our baseline finding adds a
dynamic element to the literature on absorptive capacity (page 128, Cohen & Levinthal, 1990)
which typically focuses on the ability of an organization’s static structures to facilitate
communication and coordination.

Our findings go beyond the point that internal network dynamics matter. In particular, when
organizational identification is low, change agents can more directly influence organizational
members by conveying policy aligned messages. This is consistent with our first hypothesis. For
example, when the members of a school have a weak affiliation with the school, such as when
turnover rates are high (Ingersoll, 2001), the external change agent might have greatest effect by
conveying a policy aligned message, such as through a scripted curriculum like Success for All or
Open Court in education (Borman et al., 2008) or through the use of protocols to avoid retaining
foreign bodies during surgery (Lincourt, et al., 2007).

In contrast, when organizational identification is high the change agent can more effectively
impact the organization by creating a balanced message that mitigates the divergence of behavior
and polarization of the network. This is consistent with our second hypothesis. For example, if
educators have a strong identification with their school then external change agents might
paradoxically exert the most leverage by creating professional development that communicates the
potential legitimacy of two different sets of teaching practices, even though only one may be
aligned with a policy. Or when medical professionals strongly identify with a particular hospital
then change agents might exert the most leverage by introducing messages that balance research
evidence with patient values.

Thus the change agent must weigh emphasis on the type of message against potential
divergence of behavior and polarization of the network. Choosing a policy aligned message when
organizational identification is high could create divergence of behavior, ultimately impeding
implementation. Choosing a balanced message when organizational identity is low could miss the
opportunity to direct an organization towards desired practices. It is not new to say that there are
conditions when change agents need to be cautious and others when they can act aggressively. What is new is to understand those conditions in terms of organizational identification as manifest through network dynamics.

The process of implementation itself can change intra-organizational network dynamics. In particular, a change agent who introduces a policy aligned message may accentuate existing divisions in the system. In the extreme, this can create polarization or factions, limiting the organization’s capacity for coordination. Furthermore, because changes in network structure have implications for the implementation of any innovation (Frank & Fahrbach, 1999), and because polarization may endure, the effects of change agents may go extensively beyond their immediate actions.

Methodologically, although we recognize the formal organization as defining the broad conditions of professional practice, we use agent based models to examine organizational outputs that emerge from individual action through informal intra-organizational networks. Moreover, our parsimonious agent based models allow us to describe the essential internal network dynamics in terms of two parameters, organizational identification ($\alpha$) and the strength of influence relative to that of selection ($k$). While no doubt other factors affect influence (level of expertise, trust, etc.) and selection (proximity), our models afford the theoretical exploration of two key elements of internal dynamics that affect the consequences of actions of agents external to the system.

**Guidance for External Change Agents**

Our general advice is that the change agent should select action based on the strength of organizational identification. This suggests careful measurement of organizational culture, and perhaps even network effects before introducing a change into the organization (Damschroder et al., 2009). Organizational culture is typically measured with instruments representing organizational identification (Akerlof & Kranton 2005; Ashforth & Mael, 1989), collective responsibility, trust, or other aspects of social capital flows among organizational actors (Adler & Kwon, 2002; Bryk & Schneider, 2002; Frank, 2009). Indirect measures of organizational
identification may also be obtained from administrative data regarding personnel turnover, absenteeism, etc. If there is evidence that organizational identification is low, external agents can exert leverage by introducing policy aligned messages endorsing specific behaviors. If organization identification is high and the system is prone to polarization external change agents can exert maximal leverage by conveying balanced messages. In this sense our approach extends recent work on network interventions (Valente, 2012, 2017) by formalizing and explicating the network dynamics that might occur in response to an intervention. Furthermore, in considering this guidance, the external change agent should bear in mind that there are multiple paths to divergence of behavior and polarization of a network depending in part on the timing of the intervention in the evolution of the network.

Transition to divergence of behavior and polarization of the network is sharper the stronger the influence process. This would suggest that when influence is strong change agents must be especially sensitive to initial indications of divergence and polarization. The relative strength of influence may be indirectly inferred by carefully monitoring the spread of behavior during diffusion. In this aspect, we can learn from qualitative work that attends explicitly to processes of influence and selection during implementation (Coburn & Russell, 2008; Penuel et al, 2009). More generally, external change agents must continue to monitor internal dynamics for divergence and polarization after introducing a message into an organization.

