Knowledge Sharing in a Dynamic, Multi-level Organization: Exploring Cascade and Threshold Models of Diffusion

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ABSTRACT

Studying large, dynamic organizations poses a number of challenges, such as accounting for multi-level processes and exploring changes over time. Organizational culture, informal roles, and individual attitudes interact to influence organizational processes such as knowledge sharing, a process vital to organizational performance and innovation. To explore such organizational dynamics, we developed an agent-based model (ABM) that incorporates dynamic social networks over the physical environment of a hospital in southwest Virginia. The ABM simulates attitude formation and knowledge spread within the hospital. Social networks are dynamically created as agents interact while simple rules based on cascade and threshold models of diffusion drive the decision to share knowledge. Results show that there is a strong effect by formal roles in the hospital that are important in social network development and knowledge diffusion.

KEYWORDS

Agent-based modeling, Social network analysis, Organizations, Attitude diffusion, Knowledge sharing

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1 INTRODUCTION

Organizations are complex systems comprised of many dynamic and evolving interaction patterns among individuals and groups [2]. Understanding these interactions and how patterns, such as knowledge sharing behavior, emerge are crucial to creating effective and efficient organizations. While there has been much research in this area, it remains a challenge to address the dynamics of organizations as complex systems [29]. Organizational complexity emerges from the individual level interactions within an organization [33]. Social network analysis (SNA) has been a primary empirical method used to study the interactions and connections between individuals, teams, and organizations [22, 25, 26]. SNA involves mapping and measuring the relationships and interactions between people and groups using graph theoretic methods [41]. Yet, in order to answer vital questions, such as how connections and communication change over time and how these changes correspond to changes in group composition or organizational structure, it is necessary to model these interactions in a dynamic way.

To explore such organizational dynamics, we developed an agent-based model (ABM) that incorporates dynamic social networks over a physical environment. A limited amount of research has integrated agent-based modeling with dynamic social networks over a physical environment to explore specific social phenomena (e.g., [32]). However, to the best of our knowledge, the combination of these approaches has not been applied to the study of organizations. The agents are the individuals within a hospital and agent movement occurs over the physical environment of a hospital in southwest Virginia. This pattern of movement is used to create the agents' contact (interaction) network, providing empirical input into development of the organization's social network. We develop two basic models based on the literature to simulate knowledge sharing between agents in the organization – a cascade model of knowledge sharing and a threshold model of attitude diffusion. The foundation for each model, including the agents, the physical environment, and development of the social network, remain the same. Simple rules based on classic models of diffusion drive the decision to share knowledge in each model, respectively. Results show that there is a strong effect by formal roles in the hospital, particularly when comparing the most common roles (e.g., nurses, physicians) to sitters and therapists.

2 BACKGROUND

Knowledge sharing within organizations is driven by social networks and aspects of social and cognitive psychological processes (e.g., attitudes towards sharing). In this section we briefly describe the core theoretical aspects and motivations of our work, including social networks as an important aspect of the complex organizational system, the role that individual attitudes play in influencing organizational processes, and how social networks and individual

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attitudes interact to influence knowledge sharing within organizations.

2.1 Social networks

Organizations are composed of both formal (explicit/prescribed) and informal (emergent) structures [38], which interact to influence organizational processes such as knowledge sharing. Social networks are driven by homophily, social influence, and proximity, all of which promote communication, shared attitudes, and feelings of trust [12]. The homophily effect measures the phenomenon by which agents form ties with other "similar" agents [24], which may be measured according to attributes such as occupation, gender, or shared attitudes towards a feeling, thought, or action [7]. Social influence, on the other hand, is the process by which attitudes tend to converge as individuals interact [14], creating a feedback effect between individual attitudes and the social network. Moreover, social networks are influenced by physical space as we are more likely to interact with those geographically near [40]. Eagle & Pentland [10], for instance, in his research shows that friendship networks and physical proximity networks in the workplace share similar structures.

Within these structures, individuals have both formal and informal roles. Formal roles follow the workflow and chain-of-command [15], whereas informal roles are characterized by the pattern of connections with others [39]. Informal roles emerge through the social network and can help us identify informal leaders, influencers, and brokers, all of which have key roles in information flows.

