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MANUSCRIPT

Knowledge sharing in a dynamic, multi-level organization: an agent-based modeling approach

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Abstract

Organizations are complex systems comprised of many dynamic and evolving interaction patterns among individuals and groups. Understanding these interactions and how patterns, such as informal structures and knowledge sharing behavior, emerge are crucial to creating effective and efficient organizations. Studying organizations as complex systems is a challenge as we must account for hierarchically nested structures, multi-level processes, and changes over time. Informal structures interact with individual attitudes to influence organizational processes such as knowledge sharing, a process vital to organizational performance and innovation. To explore such organizational dynamics, we integrate dynamic social networks, a cognitive model of attitude formation and change, and a physical environment into an agent-based model, the combination of which represents a novel way to study organizations. We use a hospital in southwest Virginia as our case study. The agents in the model are the healthcare workers within the hospital and agent movement occurs over the physical environment of the hospital. Results show that the simulated hospital is resilient to impacts from employee attrition but that communication approaches must be thought through strategically so as not to hinder knowledge sharing. For managers, this type of modeling approach can provide resource and planning guidance in regards to attrition-based strategies and communication approaches.

Keywords Agent-based modeling · Social network analysis · Organizations · Knowledge sharing · Artificial neural networks · Theory of reasoned action

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1 Introduction

In understanding organizational processes, research must appreciate organizations as complex systems (Anderson 1999; Pires and Vieira 2019). Organizational complexity arises from the dynamic interaction patterns among individuals and groups (Axelrod 1997; Prietula et al. 1998; Kozlowski et al. 2013). Understanding how these interactions impact organizational processes, such as knowledge sharing, is crucial for creating effective, efficient, and resilient organizations. Knowledge sharing is the transfer of information, experience, and know-how from an individual who has specific knowledge to an individual who needs the knowledge (Hinds et al. 2001). It has been shown to be vital for organizational performance and innovation (e.g., Cummings 2004; Lin 2007; Mesmer-Magnus and DeChurch 2009).

Early knowledge sharing studies mostly focused on explicit knowledge (e.g., documents, instructions) and initiatives to use technology to transfer information. However, many of these initiatives failed in part because they did not account for the multiple channels through which knowledge is shared, including face-to-face interactions (Parise 2007). This created a shift in focusing on tacit knowledge, which is primarily transferred through direct contact and observation of behavior (Mongkolajala et al. 2012). Tacit knowledge generally consists of ideas, experience, and competencies and, as such, relies more on informal roles and organizational culture (Bock et al. 2005). 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 (Dehghani et al. 2013).

Tacit knowledge sharing is influenced by informal structures such as organizational subcultures and informal roles, which emerge through the organization's social network (e.g., Cummings 2004; Lin 2007; Mesmer-Magnus and DeChurch 2009). Social network analysis (SNA) has been an important method for studying the interactions and relationships between individuals and groups within organizations (Liu et al. 2011; Merrill et al. 2007, 2008). SNA uses graph theoretic methods to map and measure the interactions and relationships between people and groups (Wasserman 1994). While social networks are often studied in a static way, understanding how relationships and communication changes over time and how these changes effect organizational structure requires that we model these interactions dynamically. Despite much research in the area, however, studying organizations as a complex system remains a challenge (National Research Council 2008).

In order to capture organizational dynamics, we integrate dynamic social networks, a cognitive model of attitude formation and change, and a physical environment into an agent-based model (ABM). The combination of these methods represents a novel way to study organizations. ABM, which is well suited for modeling complex systems, is a type of computational method that allows for the modeling of the individual localized behavior of agents and at the same time observe the macro-behaviors that emerge. Within an "artificial" society, agents interact with each other and the environment (Macal and North 2010). Kozlowski et al. (2013) stress the advantages of using computational modeling, and ABM specifically, to model the multi-level nature of organizations from the bottom-up. In addition, ABM has been promoted as particularly useful for understanding social context within organizations (National Research Council 2014). While research has integrated these methods to explore specific social phenomena (e.g., Pires and Crooks 2017; Tolk et al. 2022), to the best of our knowledge, the combination of these approaches has not been applied to the study of organizations.

Prior studies have used ABMs to investigate organizational knowledge dynamics, however, many have been highly theoretic and have not utilized empirical data (e.g., Nissen and Levitt 2004; Sáiz-Bárcena et al. 2015; Wang et al. 2009). Most have also not accounted for the physical space of the workplace beyond abstract representations of the environment (e.g., Miller and Lin 2010). However, physical spaces can potentially encourage knowledge sharing and interactions with open spaces or discourage it with functionally segmented workspaces (Jones 2005; Tagliaventi and Mattarelli 2006). Levine and Prietula (2012) use empirical data to inform the behavior of agents in an ABM of knowledge transfer across an organization, but agents are connected via a prescribed (static) social network. Other ABMs of organizations have implemented dynamic social networks (e.g., Jamshidnezhad and Carley 2015; Sánchez-Maroño et al. 2014; Vázquez and López y López 2007), but empirically grounding these models in the physical environment has not been done. For instance, Rouchier et al. (2014) found that opinions persist in an organization despite a flow of joiners and leavers.

We use a hospital in southwest Virginia as our case study. The agents in our model are the individual healthcare workers within the hospital and agent movement occurs over the true physical environment of the hospital. This pattern of movement informs the development of the organization's social network. Agents must decide whether or not to share knowledge with their colleagues. In the context of a hospital, an example of tacit knowledge is an understanding of hand hygiene practices. This work extends earlier research completed by Pires et al. (2017), where the authors demonstrate that developing a simple ABM of hospital dynamics provides insights that would be challenging to show with a static model.

2 Background

Individual interactions, informal structures, and cognitive processes such as attitude formation and change interact to influence organizational processes such as knowledge sharing. Limited research has studied these processes simultaneously (Mason et al. 2007), and to the best of our knowledge, these processes have not been studied simultaneously within a computational model of an organization. In this section, we describe informal structures as important aspects of an organizational system, discuss the role that attitudes play in influencing organizational processes, and discuss different mechanisms for simulating knowledge sharing behavior.

2.1 Informal structures in organizations

Formal (prescribed organizational hierarchy) and informal (emergent) structures in organizations interact to influence processes such as knowledge sharing (De Long and Fahey 2000; Soda and Zaheer 2012; Tichy et al. 1979; Weiss and Jacobson 1955). Informal structures emerge through the organization's social network – a social structure made up of nodes (i.e., social agents) and ties (i.e., edges between agents) (Wasserman 1994). SNA can help us identify such informal structures (National Research Council 2014; DeKlepper et al. 2013; Podolny 2010). We discuss two types of informal structures: cohesive subgroups and informal roles.

