The Role of Social Influence and Network Churn in Beliefs about Electronic Medical Record Technology

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Abstract

The successful implementation of technology often hinges on individual beliefs about the innovation being introduced. Little is known about how social networks shape these beliefs. In this study, we examine: (1) whether individual beliefs about technology are influenced by the beliefs of their peers within their social networks (network content); and (2) whether changes in the composition of the social network over time (network churn) moderates the effect of peer beliefs on individual beliefs. We offer and test hypotheses about these relationships using longitudinal social network survey data from hospital staff collected 2 – 4 months before (N = 256) and 3 – 5 months after (N = 284) the implementation of a new electronic medical record (EMR) system at a large, academic hospital. Our findings suggest that peer beliefs about new technology significantly and negatively affect individual beliefs about technology in the early stages of EMR implementation. We also find that the effect of peer beliefs on individual beliefs is stronger in more stable social networks (i.e., social networks that experience few tie deletions over time) and weaker in less stable social networks (i.e., social networks that experience many tie deletions over time). Our study examines social influence in a novel context – the implementation of EMR systems in the hospital setting – and extends network theory by conceptualizing network churn as a moderating variable that may amplify or dampen the effect of networks.

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Introduction

The successful implementation and sustained use of health information technology (IT) is difficult to achieve (Heeks, 2006; Wears & Berg, 2005), in large part, because of clinicians' resistance to the adoption of new technology (Buntin, Burke, Hoaglin, & Blumenthal, 2011; Massaro, 1993). At the root of clinicians' resistance to health IT are *individual beliefs*, which are individuals' cognitive evaluations of the consequences of a particular behavior (Agarwal, 2000). Individual beliefs are important not only because of their influence on key outcomes, such as usage (Venkatesh, Morris, Davis, & Davis, 2003), but also because they are amenable to strategic managerial interventions (Davis, 1993; Venkatesh, 1999). Hence, understanding *how* these beliefs are formed should be a central concern for research aimed at promoting the uptake of new technology in health care organizations.

Prior research on technology acceptance has identified some of the factors that affect individual beliefs, such as individual differences (e.g., age, gender) and contextual factors (e.g., training, organizational resources) (Agarwal, 2000). Little attention has been paid to the role of social networks, despite theory suggestive of their influence in shaping beliefs about many other subjects. According to the social network literature, social networks – defined as sets of actors connected by a set of social ties (Borgatti & Foster, 2003) – influence belief formation through processes such as behavioral modeling (e.g., imitating others' behaviors) (Bandura, 1986) and social information processing (e.g., processing overt statements that reflect others' assessments of the new technology) (Salancik & Pfeffer, 1978). Underlying this literature is the central idea that individual beliefs are not created in a vacuum (Butts, 1998; Contractor, Seibold, & Heller, 1996). Rather, beliefs are shaped significantly by social network structure, or the patterns of relationships among individuals (Borgatti & Foster, 2003).

There is some empirical work to suggest that social networks influence individual beliefs about technology (Rice & Aydin, 1991; Schmitz & Fulk, 1991). However, most of the studies are cross-sectional, missing an important conceptual point that social networks evolve over time (Snijders, Steglich, & Schweinberger, 2006). The content of the network – or valued resources, such as peer beliefs – that are embedded in one's social network may change over time (Burk, Steglich, & Snijders, 2007). Moreover, through a dynamic process called network churn, the composition of an individual's network can change over time as new ties are formed (i.e., tie additions) and existing ties are dissolved (i.e., tie deletions) (Vissa & Bhagavatula, 2012). By failing to account for changes in network content and network composition, existing research neglects fundamental ways in which networks evolve, and thus, potentially key determinants of whether networks are influential as theory suggests. This gap limits our understanding of how social networks impact beliefs about implementation and other organizational improvement efforts, and ultimately, the success of these efforts.

To address this gap, we examined how changes in network content and network composition affect the influence of social networks with respect to individual belief formation. Drawing from theories of social influence and the social network perspective, we hypothesize (see Figure 1) that: (1)
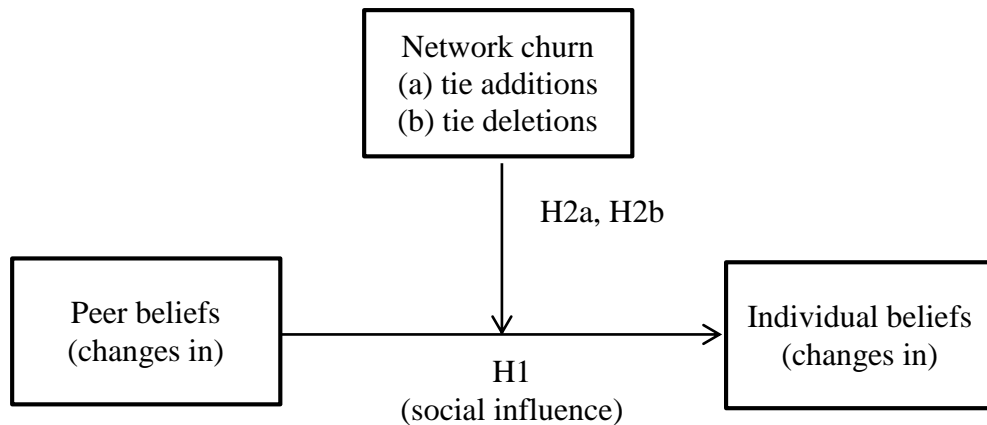
FIGURE 1: Hypothesized model

changes in peer beliefs about usefulness are positively associated with changes in individual beliefs about usefulness; and (2) less network churn (i.e., fewer tie additions or deletions) is associated with more network influence, that is, greater effect of peer beliefs on individual beliefs. We testedour hypotheses with longitudinal network data collected from hospital employees in a survey administered 2 – 4 months before (N = 256) and 3 – 5 months after (N = 284) the implementation of a new electronic medical record (EMR) system. We found that changes in peer beliefs were associated with changes in individual beliefs, and that this relationship was moderated by the number of tie deletions. The number of tie additions had no effect on the relationship between peer beliefs and individual beliefs. These findings suggest that networks influence individuals' beliefs about technology and that less network churn in the form of tie deletions enhances the effect of network influence.