2.2 Individual attitudes

Attitudes are evaluations of things, people, groups, and ideas [5] and these evaluations are formed based on interactions with the environment [11]. Attitudes represent a fundamental psychological construct because they drive behavior. In organizations, an individual's attitude towards the organization, towards other individuals, or towards various work processes (e.g., knowledge sharing, job tasks) will all influence the actions that person decides to take within the organization. Research has found that individuals' attitudes toward knowledge sharing significantly predicts tacit knowledge sharing intentions and behaviors in organizations [28, 34]. In hospital settings, subjective norms and attitude were the two strongest predictors of knowledge sharing among physicians [35].

2.3 Knowledge sharing

Knowledge sharing is a dynamic and vital process within organizations that involves transferring information, experiences, and know-how from experts, or those who have specific knowledge, to novices, or individuals who need the knowledge [18]. Knowledge sharing has been positively associated with team performance, innovative capabilities within an organization, and organization performance [e.g., 27]. This is the fundamental means through which employees contribute to the success of an organization [19].

Tacit knowledge, specifically, is primarily transferred through direct contact and observation of behavior [28]. It generally consists of ideas, experience, and competencies and, as such, relies more on informal structures [4]. For example, one study found that verbal communication between nurses was one of the most important ways to transfer tacit knowledge, whereas communicating through weblogs or emails were some of the least important ways [9].

2.4 Diffusion models

The spread of knowledge and the propagation of attitudes within an organization can be seen as types of diffusion processes. The literature stresses two basic models of diffusion: independent cascade models and linear threshold models [8]. The dynamics of diffusion are simple and occur through an "activation" process. Nodes in a network start as either active or inactive. In a cascade model, active nodes can trigger activation in inactive nodes given some success probability. Once a node has been activated, it cannot be deactivated (e.g., [16]). In threshold models agents are influenced by their neighbors, which may be physically or socially (via a social network) proximate. If the number of active neighbors exceeds a given threshold, the agent activates. Classic threshold models include Granovetter [17] and Schelling [36]. Both models demonstrate how macro-level outcomes, such as rioting and segregation, emerge from individual threshold preferences.

In this paper, we draw on this literature in our implementation of attitude diffusion and knowledge sharing. We develop two models, a simple cascade of knowledge sharing and a threshold models of attitude diffusion.

3 CONCEPTUAL MODEL

An ABM was developed in Mesa, a Python framework for agent-based modeling [23], to simulate the local interactions and attitudes towards knowledge sharing in a hospital. The ABM is grounded on empirical data collected by an earlier study of a hospital in southwest Virginia [20].

Figure 1 illustrates the conceptual diagram of the ABM. Agents, which represent the healthcare workers of a hospital, move over the physical environment of a hospital which provides the basis for creation of the agents' contact network. In turn, this network provides one of the main inputs into development of the social network. Another feature of the model is the agents' attitude towards knowledge sharing, which drives behavior. In this case, behavior is the decision to share (or not) knowledge. As a feedback system, individual attitudes dynamically provides input into the development of the social networks.

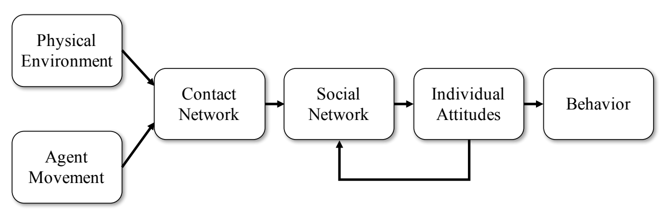


Figure 1: A conceptual diagram of the agent-based model.

3.1 The agents and model initialization

The agents in the model are the 2,127 healthcare workers of the hospital in southwest Virginia. We use empirical data collected by Jimenez [20] to create the agents and to inform their interactions and movement. Jimenez [20] collected data from 431 healthcare workers representing 30 different healthcare disciplines (e.g., physicians, nurses, nurse assistants, social workers, physical therapists) by directly observing and shadowing the employees over time spans of 4 to 8 hours during normal hospital operations. The physical layout of the hospital includes nine floors and over 1,000 locations, such as patient rooms and employee lounges. Through a population builder program in Python, Jimenez [20] developed the synthetic population of the entire hospital at the individual level representing the hospital's healthcare workers and their movements and contacts over the course of 200 days. Tables 1 and 2 below show the structure of the input data developed by Jimenez [20] and used in our model.

Table 1: The agents and their profession.

Field	Description
Agent ID	The unique identifier of the agent
Profession	The profession associated with the agent (e.g., nurse, physician)

Table 2: The agents' activity schedules.