Individuals in cohesive subgroups have strong social ties with one another. These informal subgroups are driven by homophily, attraction, agency, and proximity, all of which promotes communication, shared attitudes, and feelings of trust (Soda and Zaheer 2012; Feld 1982; Festinger 1954; Brass et al. 2004). The resulting subgroups have their distinct sets of attitudes, practices, and culture, which can distinguish them from an organization's overall culture and other subgroups (De Long and Fahey 2000). Homophily, a measure of "similarity", facilitates the formation of bonds (ties) between "similar" individuals (McPherson et al. 2001). Moreover, as ties are formed, attitudes may begin to converge, a process known as social influence (Friedkin 2006). This in turn, may strengthen social ties because individuals become more "alike", creating a potential situation of positive reinforcement. For instance, subgroups may form around functional units or professions of an organization, as members often have similar educational backgrounds or organizational experiences (Schein 1996). Research has shown that social cohesion is positively associated with knowledge sharing (Reagans and McEvily 2003).

Formal roles follow the workflow or organizational hierarchy, whereas informal roles are characterized by the pattern of connections within and across these subgroups and the broader organizational network (Ghoshal and Bartlett 1990; Tichy et al. 1979). Informal roles include informal leaders, influencers, and brokers, each of which can play critical roles in information flows (Ahuja 2000; Burt 2000). Brokers, for instance, can bridge two groups that would be otherwise disconnected (e.g., two divisions within an organization), allowing knowledge to be exchanged more effectively within a network (Ahuja 2000; Burt 2000). Informal leaders on the other hand, are highly connected individuals that may or may not serve formal leadership roles in the organization. Starting the process of knowledge sharing with such individuals may be more effective (Parise 2007).

2.2 Attitude formation and change

Attitudes are the positive or negative assessment of things, people, groups, and ideas (Bohner and Dickel 2011). The attitudes of employees towards an organization, towards their colleagues and leadership, or towards different work processes (e.g., knowledge sharing, job tasks) can impact the actions individuals take within an organization. There are a number of theories that seek to explain the process

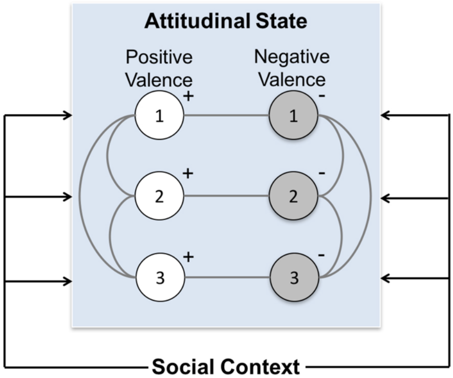

Fig. 1 A conceptual model of an agent's attitudinal state. The attitude shown is comprised of three beliefs numbered 1 to 3 and each belief is split among a positive (white circles) and negative (grey circles) valence unit. The connections between valence units within a belief is always inhibitory. The connections between different beliefs can be inhibitory or excitatory. Thus, the activation of one belief can lead to the activation or inhibition of other beliefs. The immediate social context is quantified through the value of the valence units of another agent and weight of the social tie between the two agents

of attitude formation and change. For example, the Health Belief Model (Rosenstock 1974) and the Attitude-Behaviour-Context Model (Stern 2000) were developed to study health and environmentally significant behaviors, respectively. While these theories may have aspects that apply to other types of behaviors, they have not been used to study organizational behavior. The Transtheoretical Model (Cunningham et al. 2002) has been used to study organizational processes but was found to lack specification and predictive power when compared to the Theory of Reasoned Action (TRA) (Armitage and Arden 2002). 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 (Ajzen 1991). A large body of research has utilized TRA to study worker behaviors in organizations, including organizational misbehavior (e.g., Vardi and Weitz 2002), adoption of strategic information systems by senior management (e.g., Mykytyn and Harrison 1993), use of Expert Systems within accounting firms (e.g., Liker and Sindi 1997), and knowledge sharing within organizations (e.g., Bock et al. 2005; Ryu et al. 2003; Reychav and Weisberg 2010).

An extension of TRA by Orr et al. (2013) further accounts for the dynamic nature of individual behaviors due to our social context – an important consideration given the social dynamics that are inherent in organizations. The attitudinal state of an individual at any point in time consists of a set of beliefs, valence units, and a constraint satisfaction process. Figure 1 represents a conceptual model of an agent's attitude. In this example, attitude is comprised of three beliefs as indicated by the number in each circle. Beliefs on knowledge sharing include, for example, "knowledge sharing with other organizational members will be an enjoyable experience," and "knowledge sharing with other organizational members will make me feel valued" (Bock et al. 2005). A single belief is split between positive and negative valence units. Each valence unit can have a numeric value between 0 and 1 that represents the activation of the valence for that belief. There is an inhibitory connection between the valence units where each valence of a belief constrains the other valence of the same belief to be less active. The immediate social context are the agent dyads in the social network.

Constraint satisfaction refers to the connection between different beliefs and the expectation that when certain beliefs are activated, it leads to the activation or inhibition of other beliefs (Read and Miller 1998). Each belief has excitatory, inhibitory, or no constraints with every other belief, and these constraints are reflected in connections between the beliefs. These connections are not pre-specified, but learned by the system from past experience through modification of the strength and sign (e.g., inhibitory) of the connections. For instance, given a prior social context in which knowledge sharing was seen as valued and enjoyable, we would expect an excitatory constraint between the beliefs "knowledge sharing will make me feel valued" and "knowledge sharing will be enjoyable." An agent's attitude is updated based on the input from the other agent's last attitude and the weight of the social tie between the two agents. As such, the development of dynamic social networks is critical to the process as it directly influences attitude formation.

2.3 Knowledge sharing

Diffusion is defined as "the spread of something within a social system" (Strang and Soule 1998). "Something" could include a rumor, an infectious disease, attitudes, or knowledge. There are a variety of models one could use to simulate a diffusion process such as tacit knowledge in an organization.