Our study makes several contributions. First, this work extends network theory by conceptualizing network churn as a moderating variable. To our knowledge, this is the first study to do so. This is a key contribution to the study of network influence, since network churn is extremely common, and thus should be considered as a factor that may amplify or dampen network effects. This work also contributes to the social influence literature by further demonstrating that network beliefs are significantly associated with individual beliefs, and that in the context of EMR implementation, the impact of network influence may be negative. Finally, this work has practical implications for health care management. Our findings suggest that managers seeking to build networks that support implementation efforts need to cultivate positive beliefs at the network level and be more attentive to stable networks, which can exacerbate negative views of health IT.

Background and Hypotheses

The introduction of new technology can give rise to information uncertainty, which emerges in the absence of information, producing a "shock of ignorance" (Weick, 1995). A heightened sense of uncertainty, in turn, often leads to increased communication as individuals seek to connect with

others who can provide advice and information (Saint-Charles & Mongeau, 2009). The uptick in communication during periods of heightened uncertainty provides opportunities for: (1) social influence, as individuals come into increasing contact with their social networks (Srivastava, 2015); and (2) network change, as individuals adjust their patterns of interactions as they seek to interpret changes in organizational technology (Barley, 1986; Burkhardt & Brass, 1990). In this section, we review the literature on each of these phenomena, and then use the literature to develop our hypotheses about the relationship between social influence and network change in the formation of beliefs about technology.

The role of social influence in belief formation

Multiple theories posit that social relationships play a key role in shaping individuals' beliefs. Social information processing (SIP) theory, a prominent theory of social influence in organizational settings, posits that individuals develop beliefs as a function of the information available to them through their social relationships (Salancik & Pfeffer, 1978). In an extension of SIP theory, network theorists argue that social networks provide the mechanisms by which individuals are proximate to, or exposed to, others' information (Rice & Aydin, 1991). The general argument is that the proximity of two actors in a social network is associated with greater interpersonal influence between the actors (Marsden & Friedkin, 1993); the closer the actors in a social network, the greater exposure to social information, and ultimately, the opportunity for social influence. In a similar vein, communication theory posits that beliefs are socially constructed in the course of direct interactions with others. Through the processes of contagion and social comparison, network contacts provide opportunities for comparing and interpreting perceptions, which influence the salience of information and subsequent perceptions (Ibarra & Andrews, 1993). Taken together, SIP, network, and communication theories support a relational view of social influence in which an individual is altered by his or her direct interactions with peers.

In the technology acceptance literature, cross-sectional studies of social influence have generally found a positive relationship between direct interactions and people's similarity of beliefs toward a particular information technology (Rice & Aydin, 1991; Schmitz & Fulk, 1991). For example, Schmitz and Fulk (1991) argued and empirically demonstrated that the extent to which salient others viewed electronic mail as valuable was positively associated with an individual's own beliefs about usefulness. In the health care setting, physicians who were directly connected in a professional network were more likely to report similar attitudes towards evidence-based medicine (Mascia & Cicchetti, 2011). Building on such studies, we expect that as peers change their beliefs, individuals will change their beliefs accordingly. Thus, our hypothesis:

> Hypothesis 1 (social influence): Changes in peer beliefs about the usefulness of an EMR system will be positively associated with changes in individual beliefs.

Network churn as a moderator of social influence

Social networks evolve over time through a dynamic process of tie formation and tie dissolution (Snijders et al., 2006). The evolution of networks is particularly acute during periods of heightened
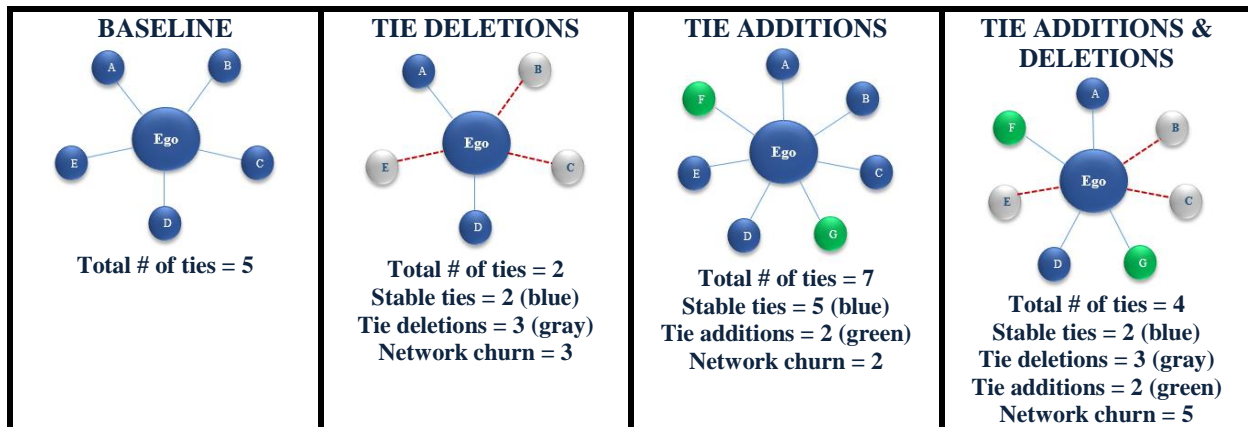
BASELINE	TIE DELETIONS	TIE ADDITIONS	TIE ADDITIONS & DELETIONS
Total # of ties = 5	Total # of ties = 2 Stable ties = 2 (blue) Tie deletions = 3 (gray) Network churn = 3	Total # of ties = 7 Stable ties = 5 (blue) Tie additions = 2 (green) Network churn = 2	Total # of ties = 4 Stable ties = 2 (blue) Tie deletions = 3 (gray) Tie additions = 2 (green) Network churn = 5

