STUDIES ON COMPLEX TASK NETWORKS BASED ON CONTEXTUAL SPECIFICS IN ELECTRONIC MEDICAL RECORDS

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Business Administration – Business Information Systems – Doctor of Philosophy

2022

ABSTRACT

STUDIES ON COMPLEX TASK NETWORKS BASED ON CONTEXTUAL SPECIFICS IN ELECTRONIC MEDICAL RECORDS

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As organizational processes have become more interconnected and interdependent, contextual factors have become central to both information systems and process management. Despite the importance of context, few studies investigate the influence of contextual factors on the structure of business processes. Thus, in this dissertation, I examine the role of contextual specifics in the structure of the clinical documentation process using data from electronic health records in outpatient clinics. The dissertation includes three essays. In the first essay, I address the influence of internal contextual factors on enacted complexity. The findings of the first essay provide a unique opportunity to theorize on the specialization in enacted complexity of process by examining the effects of: 1) the number of roles and 2) the degree of specialization. Contrary to expectations, I find that complexity decreases when a greater number of roles are involved in the clinical process and the roles are highly specialized. In the second essay, I turn my attention to the effects of exogenous shocks on the clinical process: When routines are disrupted, are some patterns of action more likely to be affected than others? I show that cohesion (defined as the consistency of context between pairs of actions) has a particularly strong influence on the persistence of action patterns. Lastly, in essay three, I suggest a path prediction model in a process based on action sequence and its contextual specifics. The model uses a recurrent neural network that models both the observed sequence of actions and the contextual factors in the process. As expected, the results show that context can improve the prediction level of predictive models. In the case of outpatient medical clinics, the strongest improvement in accuracy comes from two attributes: 1) the workstation

(location) where work is performed and 2) whether or not the system has been upgraded. Together, these essays represent a rigorous framework for analyzing the role of context in organizational processes and routines.

This dissertation is dedicated to my wife, Jieun.
Thank you for making my days happily ever after.

ACKNOWLEDGEMENTS

I am deeply grateful to my dissertation chair, Brian T. Pentland, for the warm-hearted support and guidance throughout the Ph.D. program. He has shown his belief in me ever since the day I joined the program. He was not just my advisor, but also a mentor, role model, and father of my life in the U.S. I would never have made it this far without him.

I also would like to thank my committee members, Anjana Susarla, Kenneth A. Frank, and Quan Zhang for their valuable feedback and comments. I am truly fortunate to have them on my dissertation committee. I extend my appreciation to Julie Ryan Wolf and Alice Pentland for their help in making these studies possible. I am thankful for the financial support provided by the Department of Accounting and Information Systems at Broad College of Business.

I appreciate the help and support from my office mate, Aaron Fritz, and the faculty, staff, and my fellow Ph.D. students from the AIS department. Their help and support were crucial to my journey in the Ph.D. program. I am also thankful to Jason Shin, Junghyun Mah, Sangmok Lee, and Seokjoo Lee for being my collegial colleagues and valued friends for this arduous, but worthwhile journey. Of course, I want to thank all my other friends who have supported me from both of inside and outside of academia.

I am also thankful to my parents, Doo Tae Kim and Hee Won Kim, and my brother, Hyungkyu Kim, for their unconditional love and support. They have encouraged me with love throughout my life.

Last, but certainly not least, the deepest gratitude and love to my family, Jieun and Kyuri. Jieun Kim, you are the most dedicated wife and loving mother that I could ever ask to have. This academic journey would not have even started without your immense love and support. I am also grateful for Kyuri Wynne Kim, who has become the most precious treasure in our life.

This dissertation is supported by the National Science Foundation under Grants No. SES-1734237 and BCS-2120530. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. This research was also supported in part by University of Rochester CTSA (UL1 TR002001) from the National Center for Advancing Translational Sciences (NCATS) of the National Institutes of Health (NIH). The content is solely the responsibility of the author(s) and does not necessarily represent the official views of the National Institutes of Health.