The literature describes two basic types of diffusion models: independent cascade models and linear threshold models (Das et al. 2014). These models have provided the basic mechanisms from which to simulate diffusion processes across many ABMs (e.g., Goldenberg et al. 2001; Schelling 1971). Cascade models are the simplest. Nodes (agents) in a network are said to be either active or inactive. For instance, we can say that an "active" agent is one which has received some piece of information or knowledge. Active nodes can then trigger activation in inactive nodes given some success probability. Agents in threshold models are influenced by their "neighbors", who may be physically or socially near. If the number of active neighbors surpasses the threshold, the agent may become active (e.g., Granovetter 1978; Schelling 1971). We explored cascade and threshold models in the initial implementation of this work in (e.g., Pires and Crooks 2017). Psychological theory such as the TRA, on the other hand, stresses the importance of attitudinal states in determining our intention to perform a behavior such as knowledge sharing (see Sect. 2.2). Behavior change is the result of integrating an individual's previous internal set of beliefs (related to both attitudes and social norms) with the immediate social context (e.g., direct exposure to another person's set of beliefs). Given TRAs direct link to behaviors, the theory has been used extensively in models of diffusion processes, such as the adoption of innovations by consumers and organizations (e.g., Mykytyn and Harrison 1993; Schwarz and Ernst 2009) and the social diffusion of health behaviors (e.g., Orr et al. 2013).

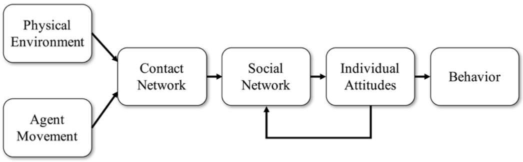

Fig. 2 Conceptual diagram of the agent-based model (reprinted with permission from Pires et al. (2017)). Agent movement occurs over the physical environment of the hospital. This pattern of movement creates the agents' contact network, providing input into the development of the organization's social network. The agents' attitude towards knowledge sharing drives behavior, which is the decision to share (or not) knowledge. Attitudes dynamically affect the creation of the social networks

Research has found that individuals' attitudes toward knowledge sharing significantly predicts explicit and tacit knowledge sharing intentions and behaviors in organizations (Bock et al. 2005; Mongkolajala et al. 2012; Reychav and Weisberg 2010; Rahab and Wahyuni 2013; Zhikun and Fungfai 2009). In hospital settings, subjective norms and attitude were the two strongest predictors of knowledge sharing among physicians (Ryu et al. 2003).

3 Conceptual model

We developed an ABM that simulates the dynamics of an organization within a hospital setting. The model was developed in Mesa, a Python framework for agent-based modeling (Masad and Kazil 2015), and uses PostgreSQL for storage and retrieval of input data. We utilize a previously developed computational formalization of TRA using artificial neural networks (ANN) for studying the dynamics of attitude formation and change (Orr and Plaut 2014; Orr et al. 2013) (see Sect. 2.2). This cognitive model is a modified version of lens (the light, efficient network simulator), a neural network simulator written primarily in C (Rohde 2002). This section describes the ABM using an adapted version of the Overview, Design Concepts, Details, and Human Decision-Making (ODD + D) protocol (Müller et al. 2013). A more detailed ODD + D, the source code, and the input data can be downloaded from https://www.comses.net/codebases/3fcbf222-fb89-499c-8859-82d48ac2b833/releases/1.0.0/.

3.1 Overview

Figure 2 is a conceptual diagram of the model. A central feature of the model is the agent, which represent the healthcare workers of the hospital. Agent movement occurs over the physical environment of the hospital. This pattern of movement creates the agents' contact network, providing input into the development of the organization's social network. The emergence of social networks gives us insight into the informal roles that emerge at the individual level and subcultures that emerge at the group level within an organization. Another feature of the model is the agents' attitude towards tacit knowledge sharing, which drives

Table 1 Agent parameters

Parameter	Description
Agent ID	The unique identifier of the agent (Jiménez 2014)
Profession	The healthcare discipline assigned to the agent (Jiménez 2014)
Activity Schedule	The agent's pre-determined schedule for the course of the simulation, including start and end times (in minutes) and the room number identifying the location of the activity (Jiménez 2014)
Knowledge	A binary variable indicating whether the agent has the knowledge
Attitudinal State	The agent's attitudinal state, which is composed of an internal set of beliefs, connection weights between and within beliefs, and an internal bias towards a positive or negative attitude towards knowledge sharing (see Fig. 1)

behavior. Behavior is the decision to share (or not) tacit knowledge. As a feedback system, individual attitudes dynamically provide input into the creation of the social networks.

3.1.1 Purpose

The purpose of the model is to explore how individual-level interactions over time and physical space interact with individual attitudes to influence the emergence of informal structures, all of which impact knowledge sharing within an organization. An ABM is integrated with a physical environment, dynamic social networks, and a cognitive model of attitude formation and change for this purpose.

3.1.2 Entities, state variables and scales

The model contains the following entities, from lowest to highest in hierarchical scale: (1) the agents, (2) the contact and social networks, and (3) the physical environment and population. The agents represent the healthcare workers in the hospital. These synthetic individuals span approximately 30 different healthcare professions (e.g., physicians, nurses, nurse assistants, social workers, physical therapists). Table 1 shows the set of agent parameters. The source of the first three parameters is Jiménez (2014). The attitudinal state of agents is discussed further in Sects. 3.3.1 and 3.3.3.

Agents' movement is driven by their activity schedules. Figure 3 provides an example schedule of the activities associated with a day shift Intensive Care Unit (ICU) nurse. As seen in the figure, an ICU nurse will perform a series of different activities throughout the day, including participating in shift meetings, assessing patients, and going to lunch.

This pattern of movement drives development of the contact network. We define a "contact" as an event where two or more agents are at the same physical location (e.g., a patient room) at the same time. The average number of activities and contacts in the hospital simulation during the course of 30 days is 8,234 and 164,176, respectively. As agents move about the hospital according to their activity schedules,