Figure 2. Illustrative example of network churn in an ego network

uncertainty, when people change their interaction patterns to cope with the uncertainty of learning new tools, devices, or techniques (Krackhardt, 1992; Saint-Charles & Mongeau, 2009; Srivastava, 2015). In the case of implementing new technology, ample research has demonstrated that the structure of social networks (i.e., patterns of social ties) change in response to the "exogenous shock" of new technology (Barley, 1986: 80). For example, in Barley's (1986) seminal qualitative work on the theory of structuring, the adoption of CT scanners by two radiology departments led to the creation of new patterns of social interactions between radiologists and radiological technologists which, in turn, led to new organizational structures (e.g., more decentralized structures in which technologists gained more autonomy over their day-to-day work). Burkhardt and Brass (1990), in one of the first studies to leverage social network methods to study how technology affects social structure over time, found that employees adjusted their patterns of interaction following the introduction of a new computer system in order to learn from those who were already adept at using the new technology. More recently, Leonardi (2013) used mixed methods to examine when the use of new information technology led to changes in the organizational advice networks of employees working at a large automobile manufacturer. From these studies, a clear picture has emerged that the implementation of new technology can significantly alter the structure of networks at the *whole* network level, in which the focus is on a bounded set of interrelated actors (Marsden, 2005). What has received comparatively little attention is the effect of technology change on altering *individuals'* social networks (i.e., ego networks) – which consists of a focal individual and the set of others to which he or she is directly tied (Cannella & McFadyen, 2013).

Recent studies suggest that the composition of an individual's network can undergo significant change as people form, change, and dissolve social ties (Kossinets & Watts, 2006; Sasovova, Mehra, Borgatti, & Schippers, 2010). Network churn refers to the change in composition of an individual's network caused by the entry of new network contacts (i.e., tie additions) and the exit of existing network contacts (i.e., tie deletions) (Vissa & Bhagavatula, 2012) (Figure 2). The focus of network churn is on the extent of turnover in the occupants of positions, which is conceptually

distinct from the number of network positions (i.e., network size) or the interconnectedness between those positions (i.e., network density).

We contend that less network churn is associated with more network influence (i.e., greater effect of peer beliefs on individual beliefs) for two reasons. First, less churn means that a network consists of longer-lasting ties, which tend to be stronger ties (Granovetter, 1973; Saint-Charles & Mongeau, 2009) characterized by high levels of trust (Krackhardt, 1992). In turn, trust is highly predictive of who is sought out when learning new technology, as people are more willing to be forthcoming about their lack of knowledge with trusted ties (Cross, Parker, Prusak, & Borgatti, 2001). As trusted ties become more proximate to the focal individual, we argue that they have greater potential to exert social influence.

A second reason why less network churn may be associated with greater influence is because lower turnover may be indicative of a better fit between the beliefs of an individual and that of his or her network. Prior work suggests that the congruency between an actor and his or her network has been associated with lower network churn (Burt, 2000; Kossinets & Watts, 2009; Leenders, 1996; McPherson, Smith-Lovin, & Cook, 2001; Vissa, 2011). For example, Kandel (1978) found that adolescent friendship pairs that do not experience network churn (i.e., are stable from time 1 to time 2) were more similar in their behaviors and values than pairs that experience network churn. In turn, individuals may be more receptive to influence from networks that are congruent with their beliefs and actions – a social process known as internalization – in order to maintain cognitive consistency (in which the induced behavior is perceived as maximizing one's own values) or affective appropriateness (in which the induced behavior is perceived as a continuous with the person's self-concept) (Kelman, 2006).

Given our preceding logic, we predict that less network churn will strengthen the positive relationship between peer beliefs and individual's beliefs (H1), which we term network influence. More formally, we hypothesize:

> Hypothesis 2a: Network churn moderates the relationship between changes in peer beliefs and changes in individual beliefs, such that fewer tie additions will be associated with greater network influence.

> Hypothesis 2b: Network churn moderates the relationship between changes in peer beliefs and changes in individual beliefs, such that fewer tie deletions will be associated with greater network influence.

Methods

Study Design and Setting

To test our hypotheses, we conducted a longitudinal (nine months) study of the effect of peer beliefs and network changes on hospital employees' beliefs towards a new EMR system. The

hospital employees worked in six clinical units of a large, academic hospital in the Northeastern region of the United States that was implementing a new EMR system. The hospital's objective in implementing the new technology, a commercial off-the-shelf EMR, was to create an integrated EMR system across hospital departments that had been using separate systems and across other hospitals in the larger health system so as to facilitate communication between providers, improve access to health information, and standardize patient care.

Sample and Data Collection

Our sample included full-time nurses, nurse managers, patient care associates, and secretaries. We focused on these roles because they were based on the units throughout the 9-month data collection period. Individuals in other roles, such as physicians and physician assistants, rotated in-and-out of the unit every few weeks (limiting the ability to collect longitudinal network data) or worked across many units (limiting the ability to set network boundaries around a finite set of actors, which is a prerequisite of social network analysis (Wasserman & Faust, 1994)).

In order to assess changes in hospital employees' beliefs towards the EMR system, social network ties, and demographics over time, we administered a pre-implementation survey at Time 1, which was 2 – 4 months prior to the "go-live," or start date, of the EMR system (October-December 2012). We then administered a follow-up survey at Time 2, which was 3 – 5 months after the EMR go-live (April-June 2013), during what is often referred to as the "shakedown" phase of technology implementation, when loss in productivity and disruption in processes occur and when potential users may most look to others for guidance on how to handle the disruptions (Sykes, Venkatesh, & Rai, 2011). The first author recruited respondents to participate in the surveys during nurse "huddles" that occurred at the beginning of each shift (i.e., morning, afternoon, and night shifts). Recruitment was conducted across all days of the week and shifts. To encourage participation, the senior nurse manager also emailed an electronic link to the survey at the beginning and end of the data collection period.