The external agent should also carefully consider the format of the message. Balanced messages might be openly conveyed in forums (on-line or face-to-face) facilitating exchanges among organizational members who already possess key knowledge (Lubell et al., 2002; Schneider et al., 2003). Policy aligned messages might be conveyed in more didactic or directed forums to introduce knowledge from outside the organization (Frank et al., 2011).

Finally, a critical point is that the agent’s message is defined relative to the mean behavior of those in the organization. It may be tempting for change agents to target organizations generally predisposed to their message and in which members have a strong organizational identification.
But if the change agent approaches such an organization with a message considerably more extreme than the norm there is the potential to accentuate existing differences in behaviors and to polarize the network. When organizational identification is high the change agent is likely to exert the most leverage with a message balanced relative to the organization, regardless of the organization’s general predisposition.

**Guidance for Internal Organizational Leaders**

Our simulations show that divergence and polarization can emerge from the internal network dynamics of the organization. The challenge for the organizational leader then is to intervene to prevent polarization while leveraging the network dynamics to increase organizational effectiveness (presumably by adopting new practices) and absorptive capacity. To do so, intra-organizational leaders can deliberately create cross-subgroup connections and increase strength of influence \(k\) so that members from different subgroups can connect and share information with each other. For example, in schools that have a strong mission or ethos one might deliberately cultivate relationships that cut across potential factions or cliques (Bryk & Schneider, 2002; Lightfoot, 2008).

The organization’s exposure to externally generated uncertainty creates a challenge for agents internal to the organization. The greater the external uncertainty, the more actors might turn to their organization as a hedge, increasing organizational identification. But the greater the organizational identification, the greater the potential for divergence of behavior and polarization. For example, when schools encountered uncertainty about NCLB in terms of its association with standardized tests or in terms of its emphasis on differences between groups of students, teachers may have turned to close colleagues to make sense NCLB and for protection should they encounter a negative evaluation. But just as they turned to their colleagues, they increased the probability of behavioral divergence and network polarization, as some may have responded more favorably to elements of NCLB than others. Thus the organizational leader must balance cultivating identification against the potential for behavioral divergence and network polarization.
Limitations

Realistic Processes. Our models are not fully realistic in their reduced complexity. We make this choice to isolate a parsimonious set of leverage points, so we can understand the network dynamics that affect a change agent’s capacity to alter practices. In the schools example we do not incorporate stakeholders such as unions because for the most part unions do not directly engage the adoption or implementation of professional practices such as pedagogy (Ingersoll & Perda, 2008; Shedd & Bacharach, 1991). We have attempted to identify the general and fundamental forces that will operate across settings that can be adapted to make a model more realistic to a particular setting.

Mandated Behaviors. We primarily attended to informal mechanisms operating through network dynamics. But of course some behavior and some connections are regulated or mandated (Hopkins & Spillane, 2015). Correspondingly, change agents could in theory seek to regulate behavior and networks. But cases in which a change agent has the capacity to regulate behavior are beyond the scope of this study, as they deal more broadly with power and institutional relationships.

Agency in the Information Exchange. Here we have attended to flows of information initiated by change agents outside the organization. But organizational members may themselves seek external agents who can convey information related to policy (e.g., a teacher may seek professional learning opportunities in networks outside her school or district). In these cases our general analysis still holds. If actors seek information consistent with their own predispositions, then actors seeking information outside their organization may well contribute to divergent practices and polarized networks within their organizations.

Other Sectors. We have developed our study in the context of organizations in the human services sector. In this sector the members of the organizations act as professionals to deliver services to clients. As such organizational members may attend carefully to information relevant

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12 Unions could play an indirect role in the implementation process by protecting teachers who decline markedly in their performance as a result of attempting to implement an innovation (e.g., because the innovation is ineffective).
to practice and to the professional climate of their organizations. This attention is the focus of the network dynamics that the change agent may leverage. But different mechanisms and network dynamics may prevail in other sectors. For example, in manual labor settings change agents may have to directly engage labor unions that bargain with ownership to control work conditions. Or network dynamics may be less relevant in the military in which there is hierarchical control. We do speculate though that the dynamics we consider here will have some relevance in almost any sector as much of human activity is socially embedded in informal networks (Granovetter, 1985).

**Heterogeneous Organizational Identification.** We have considered organizational identification as homogeneous throughout the organization. This provided parsimony for us to explore the attendant network dynamics. But organizational identification may vary within the organization depending on formal role, tenure in the organization, or subgroup membership. Correspondingly, the network dynamics that occur during diffusion could vary within the organization. One might apply our analyses here separately to components within the organization as a first approach to conceptualizing the implications of heterogeneous organizational identification.