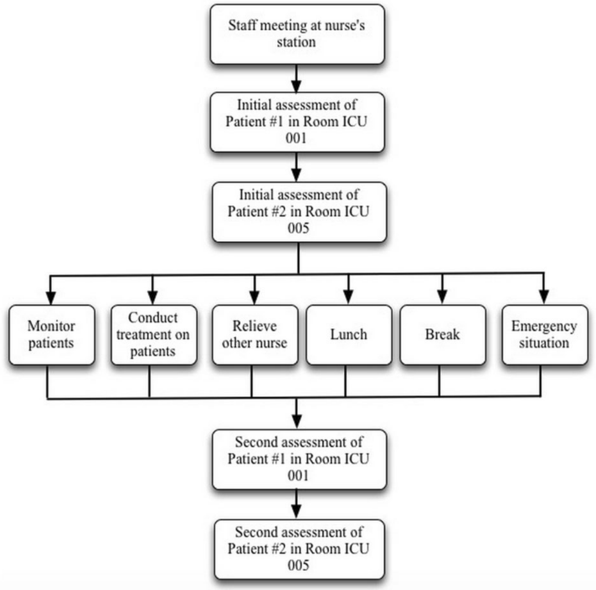

Fig. 3 An example of an activity schedule for an ICU nurse (adapted from Jiménez et al. (2013)). The ICU nurse here begins the day by attending a staff meeting at the nurse's station and then performs two patient assessments in different ICU rooms. From there, the nurse may perform one of several activities, including monitoring the patients, conducting treatment, or going to lunch. Finally, the nurse will end the day by following-up on the patients

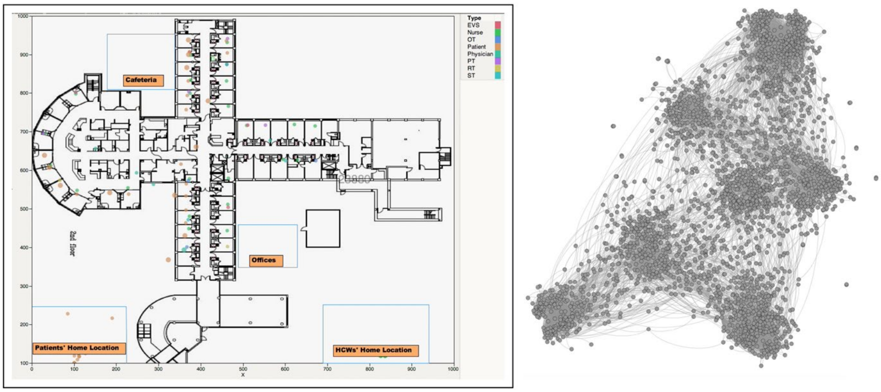

Fig. 4 The hospital simulation. (Left) The daily activities in the hospital for agents on a floor of the hospital. Each dot represents an agent. (Right) The contact network diagram of the hospital population over one month. Agents are represented by the dots and contacts between agents are represented by the lines (source: Jiménez et al. 2013)

we can visualize these contacts through the diagram in Fig. 4. The requirement that agents' be physically near provides us with an accurate estimate of physical proximity, an important consideration in the formation of social ties (see Sect. 2.1).

In addition to physical proximity, social networks are said to be driven by similarity (homophily) and social influence. We measure homophily as a function of profession and attitude similarity. Social influence is the feedback between attitude homophily and the strength of social ties that occurs dynamically as social ties increase in strength when attitudes are similar. The social network is thus a function of the contact network, profession homophily, and attitude homophily. Implementation of the contact and social networks are discussed in more detail in Sect. 3.3.3.

The physical environment is the physical layout of the hospital in southwest Virginia (Fig. 4 displays the layout for one floor of the hospital). The hospital contains nine floors and over 1,000 locations, including patient rooms and employee lounges. The population is the 2,127 synthetic healthcare workers of the hospital.

3.1.3 Process overview and scheduling

The model proceeds in one minute time steps. While employee schedules were provided by second, a minute allows us to capture the individual interactions and activity patterns that are important to the development of social networks (Torrens 2014), and at the same time, maintains the computational feasibility of running the model. Figure 5 illustrates the model's key processes (discussed further in Sect. 3.3). Agent behavior is broken out into five sub-models discussed in Sect. 3.3.3: the Activity Scheduler, the Dynamic Contact Network, the Dynamic Social Network, the Attitude Formation and Change Model, and Knowledge Sharing.

At the start of the simulation, agents run the Activity Scheduler. The Activity Scheduler pulls information from the PostgreSQL database containing the pre-determined schedules, including the start time, end time, and location of the agent's current activity. It then searches for any other agents who are at the same location, at the same time. If other agents are present, the contact network is updated, which consists of either creating a new tie (if one did not exist) or updating an existing tie. The strength of the contact tie, in addition to agent attributes, is then used as input into the computing the strength of the social tie. The agent will then evaluate its attitude in the Attitude Formation and Change Model based on interactions with other agents. Next, the agent will determine whether to share knowledge with one of the interacting agents in the Knowledge Sharing submodel. At completion of the activity, agents will evaluate their next activity by re-running the Activity Scheduler. In addition to this process, agents will periodically evaluate the need to decay any ties in their social network.

3.2 Design concepts

Decision-making is at the individual agent level. If an agent has knowledge, the agent must make the decision to share (or not) that knowledge with another agent with whom it is currently interacting with. The decision to share knowledge is a function of the agent's attitude towards knowledge sharing. In terms of *learning*, we account for past experiences and create the agents pre-existing attitudinal state by providing each agent with a set of training examples during model initialization.