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INTRODUCTION

Context changes our understanding of how the process works. In a recent review, Avgerou (2019) argues that the role of context has been a major concern in research on information systems in both theoretical and methodological ways for many years. For example, building a generalizable IS theory confronts the issue of limited contextual insight due to the simplification of contextual influence (Bamberger, 2008; Hong et al., 2004; Johns, 2006; Rousseau & Fried, 2001; Whetten, 2009), whereas context-specified research has a limitation of generalization (Cheng et al., 2016). In process management, research on context-aware process acknowledges the influence of contextual factors on the behaviors of the participants and technologies and suggests the need for a context-integrated process design (Recker et al., 2009; Rosemann et al., 2008; vom Brocke et al., 2016). As organizational processes have become more interconnected and interdependent, contextual factors have become central to both information systems and process management.

Context can also affect how we describe and model business processes. In particular, depending on how much context you consider in the process description, the process appears to change (Rosemann et al., 2008). It may seem to be the same process, but it can look very different. For example, a process looks simple when we recognize it as just a sequence of events, but it looks more complex when we consider that each event in the process has its own distinct contextual background (e.g., a distinct actor, a distinct location). As business process models get more complex with more stakeholders and technologies involved, the notion of the context-aware business process gets more important (Rosemann et al., 2006).

Despite the importance of context, few studies investigate the influence of contextual factors on the structure of business processes. Thus, in this dissertation, I examine the role of contextual specifics in the structure of the clinical documentation process.

0.1. Motivation for the Dissertation

There are three motivations for this dissertation. First, there is a theoretical motivation: how does context affect the structure and performance of a process? As previously mentioned, many studies argue the importance of contextual specifics, but how the context affects the structure of the process has not been studied yet. In this dissertation, I examine how the internal context of the clinical documentation process is associated with enacted complexity of process and how the process responds to changes in external contextual factors.

Second, there is a methodological motivation: how can I detect which factors are likely to influence the structure and execution of a process? Many factors could be considered as the contextual environment for process, but their impacts on the structure of process vary. By estimating standardized coefficients of internal factors and modeling the effects of disruption on the structure of stochastic transitions between events in a process, I can compare the impact of each contextual factor and see their influence on process dynamics.

Third, there is a practical motivation: if I can better predict the sequences of action in the execution of a process, I may be able to do a better job of supporting and perhaps automating parts of that process. Based on the factors whose impacts are demonstrated in the first two essays, I suggest a prediction model for the sequences of action for the clinic documentation process in my third essay. The prediction model improves on the current state of the art and could contribute to the automation effort (Aysolmaz et al., 2013).

0.2. Context Shapes Process

Rosemann et al. (2008) suggest the "onion model" to describe how contextual factors are layered and how these layers can shape how a process works. According to the onion model, the context of process consists of four different levels (immediate, internal, external, and environmental), which refers to the layers of context from inside to outside. Based on this metaphor, I distinguish between different layers of context. External and environmental context (that is truly "outside"), include factors such as the season or the country. Outside factors do not change during the execution of a process. Inside and immediate contextual factors, such as the person performing each action, can change during the execution of a process.

In research on process management, there is increased interest in the role of context, but usually, they mean (a) sequential context (Becker & Intoyoad, 2017; Bose & van der Aalst, 2009; Gunther et al., 2008) or (b) external/environmental context, similar to the typical exogenous variables (Avgerou, 2019). There are also studies considering and emphasizing internal contexts (Li et al., 2010; Rosemann et al., 2008; van der Aalst & Dustdar, 2012), but it is hard to find studies examining their impacts on process. Thus, in this dissertation, I examine the role of internal and external contextual factors in-process structure and how contextual information could be used for prediction.

0.3. Research Setting

All three essays use data from outpatient clinics at the University of Rochester Medical Center (URMC). Our research partners at URMC extracted audit trail data from the EPIC Electronic Health Record (EHR) system in several different medical specialties (including dermatology, orthopedic surgery, and pediatric oncology) during different periods between 2016 and 2019. Each essay uses a different specific set of data, as explained below. These records include detailed, time-stamped records of EHR utilization in tens of thousands of patient visits.