**CONCLUSION**

The intent of any policy related to evidence based practices in the human services is to change experiences of end users. Much of that experience is mediated by organizations which in turn are a function of action of organizational members (Lipsky, 2010). But organizations are not monolithic. In particular, organizations typically feature formal divisions or subgroups in which informal connections are concentrated. These subgroups define the lines of potential polarization when external messages are introduced into the organization. Ignoring this potential can generate serious unintended consequences that can undermine the immediate intent of a change agent’s action as well as the organization’s capacity to learn, coordinate, stabilize its membership, and adopt future innovations. Indeed, our results can explain why implementation strategies that work in one context do not work in another. Therefore, we urge change agents to attend to the network
dynamics as driven by organizational identification that affect an organization’s capacity to change practices.

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On-Line Technical Appendix A

The Emergence of Subgroups from Random Networks

We explore the emergence of the subgroups from the fundamental network dynamics as given by equations [2] through [4] in the main text. In Figure A1 the density of the network is 0.2, actors’ initial behaviors follow a normal distribution with a mean of 10 and a standard deviation of 2, and each actor begins with 2 pieces of positive and negative information drawn from a total of 30 pieces of unique information. A round is terminated after 50 time steps. Results show that subgroups emerge as defined by clustering coefficient >.4 (the clustering coefficient is defined as the average proportion of connections between a node’s neighbors that are realized across all nodes [Watts & Strogatz, 1998]) from random networks increasingly as organizational identification increases. For example, subgroups emerged in 80% of the rounds when $\alpha=.9$. This result is consistent with Macy et al. (2003).

We also note that when influence is strong ($k=.5$), the emergence of subgroups is first delayed but then more dramatic as organizational identification increases. This is consistent with Xu and Frank (2016). The only condition under which subgroups do not consistently emerge is when organizational identification is low. Subgroups never emerged in rounds when $\alpha=.3$, as actors constantly strive to connect with distant others. This is consistent with Buskens & Van de Rijt (2008). When organizational identification is low actors treat members of their organizations mostly opportunistically, essentially eliminating the organizational context.
Fig. A1. The emergence of subgroups from random networks. We initialize the simulations with a random network with 20 actors. (A) Clustering coefficient vs organizational identification for different levels of influence, $k$. Each data point represents 200 rounds. (B) Example steady states showing an integrated network when organizational identification is low ($\alpha=0.4$); (C) Example steady states showing subgroups when organizational identification is high ($\alpha=0.9$).
On-Line Technical Appendix B

Anchoring the Magnitude of Organizational Identification and Relative Strength of Influence in Empirical Data

We provide some guidance for the magnitude of organizational identification ($\alpha$) and strength of influence ($k$) from empirical studies in table S1. Conditional on other covariates, Frank et al. (2004) and Penuel et al. (2012) found modest to strong influence among teachers (with the coefficient for the network exposure term roughly one third to two thirds as large as that for an actor’s own prior behaviors), either in changing teaching practice or adopting innovations. Using data from Liu and Srivastava (2015) organizational identification ($\alpha$) was high but influence ($k$) was weak among senators regarding the political orientation of their voting behavior. These examples directly estimate both ($\alpha$) and strength of influence ($k$) allowing us direct empirical guidance regarding our parameters as in Table S1.

<table>
<thead>
<tr>
<th>Study</th>
<th>product of $\alpha$ and $k$</th>
<th>$\alpha$ (Organizational Identification)</th>
<th>$k$ (Strength of Influence)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frank et al (2004)</td>
<td>0.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only Influence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Penuel et al (2012)</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only Influence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liu &amp; Srivastava (2015)</td>
<td>0.05</td>
<td>0.8</td>
<td>0.06</td>
</tr>
<tr>
<td>Influence and Selection</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table. S1. Anchoring the Magnitude of Organizational Identification and Rates of Influence in Empirical Data. We use three empirical results to anchor our simulations for organizational identification ($\alpha$) and strength of Influence ($k$). The behavioral outcomes include teachers’
computer use (Frank et al., 2004), teachers’ instructional practices (Penuel et al., 2012) and senators’ voting behavior (Liu & Srivastava, 2015).