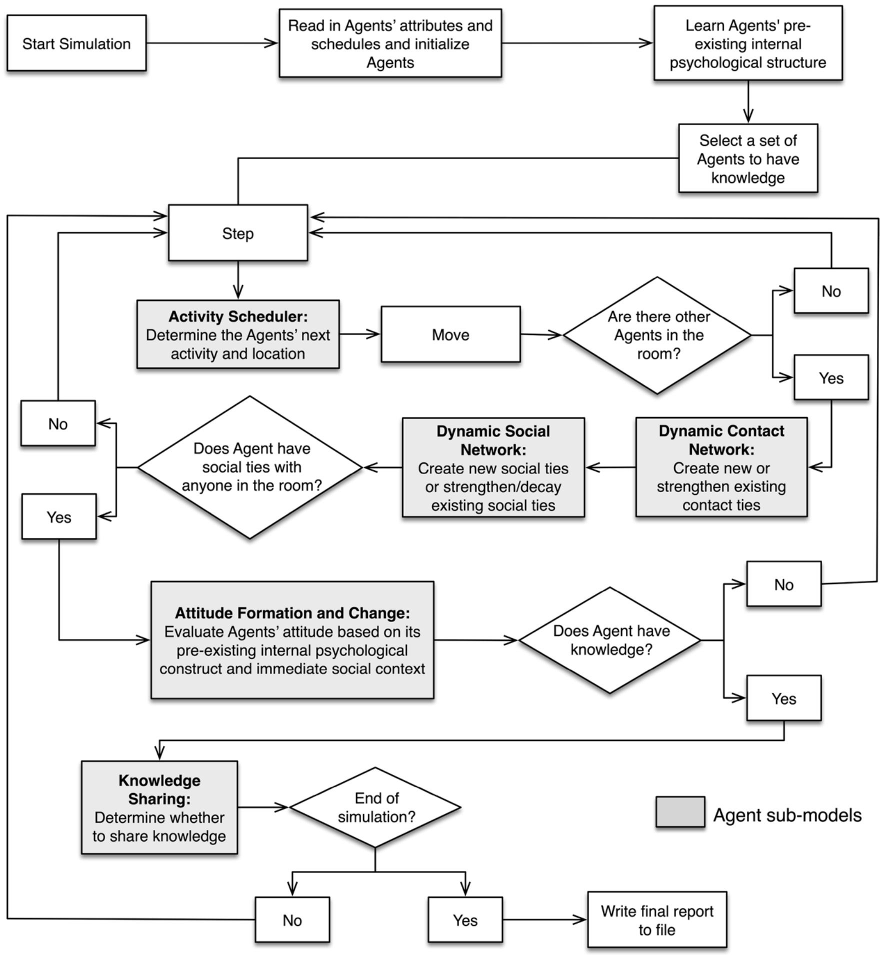

Fig. 5 Process flow diagram of the model's key processes

This process allows the model to use past experiences to learn the weights between valence units and the biases of the individual units. With respect to *sensing*, the agents are aware of their interactions and their social networks. They are aware of who in their social network currently does not have knowledge, as they will only share with those whom currently do not have the knowledge. As agents go about their routine activities, they *interact* with other agents. With each interaction, a tie in the contact network is either created or strengthened. This provides an important input into the social network. Each interaction can result in an update to the individual agent's attitude towards knowledge sharing, which subsequently effects the decision on whether to share knowledge (if the agent has knowledge). Agents are *heterogeneous* in terms of their profession, attitudinal states, and pre-determined activity schedules, which vary based on profession, shift, and department.

At the global level, we monitor several statistics: the direction of knowledge flows (i.e., from/to agent), the individual agents attitude towards knowledge sharing, the interactions (contacts) of the agents, and the social network. Agent attitudes and knowledge flows are collected by time step, while the contact and social networks are collected at the end of each simulation day. The model exports a series of files capturing these statistics.

3.3 Details

3.3.1 Initialization

Upon model initialization, agent's are assigned a profession and activity schedule and a pre-determined number of agents are selected to have the piece of knowledge. Agents must then learn their initial attitudinal state. The weights and biases of neural network s_i for agent i are determined using a supervised learning algorithm. The learning process requires that we input a set of initial conditions, including the desired output (prototype), the set of input patterns (training examples), a criterion (minimum error rate), and the maximum number of epochs (training cycles). Prototypes are binary vectors of length 20 representing either a positive attitude or negative attitude. For instance, in a positive prototype the first 10 items in the vector are 1 and the second ten items are 0. The input patterns are 50 training examples of the prototype used for learning. The criterion is the minimum error allowed, where error is calculated using a cost function. One epoch represents one cycle through the 50 training examples. We set the maximum number of epochs at 1,000. Learning will stop once the network is either below the criterion or has reached the maximum number of epochs. Initial input parameter settings were selected based on earlier research by Orr, Ziemer, and Chen (2017).

We construct two different training sets (i.e., input patterns) representing the positive and negative prototypes. All things being equal, these training sets lead to an internal bias that is captured by changes in the weights towards positive or negative attitudes of knowledge sharing, respectively. After each training cycle, the error is calculated using a cost function. If the error is greater than the criterion and the maximum number of epochs has not been reached, then the weights and bias are adjusted given the error rate. Once learning is complete, we have the weights and biases of each agent's cognitive model that will be used for the course of the simulation. This structure represents the agents pre-existing attitudinal state.

While we can think of the agents' learned attitudinal state as representing a tendency towards positive or negative attitudes on knowledge sharing, in order to initialize the model, we still need to provide each agent with an initial input activation. For this purpose, a pre-determined number of agents are seeded with a positive attitude towards knowledge sharing (a vector of length 20 with the first 10 items being 1*s* and the second ten items being 0*s*), while the remaining agents have a neutral attitude (a vector of 0*s* of length 20).

3.3.2 Input data

We utilized data collected for an earlier study that explored the potential outbreak of healthcare acquired infections in a hospital in southwest Virginia (Jiménez 2014). Data was collected from 431 healthcare workers in the hospital representing 30 different healthcare disciplines (e.g., physicians, nurses, social workers, physical therapists) by directly observing and shadowing the employees during normal hospital operations. The physical environment is the true physical layout of the hospital in southwest Virginia. The hospital contains nine floors and over 1,000 locations, such as patient rooms and employee lounges. Through a population builder program developed by Jiménez (2014), a synthetic population of the entire hospital was created including the 2,127 synthetic individuals representing the hospital's healthcare workers and their movement (i.e., activity schedules) across the hospital over the course of 200 days. Jiménez (2014) generated the activity schedules by shadowing employees over 4 to 8 hour time spans during normal hospital operation times. The synthetic individuals represent 30 different healthcare professions (e.g., physicians, nurses, nurse assistants, social workers, physical therapists).

3.3.3 Submodels

There are four sub-models that together determine agent behavior. The Activity Scheduler determines the agent's current activity and any interactions. The Dynamic Contact Network creates new contact ties and updates existing contact ties based on these interactions. The Dynamic Social Network creates new social ties and updates existing social ties based on the contact network and other effects. Attitudes diffuse or update through the Attitude Formation and Change sub-model. The Knowledge Sharing sub-model determines whether or not agents will share knowledge with interacting agents. We describe each of these sub-models in detail.

Activity scheduler. Because schedules are pre-determined, running the scheduler consists of querying the PostgreSQL database for the activity associated with the current simulation time. From the database, we get a start time, end time, and location of the activity. We then query the database for any other agents at the same location during the same time. If other agents are present, the time that the agent is in the same room as other agents is calculated. This is the interaction time of agent dyads and is used as input into development of the contact network. Given the static nature of these schedules across runs, we chose to introduce a small level of noise into these interactions. After each activity, there is a small probability that the agent will interact with an agent selected at random.

Dynamic contact network. The contact network X_c is a network of physical proximity, in that contact ties are created or strengthened only when agents are geographically near. Physical proximity to other agents is determined by cross-referencing the current simulation time with the agents' activity schedule as described in the Activity Scheduler sub-model.