Social Network Data

We used a whole network approach to data collection, in which we selected a set of nodes (i.e., full-time nurses, nurse managers, patient care associates, and secretaries working on a clinical unit) and then measured the ties between all nodes in the sample. We focused on advice-seeking ties, which are considered pathways for work-related help (Venkatesh, Zhang, & Sykes, 2011), because our objective was to explore the effects of networks on individuals' beliefs about technology used in the workplace. To elicit advice network ties, our survey used a name generator approach in which respondents were asked, "On this clinical unit, whose professional opinion do you value? Please identify specific individuals (not professional roles) who work on this clinical unit." They were further instructed to list as many names as appropriate. We also assessed the strength of the tie to each person named because "people are most likely to compare with and come to agree with others to whom they are more strongly tied" (Erickson, 1988: 115). To elicit tie strength, respondents were asked in a question located to the right of the named individuals, "How often do you ask this person for advice?" A four-point response scale ranged from "very often" (=4) to

"rarely" (=1). The social network responses were used to construct an ego "advice" network for each individual which consisted of the focal individual (i.e., "ego"), the individuals nominated by ego as someone he/she turned to for advice (i.e., "outgoing ties"), and individuals who nominated ego as someone they turned to for advice (i.e., "incoming ties"). These data were used to construct measures of peer beliefs and network change using UCINET Version 6.516 (Borgatti, Everett, & Freeman, 2002). The ego networks were open, meaning that alters could be added or deleted between time points.

Measures

Change in Individual's Belief: Perceived Usefulness. Perceived usefulness is a key construct in the technology adoption and use literature, where it refers to the extent to which a person believes that using the technology system will enhance his or her job performance. Across the many empirical tests of the technology acceptance model (TAM), perceived usefulness has consistently been a strong determinant of usage intentions, with standardized coefficients typically around 0.6 (Venkatesh & Davis, 2000). To operationalize perceived usefulness, we adapted a 4-item scale from Venkatesh et al. (2003) (Cronbach's alpha = 0.93), that included the following survey items: 1) Using [EMR name] improves my performance in my job; 2) Using [EMR name] in my job increases my productivity; 3) Using [EMR name] enhances my effectiveness in my job; and 4) I find [EMR name] to be useful in my job. To capture change in beliefs over time, we operationalized perceived usefulness as the difference in ego's beliefs between T2 (post-implementation) and T1 (pre-implementation).

Change in Peer Belief: Perceived Usefulness. Peer perceived usefulness, was measured as the mean perceived usefulness, weighted by tie strength, of an ego's network. For example, consider an ego who had nominated three alters with perceived usefulness scores of 3, 3.25, and 3.5, respectively, who had tie strengths of 1 ("rarely"), 3 ("often"), and 4 ("very often"). The weighted mean score of the ego network would then be 8.9 [(3*1) + (3.25*3) + (3.5*4) / 3]. To capture change in peer beliefs over time, we calculated a change score by subtracting mean perceived usefulness at T2 from mean perceived usefulness at T1.

Advice Tie Additions. We counted the number of new outgoing ties (i.e., individuals nominated by ego as someone he or she turned to for advice) that emerged between T1 and T2 (i.e., ties that existed at T2 but not at T1) to create a continuous measure of advice tie additions for each individual. In keeping with prior work on the evolution of social networks over time (Snijders et al., 2006; Steglich, Snijders, & Pearson, 2010), we focus on outgoing ties because of the assumption that actors have control over whom they nominate.

Advice Tie Deletions. We also counted the number of outgoing ties that dissolved between T1 and T2 (i.e., ties that existed at T1 but not at T2) to create a continuous measure of advice tie deletions. Our measure of tie deletions includes both "actively" deleted ties, in which an ego fails to nominate a T1 alter that is present in the data at T2, as well as "passively" deleted ties, in which an ego cannot nominate an alter because he or she is not in the data at T2 (e.g., transferred unit). Of the

397 ties that were deleted, 4% (N = 16/397) were "passively" deleted because the alter was no longer working on the unit at T2.

Covariates. We included a variable for change in ego network size that accounted for both outgoing and incoming ties. The size of an ego's network should be positively related to the number of tie additions given the "rich-get-richer" dynamic underlying preferential attachment models, in which those with many ties tend to accumulate even more ties over time (Newman, 2010). The size of an ego' network should also be related to the number of tie deletions given that the larger the network, the greater the likelihood that ties will be lost through random attrition (Sasovova et al., 2010). We calculated the change score of ego network size by subtracting the count of ties in an ego network at T2 from the count of ties at T1.

In an effort to control for homophily, in which individuals form social ties with others who are similar to them, we calculated Yules Q, which is a measure of similarity which ranges from -1 for perfect heterophily (i.e., no shared beliefs between ego and the network) to +1 for perfect homophily (i.e., 100% shared beliefs between ego and the network), with 0 meaning no pattern of homophily. We also included a set of indicator variables to indicate the clinical unit in which individuals worked to account for contextual effects arising from differences in workflow and other unobservable differences between the units in our sample.

Lastly, we adjusted for several social demographic characteristics of the focal individual that may affect individuals' beliefs towards technology, including gender and age (Venkatesh et al., 2003), as well as occupation. Prior research on the acceptance of health information systems shows that differences in tasks and social norms in health occupations play a powerful role in shaping the acceptance and use of such systems (Aydin & Rice, 1991; Kimberly & Evanisko, 1981). Given the diverse categories of professions in our sample (i.e., nurse managers, nurses, patient care associates, and secretaries), we controlled for the role of occupational membership by including an indicator variable for nursing status, with 1 = nurse and 0 = not a nurse. We focused on nurses because it was the largest occupational group in our sample (75%).