0.4. Representing Processes as Narrative Networks

In this dissertation, I represent processes as narrative networks (Pentland & Feldman, 2007). Narrative networks provide a useful way of summarizing patterns of actions (Pentland et al., 2010). A narrative network is defined as a directed graph consisting of actions (events) as the nodes and sequential relationships between the actions as edges (Pentland et al., 2017). A narrative network is useful for the study because the nodes can be defined by multiple contextual factors (e.g., action, actor, location) (Pentland et al., 2020). Depending on how much context you include in the process description, the structure of the process changes. It's the "same process", but it's not the same process.

FIGURE 0.1 NETWORK GRAPHS OF PATTERNS OF ACTIONS WITH CONTEXTUAL SPECIFICS

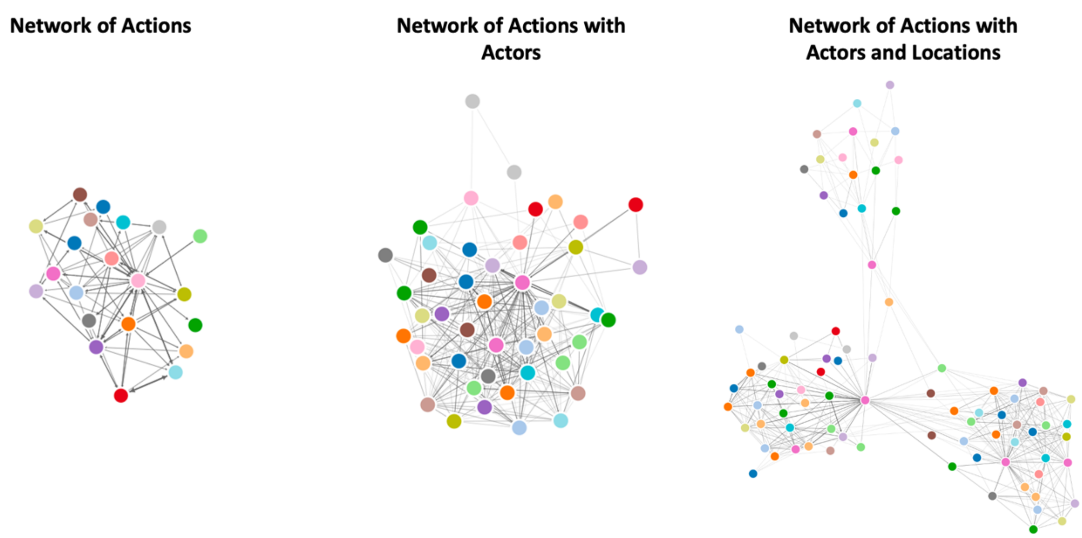

Figure 0.1 shows an example of how considering contextual specifics can change how we see patterns of actions in a process. Using *ThreadNet 3* (Pentland et al., 2020), I convert the clinical documentation process from one patient visit into a network. When the network consists of actions only (as in the left side of Figure 1), it is hard to grasp patterns and directions of actions because the actions are very densely connected. However, when I construct the network

so that nodes are described by actions and the actors who performed the actions (as in the middle of Figure 0.1), it increases the number of nodes and begins to reveal structure that was not visible with actions only. When I add another contextual factor, location (as on the right side of Figure 0.1), the additional structure becomes apparent. The clustered sections of the network reflect different locations in the clinic. This example shows how adding context can change the apparent structure of a process.

0.5. Overview of the Three Essays

This dissertation will explore the three different ways that context influences process. The three essays are described in the following sections.

0.5.1. Enacted Complexity in Healthcare Routines: Evidence from Electronic Medical Records

In the first essay, I address the influence of contextual factors on enacted complexity. Complexity has been a central problem in many disciplines including organizational studies, process management, and information systems (Anderson, 1999; Pich et al., 2002; Rahmati et al., 2020; Rettig, 2007), but context has not been considered as a factor that influences complexity. By understanding and combining patterns of actions with their contextual specifics, this essay extends our understanding of the antecedents of enacted complexity. I focus on the impact of specialization on enacted complexity. Specialization is essential in organizational processes, where most of the tasks require specified knowledge (Batista et al., 2005; Stitzenberg & Sheldon, 2005). However, there has been no agreed-upon model and no empirical research that analyzes the relationship between specialization and enacted complexity. Thus, in this essay, I investigate the research question: how does specialization affect the enacted complexity of process?