The contact network is a weighted two-mode affiliation network, 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 (Wasserman, 1994). The weight of the tie w^c_{ij} and w^c_{ji} (w^c_{ij}=w^c_{ji}, $0 \le w^c_{ij}$,$w^c_{ji} \le 1$) in X^c as shown in Equation 1 is a function of the duration of contact events e_{ij} and the total time T that has passed in the simulation.

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

Dynamic social network. In contrast to contact ties, social ties account for factors beyond agent contacts (see Sect. 2.1). The social network X^s 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} ($w^s_{ij} = w^s_{ji}$, $0 \le w^s_{ij}$,$w^s_{ji} \le 1$) as shown in Equation 2 is a function of w^c_{ij}, profession homophily P_{ij}, and attitude homophily A_{ij}. The effect size of each of these parameters on the social tie weight is represented by β_1 and β_2.

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

Attitude formation and change. We implement the computational formalization of TRA discussed in Sect. 2.2. We use a fully recurrent neural network (RNN) that allows for modeling the dynamic process of constraint satisfaction. The neural network s_i of agent i has two layers – an input layer l_1 and an output layer l_2. Each layer has 20 units $a^l \in \{1, \dots, 20\}$ representing the positive and negative valence units of ten beliefs. The weight of the connections between beliefs and valence units and the bias of each unit represents agent i's current attitudinal state s_i. Moreover, valence unit activation ranges between 0 and 1, where 0 is not active and 1 is highly active. We can think of activation as analogous to the strength of a belief within a person's memory. The stronger the activation, the stronger the belief is activated in memory (Orr and Plaut 2014).

During interactions, agents have the potential to influence another agent's attitude. This interaction between agent dyads captures the immediate social context. The stronger the social tie between the agents, the more likely they are to influence one another's attitudes towards knowledge sharing. Specifically, we compute the input vector $a^1_i(t)$ as a function of agent i's previous output activation $a^L_i(t-1)$, agent j's output activation $a^L_j(t-1)$, and the weight of the social tie $w^s_{ij}(t)$ between agents i and j, such that:

$$a^1_i(t) = \frac{a^L_j(t-1) - a^L_i(t-1)}{2} w^s_{ij}(t) + a^L_i(t-1) \tag{3}$$

This provides the dynamic input into the cognitive model. The output activation a_i^L of agent i after an interaction with agent j is therefore a function of a_i^1 and the agents pre-existing attitudinal state s_i.

$$a_i^L(t) = f[s_i, a_i^L(t-1), a_j^L(t-1), w_{ij}^s(t)] \tag{4}$$

The resulting output $a_i^L(t)$ is the agent's updated vector of valence unit values. We use $a_i^L(t)$ to determine an agent's attitude $A_i(t)$ $(-1 \leq A \leq 1)$ at time t, which is computed simply as the average of the difference between positive and negative valence units (n is the number of valence units).

$$A_i(t) = \frac{\sum_{k=1}^{n/2} a_{ik}^L(t) - \sum_{k=n/2+1}^{n} a_{ik}^L(t)}{n/2} \tag{5}$$

Agent attitudes can change over the course of the simulation. Thus, an agent's decision to share tacit knowledge changes as that agent's attitude on knowledge sharing evolves.

Knowledge Sharing. The probability p that agent i will share knowledge at time t is a function of $A_i(t)$. This is operationalized through the logistic function below, where r is the rate at which the curve rises or falls $(0 \leq r \leq 10)$.

$$p_i(t) = \frac{1}{1 + e^{-A_i(t)r}} \tag{6}$$

4 Results

In this section we discuss the results of the model, focusing in particular on the social networks that emerged and the dynamics of knowledge sharing. The simulation ran for 4 simulation weeks (40,320 ticks) at full scale (2,127 agents). At initialization, 10 agents are randomly selected to have the knowledge. The effect of the initial number of agents has an increasing but weak effect on the rate of knowledge spread as determined through sensitivity analysis. Knowledge sharing begins on simulation day 7 (tick 10,080). We select day 7 because we wanted to ensure network structures were stable before starting the process of knowledge sharing in the simulation.

4.1 Social networks

Few ABMs have integrated empirically-grounded social networks that emerge dynamically as a consequence of agent interactions and social influence (e.g., Pires and Crooks 2017). Because the structure of the social network is not pre-determined, we have the unique opportunity to perform a social network analysis on emergent, synthetic network structures. We use metrics from SNA to explore differences in network structures over time and across simulation runs. These methods

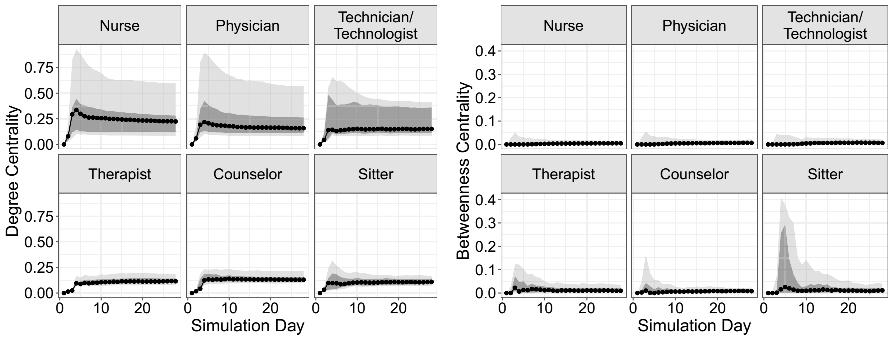

Fig. 6 Standardized degree and betweenness centrality results by profession. The dotted line indicates the median value across all agents of the profession, the dark shaded area represents the 25th and 75th quantiles, and the light shaded area represents the 90th and 10th quantiles

help us identify informal structures, such as prominent agents (e.g., informal leaders, influencers, or brokers) and subcultures. We show results by the most common professions in the hospital: nurses, physicians, counselors, technicians, therapists, and sitters.[1]

The most commonly used network measures are those that indicate the centrality of an agent (Frantz and Carley 2009). 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 (Wasserman and Pattison 1996; Long et al. 2013). We operationalize a prominent agent as one who has high centrality (see Brass et al. 2004; Ibarra 1993). Figure 6 shows centrality results of the social network by profession. The line indicates the median value across all agents of that profession, the dark shaded area represents the 25th and 75th quartiles, and the light shaded area represents the 90th and 10th quartiles. We find that network centrality stabilizes for most professions around day 4 of the simulation, potentially indicating that social networks are well established at that point. We find that nurses and physicians, followed by technicians, have the highest variation in degree centrality while counselors and sitters have higher variations in betweenness centrality.