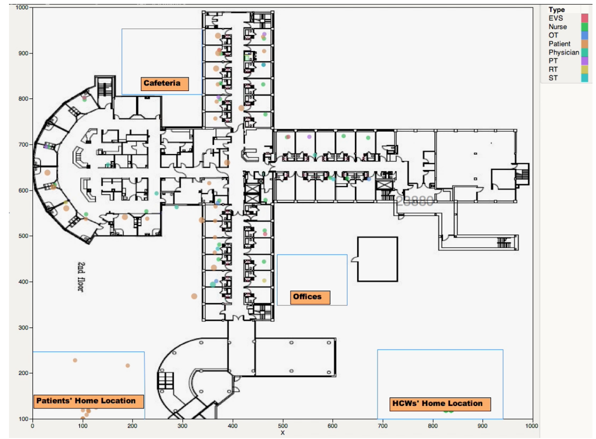
Field	Description
Agent ID	The unique identifier of the agent
Start	The start time (in seconds) of the activity
End	The end time (in seconds) of the activity
Location	The room number identifying the location of the activity

Agents have three attributes: their profession, their attitude towards knowledge sharing, and a binary attribute that indicates whether they have the knowledge. Moreover, agents are assigned their pre-determined schedules for the course of the simulation, which includes a start time, end time, and location (e.g., room in the hospital) of each activity. When the model initializes, one or more agents are randomly "given" the knowledge. The agents' knowledge sharing behavior is evaluated at each time step of the simulation (each time step represents one minute).

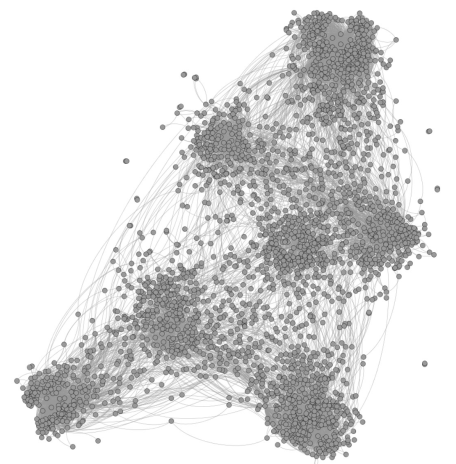
3.2 Social network development

As discussed in Section 2.1, physical proximity in addition to homophily and social influence are important drivers of social networks. We operationalize physical proximity in our model as a "contact" – an event where two or more agents are at the same physical location (e.g., nurses' station) at the same time. Agents' activities patterns (schedules) across both physical space and time allows for the development of the healthcare workers' contact network X^C. As agents move about the hospital, we can visualize these contacts through the network diagram in Figure 2.

The contact network X^c is a weighted two-mode affiliation, where agents a_i (i=1 to n number of agents) and a_j (j=1 to n-1) represent the first mode and the events e_{ij} that affiliate the agents represent the second mode [41]. As shown in Equation 1, the weight of the tie w^c_{ij} and w^c_{ji} (w^c_{ij}=w^c_{ji}) is a function of the duration of



(a)



(b)

Figure 2: The hospital simulation. (a) The daily activities in the hospital for agents on a floor of the hospital. Each dot represents an agent. (b) The contact network diagram of the hospital population over one month. Agents are represented by the dots and contacts between agents are represented by the lines [source, 21].

events e_{ij} and the total time T that has passed in the simulation. The weight of tie w^c_{ij} decays over time when agents are not in contact.

$$w^c_{ij}(t) = \frac{\sum_0^t e_{ij}(t)}{T} \quad (1)$$

In contrast to the contact network, the network ties in the social network are not brief events (e.g., one encounter or contact) but are instead states that can sustain over time. According to Snijders et al. [37], the aggregation of event intensity over a specified time can be used as an indicator of states. The social network X^s in the model is a weighted one-mode network between agents a_i (i=1 to n) and a_j (j=1 to n-1). The weight of the tie w^s_{ij} and w^s_{ji} (w^s_{ij}=w^s_{ji}, 0

$\leq w^s_{ij}, w^s_{ji} \leq 1$) and is a function of w^c_{ij}, profession homophily P_{ij}, and attitude homophily A_{ij} as shown in Equation 2. The weight of the social tie w^s_{ij} is stronger for agents with similar attitudes and professions.

$$\begin{aligned} w^s_{ij}(t) &= \beta_1[w^c_{ij}(t)] + \beta_2[e^{|A_{ij}(t-1)|} + P_{ij}], \\ \text{where } A_{ij}(t-1) &= A_i(t-1) - A_j(t-1), \\ 1 &\leq A_i, A_j \leq 1, \\ P_{ij} &= \begin{cases} 1, & \text{if } P_i = P_j \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{2}$$

As agents move and interact across the hospital, the contact and social networks are dynamically created in parallel.