Analysis

We began by calculating descriptive statistics and a correlation matrix for our study variables. For Hypothesis 1, we used multivariable linear regression to estimate changes in the perceived usefulness (PU) of ego (i) who works on clinical unit (c) as a function of changes in the perceived usefulness of his or her peers (j), the individual's measured characteristics (X), and an unobserved error term:

$$(1)\ PU^{Ego}_{ic,(T2-T1)} = \theta_1\ PU^{Peer}_{jc,(T2-T1)} + \beta X^{Ego}_{ic,(T2-T1)} + \varepsilon^{Ego}_{ic,(T2-T1)}$$

Model 1, which serves as our baseline model, is a first-differenced equation, in which the variables are differenced over time in order to remove time-invariant, unobserved attributes (Wooldridge, 2009). This approach allows us to explicitly consider our research question: how changes in peer

beliefs over time affect changes in individual beliefs over the same time period – while controlling for unobserved heterogeneity that may bias estimates of social influence (Nanda & Sørensen, 2010).

To test Hypotheses 2a and 2b about whether network churn (i.e., tie additions and tie deletions) moderate the relationship between peer perceived usefulness and individual's perceived usefulness, we first mean-centered variables and then added the interaction terms tie additions*peer perceived usefulness and tie deletions*peer perceived usefulness to create Models 2 and 3, respectively.

For all of the models, individuals were clustered within clinical units and thus violated the independence of errors assumption of the ordinary least squares (OLS) regression. To correct for this multilevel clustering, we used the Huber-White robust variance/covariance matrix, which assumes that the error terms are correlated within clusters, but uncorrelated across clusters (White, 1982). We also calculated the variance inflation factor for each variable in our regression models to test for multicollinearity. All analyses were conducted using SAS (Version 9.4; SAS Institute, Cary, NC).

Results

The survey response rate was 60% (N=256/429) for the pre-implementation survey (T1) and 68% (N = 284/415) for the follow-up survey (T2). We collected longitudinal data for 192 individuals out of the 232 individuals who completed the pre-implementation survey and were still working on the units at follow-up. The mean age of respondents was 36.57 years old and females were 91.15 percent of respondents (Table 1). In terms of clinical roles, there were 144 nurses (75%), 6 nurse managers (3.1%), 20 patient care associates (10.4%), and 22 secretaries (11.5%).

Tables 1 and 2 present descriptive statistics and correlations for our study variables. As illustrated in Figure 3, individual's perceived usefulness decreased by 0.76 points (on a 5-point scale), falling from 3.49 at T1 to 2.73 at T2 on a 5-point scale (t-value = 10.22; p < 0.001). Similarly, peers' perceived usefulness decreased by 0.81 points, from 3.45 at T1 to 2.64 at T2 (t-value = 14.43; p < 0.001).

In terms of network change, we find evidence of a substantial amount of network churn via tie additions and tie deletions. On average, an ego network had 2.35 ties at T1, and 1.26 ties were added (54% increase) and 1.31 ties were deleted (56% decrease) between T1 and T2.

Table 3 presents the results of the regression models used to test our hypotheses. Model 1 provides the test for Hypothesis 1, which predicted that changes in peer perceived usefulness will be positively associated with changes in individual's perceived usefulness. The model shows a positive, significant coefficient for peer perceived usefulness (p < 0.01), lending support for Hypothesis 1.

Table 1: Descriptive statistics

		Clinical Unit						
		Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Total
N		24	22	35	60	16	35	192
Age		34.27	35.62	44.01	36.14	33.81	32.47	36.48
Gender (% Female)		95.83%	86.36%	91.43%	85.00%	100%	97.14%	91.15%
Nurse (% Nurses)		62.50%	77.27%	91.43%	78.33%	56.25%	65.71%	74.48%
Tie Additions		0.96	1.59	1.31	1.12	1.31	1.4	1.26
Tie Deletions		1.67	1.68	1.4	0.95	1.88	1.11	1.31
Average Ego Network Size	**T1**	2.58	3.09	2.6	1.42	3.69	2.46	2.35
	T2	1.88	3	2.51	1.58	3.13	2.74	2.29
Ego Perceived Usefulness	**T1**	3.81	3.42	3.23	3.49	3.69	3.49	3.49
	T2	3.29	2.76	2.29	2.58	2.63	3.06	2.73
Peer Perceived Usefulness	**T1**	3.7	3.42	3.29	3.3	3.75	3.5	3.45
	T2	3.11	2.74	2.12	2.33	2.79	3.13	2.64
Homophily (Yules Q)	**T1**	-0.02	0.08	-0.04	0.07	0.05	0.06	0.03
	T2	-0.05	0.03	0.15	0	0.27	0.06	0.07

Table 2: Correlation matrix

	Variable Name	1	2	3	4	5	6	7	8
1	Change in Perceived Usefulness								
2	Change in Peer Perceived Usefulness	0.23**							
3	Tie Additions	0.02	-0.07						
4	Tie Deletions	-0.16*	-0.14	-0.02					
5	Change in Network Size	0.13	0.02	0.80**	-0.59**				
6	Change in Homophily (Yules Q)	-0.16	-0.01	0.09	0.17*	-0.06			
7	Gender (% Female)	0.02	0.01	0.03	0.01	0.02	0.04		
8	Age	-0.13	-0.04	-0.10	0.02	-0.09	0.04	0.02	
9	Nurse (% Nurses)	-0.13	-0.12	0.09	-0.01	0.08	-0.12	-0.14	-0.18*