In terms of knowledge flows, the outliers (those with high betweenness centrality in particular) may play a critical role. These agents will have few direct ties but will be linked to highly connected agents and may be potential brokers in the network. In Fig. 7, we can identify these individuals as those in the bottom right-hand corner of the plot. We can further visualize specific individuals as in the network shown on the left. The larger blue circle is the "sitter" agent shown in the far right hand corner of plot on the left. This agent is serving the role of connecting directly to agents across multiple clusters, a potentially critical role for information flows. We can further identify highly connected agents as shown in the figure and potential informal

[1] Sitters are healthcare workers that monitor and interact with patients (particularly high-need patients).

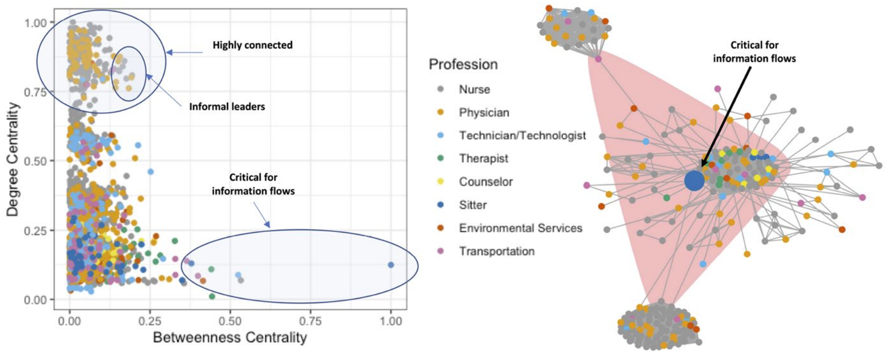

Fig. 7 Degree and betweenness centrality results in the social network by profession. (Left) Standardized degree centrality on the y-axis and standardized betweenness centrality. The dots represent median values of individual agents on day 28 across all simulation runs. Dot colors represent the agents' professions. (Right) The ego network (order = 2) of the "sitter" at the very lower right-hand corner of the plot to the right. The larger blue node is the "sitter" agent. The connecting nodes are colored based on the profession of the agent

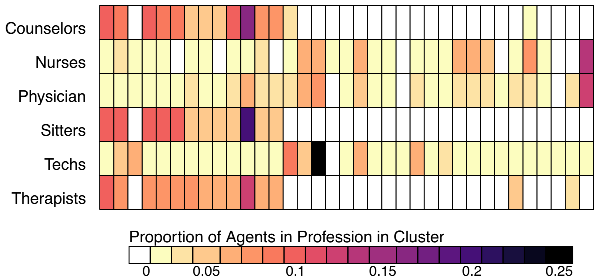

Fig. 8 Hierarchical cluster analysis for a simulation run. The horizontal axis are the most common profession categories and each rectangle represents a cluster. The shading indicates the proportion of agents of the same profession that are clustered together

leaders, i.e., those with both high degree and high betweenness centrality. We find that most of these agents are nurses and physicians, similar to what we found in Fig. 6.

Positional analysis can identify those groups of agents (clusters) that have similar patterns of relationships in a social network. Positional analysis requires that we define a measure of structural equivalence and an algorithm for grouping agents that are similarly structurally equivalent. We selected to use hierarchical clustering in our analysis as it provides clearly specifiable criteria for partitioning agents into groups and is well suited for partitioning agents into positions (Wasserman 1994). We evaluate results by profession to see if there is a relationship between the agents formal (prescribed) role and their position in the social network. If clusters align with professions this is evidence that formal roles are important in the structure of the informal network, and therefore, in information flows. The results of the cluster analysis are shown in Fig. 8. We find that a large proportion of nurses and physicians (approximately 15%) are assigned to the same cluster and 25% of technicians are in

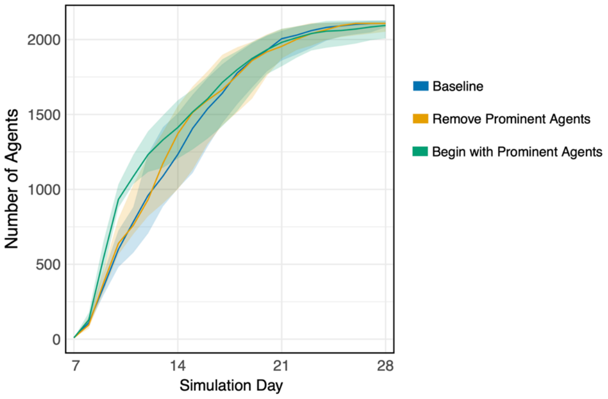

Fig. 9 The number of agents with knowledge by simulation day. The solid lines represent the median values for the three scenarios. The shaded regions represent the minimum and maximum values

the same cluster. Counselors, sitters, and therapists, on the other hand, are clustered almost exclusively together, but across 12 to 13 clusters. These results indicate that the agents' professions play a role in the hospital's informal structure, but the degree to which formal roles matter varies across professions.

4.2 Dynamics of knowledge sharing

We explore the rate of knowledge spread under three scenarios: (1) ten random agents are seeded with knowledge at model initialization (this is the baseline scenario described in the above section), (2) ten random agents are seeded with knowledge but ten prominent agents in the network are removed, and (3) the prominent agents are seeded with knowledge. Prominent agents are those with the highest centrality (e.g., degree, betweenness) in the network.

We find that removing prominent agents has little effect on the rate of spread when compared to the baseline. On the other hand, seeding the knowledge with prominent agents resulted in a substantial decrease in the rate of knowledge spread. Investigating this revealed that the "prominent" agents were all from the same subgraph. Once knowledge has been shared within this subgraph, it took a longer time to reach other subgraphs in the network.

These results led us to redefine a prominent agent as one with high centrality within a subgraph/subculture. From the ten largest subgraphs, we selected the agents with the highest centrality within each subgraph. Figure 9 compares the rate of knowledge spread using the redefined version of prominent agents. While removing prominent agents again has little effect, seeding knowledge with prominent agents has a small but increased rate of knowledge spread.