3.3 A phased approach to modeling attitude diffusion and knowledge sharing

We developed two models of attitude diffusion and knowledge sharing (see Section 2.4). The foundation of each model, including the agents, the physical environment, and development of the social network, remains the same. We are only adding complexity to the rules for attitude diffusion and knowledge sharing. The two models are outlined in Table 3 and described in more detail below.

Table 3: Models of attitude diffusion and knowledge sharing.

Model	Attitude Diffusion	Knowledge Sharing
Model 1: Cascade model of knowledge sharing	None	Diffusion with probability p
Model 2: Threshold model of attitude diffusion	Attitude A changes using a threshold value, where $A \in \{1, -1\}$	Diffusion with probability p occurs only when $A = 1$

Model 1: Cascade model of knowledge sharing. An active node in this model is an agent that has the knowledge. Knowledge spread can occur in between two interacting agents (i.e., two agents that are that the same location at the same time). If an agent has the knowledge, it will share that knowledge with an interacting agent that does not have the knowledge with a given success probability. Attitude towards knowledge sharing is not modeled in this case. Agents in this model can spread knowledge to any interacting agent, the strength of the social tie between agent dyads are not considered.

Model 2: Threshold model of attitude diffusion. We use a linear threshold model to simulate the diffusion of attitudes. Attitude in this model is a simple binary variable $A \in \{1, -1\}$, representing whether an agent has a positive or negative attitude towards knowledge sharing. An agents attitude can "flip" if agents are influenced enough by those in their social network with the opposite attitude. In other words, the sum of the strength of the ties of the agents must exceed some threshold. Heterogeneous thresholds are randomly assigned to agents at the beginning of the simulation. If an agent has the knowledge *and* has a positive attitude towards knowledge sharing, it will share that knowledge with an interacting agent that does not have the knowledge with a given success probability.

3.4 Model output

The model exports a series of files. These output files include the interaction times between all agent dyads, attitude values of each agent, the contact network, the social network, and the agent dyads participating in knowledge spread. Attitude and knowledge data are collected by time step, while network data are collected at the end of each simulation day.

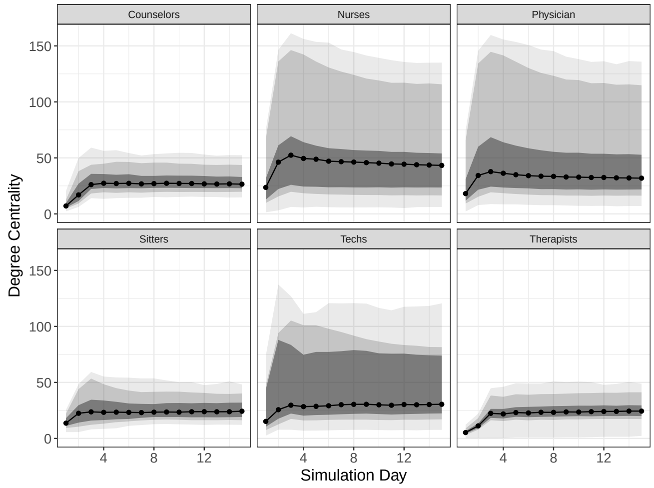
4 RESULTS

This section discusses preliminary results of the ABM. Ten runs each of Models 1 and 2 (see Section 3.3) were performed. Each simulation ran for 15 simulation days (21,600 ticks). At initialization, ten agents are randomly selected to have the knowledge and in the case of Model 2, agents are randomly assigned either a positive (+1) or negative (-1) attitude towards knowledge sharing. Results explore trends in the social network and in the spread of knowledge across time and profession.