$* p < 0.05$, $** p < 0.01$

For individuals who deleted fewer ties (i.e., had more stable networks/less churn), there is a strong, positive relationship between changes in peer beliefs and changes in ego's beliefs (t-value of the simple slope = 3.55; p = 0.001). In contrast, for individuals who deleted many ties (i.e., had less stable networks/more churn), there is no relationship between changes in peer beliefs and changes in ego's beliefs (t-value = -0.68; p = 0.51). Thus, in the case of tie deletions, network stability was associated with greater influence of social networks, whereas network instability had no effect on the influence of networks.
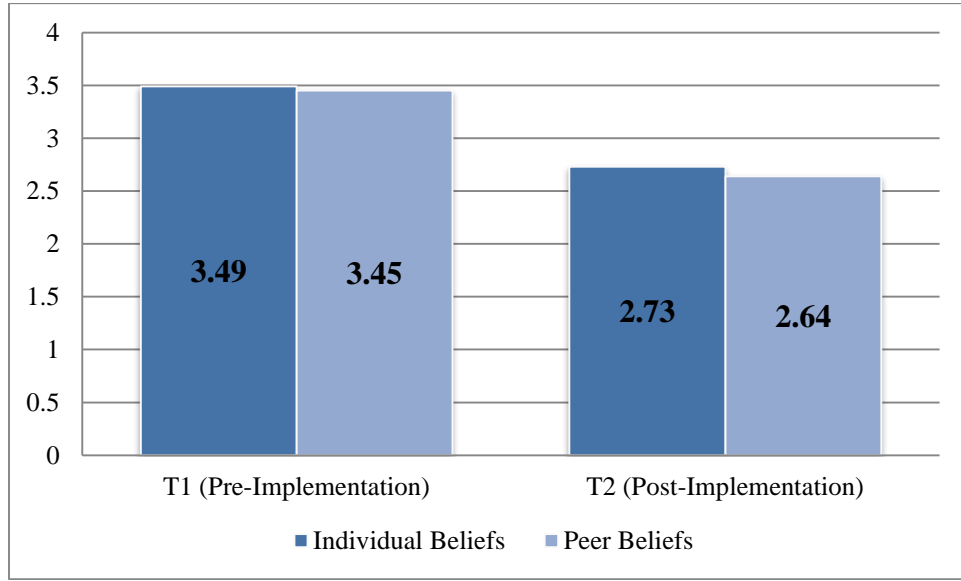
Figure 3. Differences in beliefs about perceived usefulness from T1 to T2

When we excluded the interaction terms from Models 2 and 3, we did not find evidence of a direct effect of tie additions or tie deletions, respectively, on individual's perceived usefulness (p > 0.05). Thus, it appears that network churn – via tie deletions – operates through its effect on the relationship between peer and individual beliefs, rather than directly impacting individual's beliefs.

Across Models 1-3, we also found a significant, negative effect of age (p < 0.05) and nursing status (p < 0.01) on changes in individual's perceived usefulness, such that individuals who were older and belonged to the nursing profession were less likely to change their beliefs from T1 to T2.

Robustness Checks

In order to test the robustness of the effect of peer beliefs on individual beliefs (Hypothesis 1), we used an alternate specification of a "social network effects" model that was adapted from Sasovova et al. (2010). This specification uses the perceived usefulness (PU) of an individual (i.e., Ego) (i) who works in clinical unit (c) at time T2 as a function of the individual's previous PU, the individual's measured characteristics (X), peers' (j) previous and current PU, clinical unit (c), and an unobserved error term:

$$PU_{ic,T2}^{Ego} = \theta_1 PU_{jc,T2}^{Peer} + \theta_2 PU_{jc,T1}^{Peer} + \theta_3 PU_{ic,T1}^{Ego} + \beta X_{ic,T2}^{Ego} + \varepsilon_{ic,T2}^{Ego}$$

In this model, the key variable of interest is peers' perceived usefulness at time T2, as a significant coefficient suggests that peer beliefs affect individual beliefs. In the alternative specifications of Models 1-3, the coefficient is positive and marginally significant (p < 0.10), providing added support for the influence of peer beliefs on individual beliefs over time (Hypothesis 1). Moreover,

Table 3: OLS regressions of individual's perceived usefulness (change score) on covariates

	Model 1	Model 2	Model 3
Intercept	0.04 (0.65)	0.09 (0.65)	0.25 (0.64)
Change in Peer Perceived Usefulness	0.30 (0.11)**	0.33 (0.11)**	0.35 (0.12)**
Change in Network Size	0.01 (0.04)	0.04 (0.04)	0.03 (0.04)
Homophily (Yules Q) (change score)	-0.18 (0.09)*	-0.18 (0.09)*	-0.18 (0.09)*
Gender	0.01 (0.29)	0.01 (0.29)	-0.11 (0.29)
Age	-0.02 (0.01)*	-0.02 (0.01)*	-0.02 (0.01)*
Nurse	-0.41 (0.17)*	-0.49 (0.18)**	-0.48 (0.18)**
Clinical Unit (reference = Unit 6)			
Unit 1	0.29 (0.26)	0.35 (0.27)	0.42 (0.25)
Unit 2	0.17 (0.28)	0.22 (0.28)	0.26 (0.26)
Unit 3	0.25 (0.31)	0.27 (0.32)	0.19 (0.30)
Unit 4	0.10 (0.26)	0.12 (0.26)	0.13 (0.27)
Unit 5	-0.21 (0.31)	-0.13 (0.31)	0 (0.33)
Tie Additions		-0.03 (0.07)	
Tie Additions x Peer Perceived Usefulness		0.09 (0.12)	
Tie Deletions			-0.03 (0.08)
Tie Deletions x Peer Perceived Usefulness			-0.33 (0.12)**
Adjusted R^2	0.07	0.07	0.12
N	141	137	137