To answer this question, I consider the implications of specialization for process enactment. I investigate the effects of specialization in two distinct ways: 1) the number of specialized roles in process and 2) the degree of specialization in each role. First, the involvement of specialized roles is an important determinant of specialization. The more specialized roles are involved, the more specialized a process is. However, adding roles may make the process more complex as it adds more tasks. The degree of specialization of each role provides another way to address the same basic question. Although a process is enacted by many roles, the extent to which each role in the process is specialized may be different so the degree of specialization differs depending on who is involved.

0.5.2. Dynamics of digitalization: Mechanisms of stability and change in digitalized work processes

In the second essay, I turn my attention to the effects of exogenous shocks on routines: What mechanisms shape the dynamics of digitalization? Does the structure of the routine itself influence the dynamics of digitalization and vice versa? More broadly, I investigate the mechanisms through which organizational routines react to external disruptions.

To address these questions, I model routines as directed graphs (Pentland et al., 2017; van der Aalst, 2019). Using latent factor selection models (Hoff, 2005), I study the hypothesis that the effects of a technological change, a major upgrade of an EHR system, may influence structure and patterns of action by discovering and comparing patterns of action pre-post disruption (Pentland & Kim, 2021). In social networks, mechanisms like reciprocity, homophily, and preferential attachment contribute to the formation and dissolution of network ties (Snijders, 2001), but analogous network-based mechanisms have never been defined or investigated in the context of organizational routines. This essay contributes to current research on routine dynamics as network dynamics (Feldman et al., 2016; Goh & Pentland, 2019) by providing a novel application of dynamic network models (Hoff, 2005; Minhas et al., 2019) to theorize about the dynamics of digitalization. The employed theory and method in this essay provide a way to reinvigorate the sociotechnical foundations of the information systems field by explicitly examining the systemic connections between technology and patterns of action.

0.5.3. Predicting Next Action based on Contextual Specifics: Evidence from Electronic Medical Records

Lastly, in essay three, I investigate how a predictive process model can be qualified based on contextual specifics. In my first two essays, I focus on the influence of contextual factors on complex networks and their stability from an exogenous disruption, a system upgrade. In this essay, I utilize contextual specifics as ingredients to boost the prediction level of the flow of the clinical documentation process.

While the use of EMR systems was expected to make the documentation process convenient and concise, the process is still complex because clinicians must record every step in the system. As a result, complexity in the documentation process contributes to administrative costs in the healthcare systems (Shrank et al., 2019). However, on the flip side, if there is a way to find recognizable patterns and predict paths in the early stage, it may be possible to simplify the process and save wasted costs and time (Lee & Dale, 1998).

For an accurate prediction of the process, in this essay, I use different types of contextual specifics as attributes for the prediction of actions in the process. As the clinical documentation process is composed of careful collaborations of various specialists and occurs in real-time when patients visit, the immediate contexts (actor and location) studied in essay 1 need to be used. In addition, the external and environmental factors also can be good elements for the prediction because, as shown in essay 2, the shape of the process is influenced by the external factors.

Towards this end, I use a Recurrent Neural Network (Long short-term memory, LSTM) to find recognizable patterns, which access and modify the sequence based on three types of gates (input, output, and forget) (Hochreiter & Schmidhuber, 1997). I train the prediction models to see if the prediction level changes when considering contextual factors as additional attributes, which contextual factors are most impactful, and how much the contextual specifics can improve the prediction level.