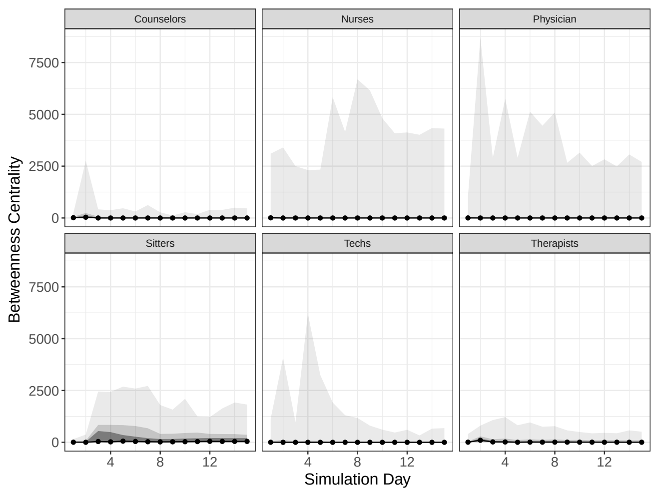
Central agents. The most commonly used network measures are those that indicate the centrality of an agent [13]. Agents with high degree centrality are typically "most visible" in a network, while agents with high betweenness centrality potentially have some level of control over the communication between two agents or two cluster of agents [42]. Figure 3 shows centrality results of the social network by profession. The line indicates the median value across all agents and ten runs of the model, the dark shaded areas represent the 25th and 75th quartiles, the medium shaded areas represent the 90th and 10th quartiles, and the light shaded area represents the remaining outliers. We find that network centrality tends to reach a steady state for most professions around day 4 of the simulation, indicating that social networks are well established at that point.

Nurses and physicians, followed by technicians, have the highest variation in both degree and betweenness centrality. In terms of knowledge flows, the outliers (those with high betweenness centrality in particular) likely play a more significant role. We can take a deeper look at the population that has high betweenness and low degree centrality. These agents will have few direct ties but will be linked to highly connected agents and are typically crucial for information flows.

Patterns of relationships. Hierarchical clustering can help identify those groups of agents that have similar positions in a social network. We evaluate results by profession to see if there is a relationship between the agents formal/prescribed role and their position in the informal network. Clusters that align with profession may demonstrate that formal structures play an important role in the structure of the informal network, and subsequently, in information flows. Figure 4 shows the degree to which agents with similar professions were clustered together in one run of the model. While the majority of nurses and physicians are clustered together (cluster 33), there is still a large spread across the other clusters. Counselors, sitters, and therapists, on the other hand, are similarly clustered almost exclusively in clusters 1 through 15.



(a)



(b)

Figure 3: Centrality results in the social network by profession at the end of simulation day 15. The line indicates the median value across all agents and runs, the dark shaded areas represent the 25th and 75th quartiles, the medium shaded areas represent the 90th and 10th quartiles, and the light shaded area represents the remaining outliers. a: Degree centrality. b: Betweenness centrality.

Knowledge spread. While development of the social network is similar in both models, the dynamics for which knowledge is spread is distinct. Figure 5 shows the number of agents that received the knowledge after each simulation day. As expected, we find that knowledge spread is faster in the cascade model than the threshold model. This is because agents will spread knowledge regardless of their attitude towards knowledge sharing. The effect of shifts in the schedules is also clearly visible as knowledge spread tends to plateau during nighttime hours when less employees are likely to be on site.

Table 4: Agents with high betweenness centrality and low degree centrality. Results shown are median values across multiple runs of the model.

Profession	Count of Population (Median)	% of Population (Median)
Counselors	5.0	7.9%
Nurses	47.5	4.2%
Physician	26.0	5.0%
Sitters	17.5	43.8%
Technicians	4.0	2.8%
Therapists	22.5	28.1%

NOTE: Sitters typically monitor and interact with patients, especially high-need patients.

Figure 4: The distribution of agents by profession in each cluster for one run of Model 1.

Even though the model runs for 15 days, we find that knowledge stops spreading by day 3 and day 8 and caps at 827 agents and 785 agents, in Models 1 and 2 respectively, leaving approximately 1,300 agents without knowledge. This is a result of the social network being composed of many disconnected subgraphs. Figure 6 provides an example of such a subgraph. While there over 2,000 agents in the model, the 105 agents in this subgraph do not communicate beyond this network. We also find in this example that six nurses serve as bridges (or cutsets) between the two networks.