To calculate the product of $\alpha$ and $k$ we estimated the influence model based on equation [4] in each dataset (controlling for other covariates), and used the ratio between standardized OLS estimates of the prior ($y_{it-1}$) and the network exposure term as an indicator for $\alpha k$. For example in Frank et al. (2004) standardized OLS estimates of the prior term was 0.32 and 0.21 for the network exposure term. Therefore $\alpha k$ is calculated as $0.21/(0.32+0.21)=0.4$. To calculate $\alpha$ we estimated the selection model based on [3], and as above we standardized estimates of homophily to anchor $\alpha$. Then we used the expression $k=\alpha k/\alpha$ to calculate $k$, the rate of influence relative to selection. For example in Liu & Srivastava (2015) we first estimated $\alpha k$ and $\alpha$ as in the table, and then $k$ is calculated as $\alpha k/\alpha=0.05/0.8=0.06$. This implies that one can estimate $\alpha$ and $k$ from data that include both actors’ beliefs/behaviors as well as connections between actors over time (Frank and Xu, forthcoming).

Generally, organizational identification and influence have been found to be lower (e.g., $0<\alpha k<0.2$) among professionals in stable working environments, (e.g. Coleman et al., 1957, and Nair et al., 2010, found small to modest influence among physicians in prescribing new drugs), but higher $0.2<\alpha k<0.8$ among adolescents or during periods of intense socialization such as in military or religious settings (Frank et al., 2008; Stouffer et al., 1949; Gellner, 2015; Durkheim & Swain, 2008). For example, studies have consistently found strong homophily and moderate to strong influence among adolescents, indicating organizational identification ($\alpha$) was high and influence ($k$) was moderate to high (Engels et al., 1997; Matsueda & Anderson, 1998; Mercken et al., 2010).

References


On-Line Appendix C

Polarization in Networks in the Main Experiments

In this appendix we show the extent of network polarization (defined as the separation of networks between the subgroups) in the main experiment, and how it changes with organizational identification ($\alpha$). Specifically, we plot (i) the probability of factions (zero connections between the subgroups) emerging in the networks and (ii) network modularity (Newman, 2006) for different levels of organizational identification and relative strength of influence (k). Consistent with results in the main text, Figure C1 shows that: (1) both the probability of factions emerging in the networks and extent of network modularity increases with organizational identification ($\alpha$); (2) As organizational identification ($\alpha$) increases, both the probability of factions emerging in the networks and network modularity increase more sharply when the change agent conveys a policy aligned message than a balanced message; (3) the difference between the effects of the different messages is larger when influence is stronger (k=.5).
Fig. C1. Polarization in the networks in the main experiments. (A) Probability of factions emerging vs organizational identification ($\alpha$) when influence is weak (k=0.1). (B) Probability of factions emerging vs organizational identification ($\alpha$) when influence is strong (k=0.5). (C) Network modularity (extent of clustering) vs organizational identification when influence is weak.
(k=0.1); (D) Network modularity (extent of clustering) vs organizational identification when influence is strong (k=0.5). Each data point represents 200 rounds of simulation.
On-Line Appendix D

Equilibria Resulting from Messages Expressed by Subgroup Leaders

We have focused on the action of the external change agent to represent how innovations or policies outside an organization become integrated into an organization. In this appendix we consider scenarios in which messages are expressed directly by subgroup leaders (those with high intra-subgroup in-degree). As shown in Figure D1, the effects of messages expressed directly by subgroup leaders are consistent with the effects of external change agents, but the magnitude of the effects of messages expressed directly by subgroup leaders are weaker. This is because the intra-organizational subgroup leader, unlike the external change agent, is influenced by others and can change network connections. Therefore, leaders are integrated into the organization, weakening their leverage on the system relative to stable messages that originate from outside the organization.
Fig. D1. Messages expressed by subgroup leaders. We initialize each round with two subgroups as in the main experiment. At time 30, we create two experimental conditions: (1) we give the actor with the highest in-degree in the positive subgroup 3 pieces of positive information that are new to the system; (2) we give the actor with the highest in-degree in the negative subgroup 3 pieces of positive information that are new to the system. Results are generally consistent with the main results. The effects of messages expressed by the positive subgroup leader have the same direction
as policy aligned messages expressed by external change agents, and the effects of messages expressed by the negative subgroup leader are similar to those for balanced messages expressed by external change agents. In both cases the magnitude of the effects of messages expressed by subgroup leaders are weaker than for the external change agent. (A) Probability of full information diffusion vs organizational identification ($\alpha$) when influence is weak ($k=0.1$). (B) Probability of full information diffusion vs organizational identification ($\alpha$) when influence is strong ($k=0.5$). (C) Mean behavior of each subgroup vs organizational identification when influence is weak ($k=0.1$); (D) Mean behavior of each subgroup vs organizational identification when influence is strong ($k=0.5$). Each data point represents 200 rounds of simulation.