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CHAPTER ONE:

ENACTED COMPLEXITY IN HEALTHCARE ROUTINES: EVIDENCE FROM ELECTRONIC MEDICAL RECORDS

1.1. Introduction

Specialization of tasks in organizations contributes to enhanced performance with more efficient productivity. By specialization, I mean the concentration on particular components of an organization's task (Fahrenkopf et al., 2020). The benefits of specialization have long been studied across diverse organizational settings (Fahrenkopf et al., 2020; Flueckiger, 1976; Narayanan et al., 2009; Staats & Gino, 2012). Specialization allows organizations to reduce costs and manage complexity (Crowston, 1997; Staats & Gino, 2012). Specialization sets the context in which a process is performed (Rosemann et al., 2008)

Complexity is a tremendous problem in organizations as processes have become more interconnected and interdependent (Rahmati et al., 2020; Rettig, 2007; Sturmberg & Martin, 2013). While this is especially true in healthcare, where there is a growing concern about the consequences of complexity (Shrank et al., 2019). Specialization is essential in healthcare, where most of the tasks require specified knowledge (Batista et al., 2005; Stitzenberg & Sheldon, 2005), but there are no agreed-upon models for analyzing the relationship between specialization and the complexity of healthcare work.

In this study, I consider the implications of specialization for process enactment. Healthcare services are embedded in a web of intersecting specialties, roles, and other contextual factors. In the clinical process, each role participates in the process with a specialized set of skills and patterned social behaviors (Turner, 2001). For example, a patient who arrives at the orthopedic surgery clinic with a broken leg might engage with several provider roles, including office staff, insurance pre-authorization, nurse, physician, and radiology technician. Later, the same patient may have a follow-up visit for physical therapy, and he/she would not need as many clinicians as the first visit. These two cases are differentiated from each other in that the number of participants and the types of involved roles are different. In this case, how can we assess the effects of specialization on this diverse set of possible workflows?

To address this issue, I examine the effects of specialization in two distinct ways; 1) the number of specialized roles in a process and 2) the degree of role specialization in a process. First, the involvement of specialized roles is an important determinant of specialization. The more specialized roles are involved, the more specialized a process is. However, adding roles may make the process more complex as it adds more tasks. The degree of role specialization is also another important factor to consider. In addition, the extent to which each role in the process is specialized may vary, so the degree of specialization differs depending on which roles are involved. For example, when a patient visits the clinic, the degree of specialization of a nurse is lower than either clinical or administrative technicians because the nurse can cover a larger variety of tasks.

Based on these two aspects of specialization, I investigate the effects of specialization on the enacted complexity of digitalized work processes in healthcare organizations. The relationship between specialization and enacted complexity of work process in organizations is especially important in healthcare organizations because the healthcare process consists of intersecting specialties and other contextual factors and administrative procedures, such as billing and insurance, are also very complex (Gottlieb et al., 2018; Sakowski et al., 2009). Complexity has been considered as one of the main practical problems in healthcare service (Kannampallil et al., 2011; Sturmberg & Martin, 2013; Thompson et al., 2016). The complexity of organizational processes in clinical settings has been studied and characterized within the process and its tasks.

I focus on the relationship between specialists who concentrate on specific components of tasks and enacted complexity of the process. I address the following specific research question: **Does specialization increase or decrease enacted complexity of a process?**

To answer this question, I convert the work process into a narrative network (Pentland & Feldman, 2007) and see the influence of specialization on the number of paths in the network (Goh & Pentland, 2019). A narrative network is a special kind of "directly follows graph" (van der Aalst, 2019) where the nodes are defined using additional contextual features, such as actors, artifacts, locations, and so forth (Pentland et al., 2017). The intuition behind this measure of enacted complexity is simple: a process with more alternative paths is more complex. This measure embodies the idea that task complexity is indexed by the number of paths in the network of events that lead to the attainment of task outcomes (Hærem et al., 2015).

Using EPIC EMR[1] audit trail data from three different types of clinics (dermatology, orthopedic surgery, and pediatric oncology), I first examine if more involvement of specialized roles in a process has causal effects on enacted complexity of patient visits. Intuitively, the involvement of roles should increase enacted complexity because each role provides a differentiated service from others. Adding more roles tends to add steps in the clinical process, and more steps are associated with greater complexity (Wood, 1986). I also examine the effects of role specialization on the complexity of patient visits. As I describe below, there are reasons to expect that the effect could either increase or decrease enacted complexity.