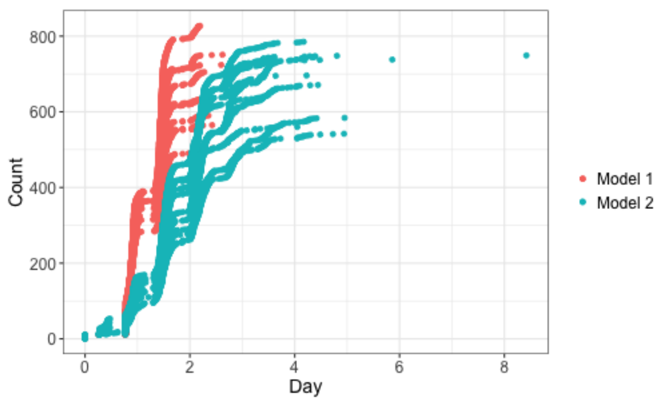


Figure 5: The number of agents that have received the knowledge over time.

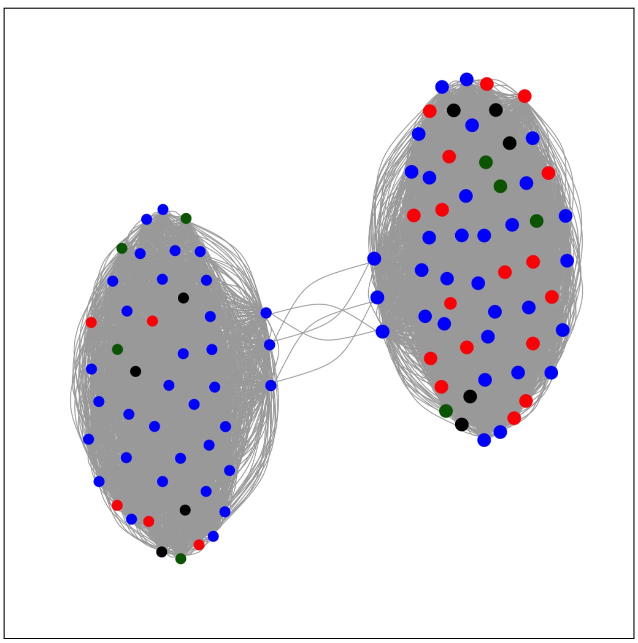


Figure 6: A subgraph in the social network. Blue nodes are nurses, red nodes are physicians, green nodes are technicians, black nodes are other professions such as housekeepers and internal transport medics.

5 CONCLUSION

Organizations are complex systems composed of dynamic networks of interacting individuals that change and adapt at both the individual and group levels. Agent-based models are ideal for modeling dynamic processes, such as individual level interactions, decisions, and actions in an organization (e.g., knowledge sharing, social network formation) [3, 6]. In this paper, we attempt to demonstrate that integrating agent-based modeling with dynamic social networks over a physical environment, is an approach to modeling organizations that provides unique insights that would be difficult, if not impossible, to gain with a static model.

Results found that that the social network of the hospital is made-up of many disconnected subgraphs which can potentially interfere with knowledge flows. This was further evidenced when we noted that knowledge spread stops by day 8 of the simulation. While nurses and physicians have the highest degree centrality, the more significant nodes in regards to information diffusion may be the outliers that have high betweenness centrality, as we saw in the case of the nurses in Figure 6. These agents are able to mitigate communication flows between otherwise disconnected graphs. In other subgraphs, sitters and therapists may play an interesting role when it comes to information flows given the high percentage that have high betweenness but low degree centrality. While hierarchical clustering found that agents sharing the same profession were often spread across many clusters, there still maintains a pattern to the clustering that follows these formal roles. This suggests that formal structures are important in the creation of informal networks and in knowledge flows. However, their importance may be less significant than expected given the large variation in centrality measures by profession and the spread across many clusters.

In future work, we will develop a third model that implements a cognitive model of attitude formation and change based on the Theory of Reasoned Action (TRA). TRA posits that attitude towards a behavior (e.g., knowledge sharing is good) and perceived social norms around the behavior (e.g., most of my coworkers share knowledge) determine the intention to perform the behavior [1]. Moreover, TRA takes into account the social context which is important considering the social dynamics that are inherent in organizations. We will utilize a previously developed computational formalization of TRA designed to study the dynamics of attitude formation and change [30, 31]. We will conduct additional runs across all three models and perform scenario analysis. For example, we will remove a "central" agent to evaluate the impact of attrition on knowledge diffusion across the hospital.

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