![Diagram](image)

Fig. D2. Example steady states for systems when the message is delivered by the subgroup leader. Organizational identification and influence are strong ($\alpha=0.9, k=0.5$) in both cases: (A) factions inhibit information diffusion when messages are expressed by a positive subgroup leader; (B) weak between-subgroup connections allow information diffusion when messages are expressed by a negative subgroup leader. Green indicates the positive subgroup and red indicates the negative subgroup, darker green and brown nodes indicate subgroup leaders.
On-Line Appendix E

Implications of Messages Introduced at Different Time Points

In the main text we considered introducing a message at time step 30, the time at which the organization structure had reached steady state in most simulation rounds. In this appendix we consider scenarios in which messages are introduced at time step 2. As shown in Figure E1, the effects of introducing a message at time step 2 are consistent with the effects of messages introduced at time step 30 presented in the main text, but the magnitude of the effects are slightly greater, especially when organizational identification ($\alpha$) is moderate to high. That is, policy aligned (balanced) messages have greater potential to polarize (integrate) the organization the earlier they are introduced. However, the effect of the timing on the overall changes in behavior and networks is small.
Fig. E1. Effects of introducing messages at an early time step. We initialize each round with two subgroups as in the main experiment. At time 2, we introduce a policy aligned message or balanced message as in the main experiment. Results are generally consistent with the main results, in both cases the magnitude of the effects are slightly stronger when messages are introduced earlier. (A) Probability of full information diffusion vs organizational identification ($\alpha$) when influence is weak ($k=0.1$). (B) Probability of full information diffusion vs organizational
identification ($\alpha$) when influence is strong ($k=0.5$). (C) Mean behavior of each subgroup vs organizational identification when influence is weak ($k=0.1$); (D) Mean behavior of each subgroup vs organizational identification when influence is strong ($k=0.5$). Each data point represents 200 rounds of simulation.
Appendix F: Visualization of the Simulation Process
(Online or author’s website)

Each round of simulation begins with an assignment of actors to initial conditions consisting of their connection network, their behaviors, and possession of information. For example, at the top of Figure F1, there are 10 actors assigned to each of two subgroups (10 red nodes and 10 green nodes). Network connections are randomly assigned to actors such that there are more connections within subgroups (density=.4) than between (density=.02). In addition, the green nodes have a stronger predisposition to the behavior (e.g., the extent to which they support basic skills instruction or evidence-based practices).

Once the initial conditions have been established, in a single time step actors seek information, are potentially influenced, and then make decisions about dissolving connections and selecting new ones. Describing this process for a single ego, at time t-1 (top left of Figure F1) ego seeks information from each alter, as represented by alter 1 in Figure F1 (top right) with whom ego already has a connection. In the example of alter 1, if alter 1 provides information the path marked by the red ovals is followed back to ego. In this particular case ego updates the initial behavior of 5 to a new behavior of 4.56 based on receiving one piece of (red) information that does not support the behavior and an exposure to an alter with a behavior of 4 (with strength of influence $k=.5$ and organizational salience $\alpha = .5$). The information and normative effects across all alters are balanced according to equation 4. Note an alter contributes to a change in ego’s behavior only when the alter provides new information to the ego. Note also that actors respond to the information and norms of those from whom they receive new information, even if they subsequently sever the connection.
After the influence process has been evaluated, the ego engages the selection process (as in the middle of Figure F1). First, ego considers whether to maintain existing connections, favoring the preservation of connections with alters who have provided new information (as described in equation [2]). If the ego severs a connection the ego may then initiate a new connection. The selection of new connections is based on the balance between new information available from those with whom ego has long network paths (e.g., length 2 or 3 in Figure F1) versus homophily with others who engage in similar behaviors (as expressed in equation [3]). A single time step occurs after all actors have cycled through the processes of information seeking, influence and selection.

Overall, Figure F1 shows how the processes of information seeking, influence, and selection generate the fundamental network dynamics through which actors change their behaviors and modify their networks. In the end, these dynamics can produce final steady states or equilibria such as at the bottom of Figure F1. In particular, the final state may consist of a near random network as on the left, or a polarized network as on the right. In the polarized network the connections occur exclusively within subgroups and behaviors diverge between the two subgroups.
Initial Condition: (1) two subgroups with dense networks within and sparse networks between; (2) one subgroup with higher level of mean behavior (positive green subgroup) and the other with lower level of mean behavior (negative red subgroup); (3) Each actor possess 5 random pieces of information.
Fig F1. Network Dynamics Defined by Information Seeking, Influence and Selection that Shape organizational Responses to Implementation.