* $p < 0.05$, ** $p < 0.01$

the coefficient on the interaction term between tie additions*peer perceived usefulness is not significant (Model 2), whereas the coefficient on the interaction term between tie deletions*peer perceived usefulness is significant (Model 3). These findings provide added support for the moderating effect of tie deletions, and not tie additions, on the relationship between peer beliefs and individual beliefs.
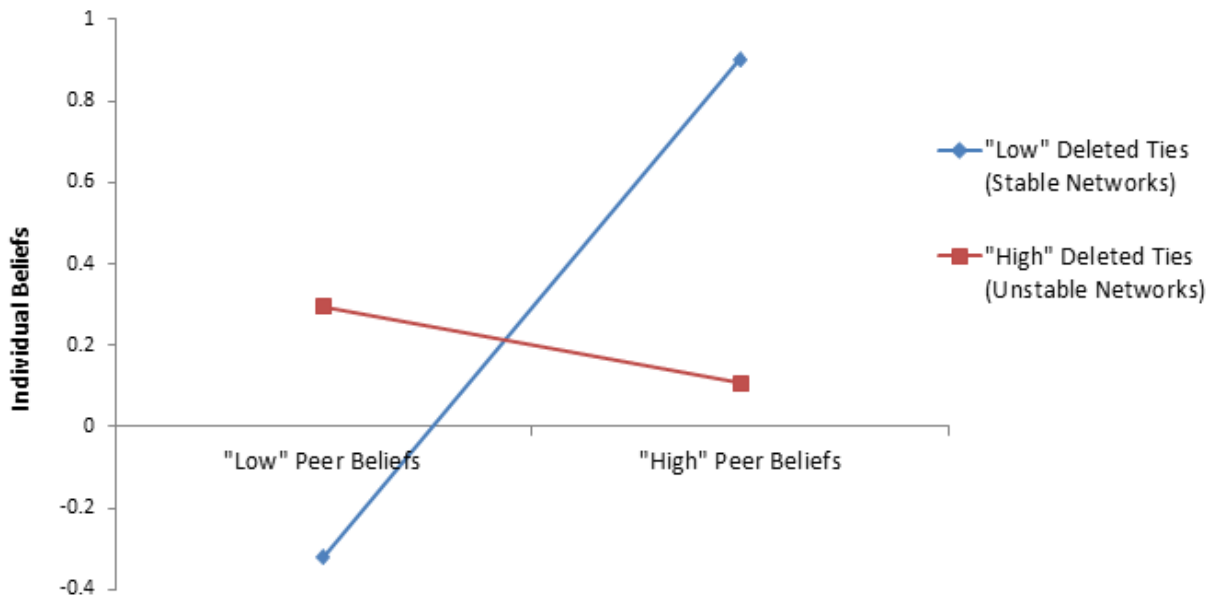
Figure 4: Moderating effect of network tie deletion on the relationship between changes in peer beliefs about usefulness and changes in ego's beliefs about usefulness

To further consider the effect of peer beliefs on individual beliefs (Hypothesis 1), we restricted the analyses to "strong" ties, which tend to be associated with greater social influence (Hansen, 1999; Suarez, 2005). In keeping with Granovetter's (1973) treatment of strong ties as reciprocated ties (i.e., ties that are acknowledged by both members of the dyad), we focused on reciprocated ties. However, due to insufficient sample size (N = 15 with reciprocated ties at both T1 and T2), we did not have enough power to estimate the effect of changes in network beliefs on changes in individual beliefs (Model 1).

Lastly, our measure of tie deletions included both "actively" deleted ties, in which an ego fails to nominate an alter that is present in the data at T2, as well as "passively" deleted ties, in which an ego cannot nominate an alter because he or she is not in the data at T2. When we excluded "passively" deleted ties, which comprised 4.15% of all tie deletions, the results were quantitatively similar to the original specification. Thus, "actively" deleted ties appear to be driving the moderating effect of tie deletions on the relationship between peer beliefs and individual beliefs (Hypothesis 2b).

Discussion

Implementation success – or failure – often hinges on individual beliefs about the innovation being introduced (Klein & Sorra, 1996; Rogers, 1995). Both theory and practice suggest that social networks and their influence play a vital role in shaping these beliefs; however, the static view of

networks that has predominated the literature has limited our understanding of network influence. In light of mounting evidence that suggests that social networks change over time (Snijders et al., 2006), we sought to examine how network churn affects a social network's influence with respect to individual belief formation. We find that peer beliefs significantly affect individual beliefs about technology and that less network churn via tie deletions enhances the influence of networks during new IT implementation, a time often characterized by much uncertainty for workers.

Our findings extend network theory by demonstrating the effects of network churn as a moderator of network influence. Recent studies on network churn have provided insight into antecedents of network churn, such as self-monitoring personality (Sasovova et al., 2010) and the degree of network cohesiveness (Gargiulo & Benassi, 2000), as well as the direct effect of churn on outcomes, such as entrepreneurs' portfolio of exchange partners (Vissa & Bhagavatula, 2012). To our knowledge, this is the first study to conceptualize network churn as a moderating variable that may amplify or dampen the effect of networks. In light of how common network churn appears to be, with several studies finding that about half of ties are replaced over time (Moody, 1999; Sasovova et al., 2010; Van de Bunt et al., 1999), this is a key contribution to the study of network effects.

In considering the role of network churn, it is important to note that tie deletions – but not tie additions – moderated the extent of network influence. Prior work suggests that tie deletions may have a greater effect than tie additions in certain contexts. For example, in a study of network churn in entrepreneurs' personal networks, Vissa and Bhagavatula (2012) found that tie deletions had a strong effect on their outcome (i.e., venture's portfolio of exchange partners), whereas the effect of tie additions was weaker. One possible explanation for the differential effect is the actor's level of control in forming or dissolving the relationship. Tie deletions are considered to be unilateral (i.e., an ego can dissolve a tie without the permission of the other), whereas tie additions are bilateral (i.e., a new tie has to consent to form a new relationship with an ego) (Burger & Buskens, 2009). Given the uncertainty that characterized our study context, it is possible that individuals who actively deleted ties may have been more influenced by relationships in which they had a greater sense of control. Alternatively, the significant effect of tie deletions may have stemmed from the managers', not the individuals', control over the tie deletion process. In our study, beliefs decreased significantly from T1 to T2. Managers may have observed this trend and sought to disrupt the spread of negative influence by changing employees' interaction patterns. Although future research is needed to test these hypotheses, both explanations suggest that control over the network churn process – whether via individuals' internal control or managers' external control – may have contributed to the significance of tie deletions in our study context.