Comparing the professions of prominent agents according to the two definitions, we find that the ten most prominent agents under the original definition include only nurses and physicians. When prominent agents are redefined, professions include

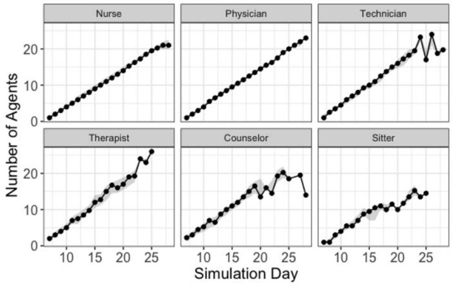

Fig. 10 The rate of knowledge spread by profession. The dotted line indicates the median value across all agents of the profession, i.e., the median number of agents information has been shared with. The shaded area represents the minimum and maximum values

nurses, physicians, technicians, and sitters. We get more variation both in the agents' professions and potentially in network positions. Recall that nurses and physicians generally have high degree centrality but sitters have high betweenness and low degree centrality (see Figs. 6, 7).

We can further explore the rate of knowledge spread by profession. Figure 10 shows the median cumulative number of agents that information was shared with by profession. For instance, by the end of a simulation run (day 28), a nurse had typically shared knowledge with 20 other agents over the course of the run. Interestingly, therapists spread knowledge to more agents than any other profession. They likely have critical positions in the network that were not identified in our network analysis. On the other hand, sitters spread information to the the least agents, but we know they play an important role in the network due to their brokerage positions. They are likely responsible for spreading knowledge to some of the most highly connected agents, such as nurses and physicians.

5 Discussion and conclusions

Organizations represent complex systems in that they are composed of dynamic networks of interactions among individuals and groups that change and adapt at both the individual and group levels. We demonstrate that the integration of ABM with dynamic social networks and a physical environment is effective for exploring dynamic organizational processes such as knowledge sharing. The integration of these approaches provides a complex systems approach to modeling organizations in a way that could not be accomplished by each method alone.

Given the importance of relationships in an organization's informal structure and in tacit knowledge sharing, social networks are a vital component of understanding organizational dynamics and knowledge sharing (e.g., Prietula et al. 1998; Reagans and McEvily 2003; Wang and Noe 2010; Parise 2007; Ahuja 2000). While social networks are often studied in a static way, the addition of a physical environment (i.e., the true spatial location of agents) provided a spatiotemporal component by mapping location and changes over time. This is important since geography can impact the likelihood that an individual physically interacts with someone else in the environment (Crooks and Castle 2012; Tobler 1970). Development of the contact network in our model was directly influenced by the physical movement and interactions of the healthcare works in the hospital. Moreover, certain activities within an organization, such as tacit knowledge sharing, depend on in-person contact (Mongkolajala et al. 2012). A physical environment alone, however, would not be ideal for dynamic modeling (Crooks and Castle 2012).

Using ABM, dynamic interactions over physical and social spaces were created with relative ease allowing us to model agent-to-agent and agent-to-environment interactions spatiotemporally (Axtell 2000). Modeling at the individual agent level gave us the flexibility to implement rules of behavior and cognitive capabilities that can range from simple decision-making heuristics (e.g., cascade or threshold models of diffusion, see Pires et al. (2017)) to complex computational models of cognition grounded in psychological theory. The integration of SNA further allowed us to account for social context in individual behavior. The development of the cognitive framework in turn represented the feedback between activities being performed in physical space, interactions occurring in social and physical space, and the agent's internal model. This process was critical in simulating the reinforcing, nonlinear nature of this system.

Within the hospital simulation, we found that seeding "prominent" agents with knowledge can actually slow knowledge spread if not done strategically. This would be analogous to providing information to only the largest department in an organization rather than distributing knowledge across multiple, even if smaller, departments. Studies have found that starting the process of knowledge sharing with certain individuals may be more effective and could inform how organizations can better leverage their network structure (Parise 2007). Removing prominent agents, however, had little impact on network structures or knowledge spread. This suggests that the network in this hospital is resilient to some attrition impacts, and losing agents (even prominent ones) will result in little impact to the organization's cohesion and knowledge flows.

In terms of the relationship between formal roles (i.e., profession) and information structures, we found that formal roles are important in the creation of informal networks and in knowledge flows. Nurses and physicians for instance, have the highest degree centrality. However, the more significant nodes in regards to information diffusion may be the outliers with extreme betweenness centrality. These agents are able to mitigate communication flows between otherwise disconnected graphs. In other subgraphs, counselors, sitters, and therapists may play an interesting role when it comes to information flows given the high proportion that have high betweenness but low degree centrality. Moreover, we found that therapists have spread knowledge to the most number of agents. Further exploration of the network structures surrounding these agents is needed to better understand the role they play. Hierarchical clustering found that agents sharing the same profession were often spread across many clusters, however, 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.

As with all modeling endeavors, however, there are some limitations with the current model that could play a role in the dynamics of the social networks and knowledge sharing. This is why we have tried to be as transparent as possible by providing the detailed ODD+D, the source code, and data to run the model. In future work, we may want to introduce uncertainty into the contact networks beyond the small level of “noise”. By establishing the rules for how the agent’s activity schedules are created, for example, schedules could be modeled dynamically, allowing them to respond to changes in the environment and to the behavior of other agents and their interactions. A deeper evaluation of the factors that impact the decay and creation of social ties could also be performed. We could also refine what we mean by knowledge by concretely defining the type of knowledge being modeled and implementing dynamic processes for the encoding, recollecting, and degradation of knowledge over time. Even with these limitations, however, this model sheds some light into the underlying network structures and dynamics of knowledge sharing in a hospital setting.

Effective attrition and leadership policies require the acknowledgement of the existence of informal structures and an individual’s dual role in explicit and implicit structures. Interactions within organizations are not limited to the official organizational chart. Personnel policies must acknowledge and support employees in both roles to increase organizational effectiveness. The impact of attrition on informal structures and knowledge sharing may be difficult to anticipate. However, understanding such patterns are important. Using the modeling approach here, we can simulate a scenario by which specific employees are removed or we can observe outcomes when communication strategies are changed, such as starting knowledge with different employees based on their unique positions within an organization. We can then observe the impact these changes have on network structures, attitudes, and ultimately, knowledge flows within the organization.

For managers, understanding the informal structures, such as informal roles and subcultures, that emerge and interact with the formal organizational hierarchy is crucial for understanding the underlying dynamics of an organization. By “re-creating” the movements and interactions of employees within an organization and applying theory to model attitude and network formation, we can simulate and potentially anticipate the impact of different resource planning and communication strategies on organizational processes and outcomes, such as knowledge sharing.

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