In addition to advancing research on network churn, this work contributes to the social influence literature by providing support for the notion that social networks influence individuals' beliefs. The current study adds robustness to prior work that found a significant, positive relationship between peer beliefs and individual beliefs about technology (Rice & Aydin, 1991; Schmitz & Fulk, 1991) through the use of longitudinal data and a novel study context (i.e., health care practitioners in the context of EMR implementation). It is important to note, however, that the positive relationship between peer beliefs and individual beliefs does not mean that the impact of

network influence is necessarily positive from the vantage of those implementing the system. We found that beliefs decreased significantly from T1 to T2, with declines in peer beliefs associated with declines in individual beliefs. This decrease corresponds to prior work finding significant declines in nurses' beliefs from pre-implementation to post-implementation periods (Smith et al., 2005) and may reflect a "worse-before-better" dynamic in which beliefs are more negative immediately after implementation (the period covered by this study) than before they have experience with the technology, and improve over time as staff become more accustomed to the technology (Carayon et al., 2011; Lee et al., 2008). Most prior work on technology acceptance focuses on the positive aspects of network influence; here, our findings suggest that health care practitioners may also negatively influence one another's beliefs towards new technology.

This work offers several practical insights for health care managers implementing new technology. First, health care managers should take steps to cultivate supportive beliefs at the network level, as positive changes in peer beliefs are associated with positive changes in individual beliefs (and conversely, negative changes in peer beliefs are associated with negative changes in individual beliefs). Opinion leaders, defined as individuals perceived as having significant influence on the beliefs and actions of their colleagues (Locock, Dopson, Chambers, & Gabbay, 2001), can play a critical role in such efforts by leveraging their influence to create buy-in and support for implementation efforts. Opinion leaders can be identified using social network methods that involve surveying all of the members in a bounded network, constructing a social network matrix, and then using network centrality measures (e.g., degree centrality or betweenness centrality) to identify who is most influential (Hersh, 2004). Once identified, opinion leaders can be targeted for additional training or matched with others whose beliefs (e.g., negative beliefs) or behaviors (e.g., ineffective system use) may be stalling implementation efforts (Valente, 2012). Second, managers seeking to leverage networks to support implementation efforts need to consider network churn. When positive beliefs are circulating in a network, managers could amplify the effect of network influence by facilitating interactions between practitioners and their long-lasting ties. Conversely, when negative beliefs are circulating, managers could dampen the effect of negative influence by disrupting long-lasting ties. For example, in our study setting, managers had at least partial control in assigning health care practitioners' shifts, patient assignments, and the "super user" (i.e., practitioners who received extra training on the selected EMR system) who served as the practitioners' "go-to" person for technical support. Managers could take steps to disrupt long-lasting ties by changing these assignments so that practitioners' are less proximate to their long-lasting ties. Lastly, the significant dip in beliefs between T1 and T2 can inform when managers should time network interventions. In this study, we focused on the early stage of the implementation process known as the "shakedown" phase, which refers to the period from "going live" until routine use has been achieved (Sykes et al., 2011). The shakedown phase is critical because it sets the tone for individuals' future interactions with the system. Thus, an important implication is that training programs should not be seen as a "one-shot" solution typical of most EMR implementations, but should be offered throughout the shakedown phase to help health care practitioners throughout the transition process.

Several limitations should be considered when interpreting our study's findings. First and foremost is the challenge of separating social influence effects from the effects of partner selection (i.e.,

homophily) and the social context. Although we attempted to account for selection and contextual effects, future work would benefit greatly from the use of stochastic actor-based models, such as the model proposed by Vogelsmeier, Halbesleben, and Scott-Cawiezell (2008), which not only assesses the effects of selection and influence simultaneously, but also explicitly account for the mutual dependence between network and behavior, coevolving in continuous time.

A second limitation stems from missing data, as the response rate for the pre-implementation and post-implementation surveys were 60% and 68%, respectively. Respondents lost to follow-up (i.e., those present at T1 but not at T2) did not differ significantly from respondents with longitudinal data (i.e., those present at both T1 and T2) in terms of the dependent variable (individual beliefs about usefulness), the independent variable (peer beliefs about usefulness), and the covariates: age, gender, and homophily (Yules Q). Given that the respondents lost to follow-up did not differ significantly from respondents, we assumed that the dropouts were "missing at random" and excluded the missing data points from the analysis (Kristman, Manno, & Côté, 2004). The size of the ego network was the only measured variable that differed significantly between groups (t-value = -2.13; p = 0.03); individuals lost to follow-up had significantly smaller networks at baseline (mean = 3.22 ties; s.d. = 3.41) than individuals with longitudinal data (mean = 4.37 ties; s.d. = 3.84). Differences in personality traits may offer a possible explanation, as individuals with larger networks may also be more extroverted or exhibit more prosocial behaviors. It would be interesting for future research to explore the relationship between personality traits, network size, and the level of network churn.

A third limitation relates to the generalizability of our findings given our focus on health care practitioners in a single study site (a large, academic hospital) using a mandated EMR system. Further research would be needed to assess the generalizability of the findings to other sectors and implementation contexts. Fourth, this study represents an initial test of the moderating effect of network churn on the relationship between peer beliefs and individual beliefs. Future work could add robustness to our findings by exploring other aspects of network churn (i.e., patterns of network churn), attributes of peers (e.g., status or centrality in a network), and outcomes (e.g., other network beliefs and actual system use). In addition, future work should seek to understand why particular ties are deleted or added, particularly in the case of the former, as our findings suggest that tie deletion may play an important role in moderating the effects of networks. Lastly, the duration of the study period (9 months) was relatively brief. It will be important for future work to examine how network churn evolves over time, and in response to what stimuli.

Conclusion

This work provides insight into how changes in network content and network composition affect individuals' beliefs about medical technology. Our results suggest that networks significantly, and negatively, influence individual beliefs about technology, and that less network churn in the form of fewer tie deletions enhances the effect of network influence. As researchers and managers seek to understand the relationship between networks and individuals' beliefs about new technology, it may be important to consider the role of network churn.

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