[1] EPIC is the largest vendor of electronic medical record systems (Adsit et al., 2014; Holmgren et al., 2022)

My main results are quite surprising. While individual-level theory of task complexity (Campbell, 1988; Wood, 1986) suggests that more specialization should increase complexity, my OLS regression results show that both indicators of specialization have significant, negative effects on enacted complexity. This result may have been confounded by other important factors, so I investigate the causal effects of specialization using a casual effect estimation, a generalized propensity score matching method (Hirano & Imbens, 2004; Wu et al., 2018).

I organize this essay as follows. In the next section, I provide theoretical background for the development of models for the relationship between enacted complexity and contextual factors and develop hypotheses. I then describe the research context and the dataset for the empirical test and introduce the research model. Next, I interpret the results to explain how and why specialization reduces enacted complexity. In the last section, I discuss the implications and generalizability of this study.

1.2. Theoretical Background

1.2.1. Enacted Complexity

For this study, I first need to understand the concept of ***enacted complexity*** in a process. Complexity has been studied as a key concept in diverse fields including business process, IS and organization theory (Byström & Järvelin, 1995; Merali, 2006; Moldoveanu & Bauer, 2004; Rivkin & Siggelkow, 2007; Simon, 1969; Zhou, 2013), but the traditional standard framework of task complexity has been developed based on the concept brought from organizational psychology (Campbell, 1988; Weick, 1965; Wood, 1986). Traditionally, task complexity is described as the relationship between task inputs; required acts, and information cues to complete tasks (Wood, 1986) and generally focuses on the individual level. The traditional model of task complexity (Campbell, 1988; Wood, 1986) is based mainly on the number of “required acts” (Liu & Li, 2012; Wood, 1986), independent of who performs the acts or where they are performed. This point of view on complexity is based on decontextualized actions, so it overlooks potential contextual factors, such as the role of the person performing the work (Hackman, 1969).

However, most organizational processes (such as outpatient clinical visits) are not enacted by single individuals (Hærem et al., 2021; March & Simon, 1958; Nelson & Winter, 1982) and they are deeply enmeshed in organizational context (Avgerou, 2019; Rosemann et al., 2008). Thus, I need a concept of complexity for organizational processes that is distinct from the individual level task complexity.

To address this problem, Hærem et al. (2021) introduce the idea of enacted complexity to describe processes that are enacted by multiple actors within the organizational routines. Hærem et al. (2015) extended the concept of task complexity to tasks that multiple actors perform and integrate the concept with material context. The extended concept assumes that tasks are embedded in a socio-material context (D'Adderio, 2011; Leonardi, 2011). The concept of enacted complexity has started to appear in empirical research (Danner-Schröder & Ostermann, 2022; Goh & Pentland, 2019; Hansson et al., 2021).

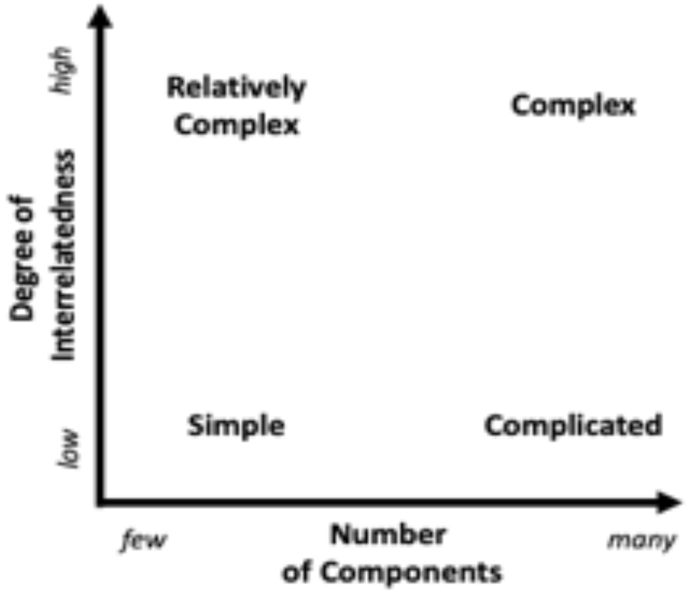
It is important to note that enacted complexity refers to EMR utilization (the record-keeping process), not the complexity of the underlying EMR system. Complexity is not an absolute property of an object or a system but depends on how the system is represented. Any measure of complexity starts from a description of the identifiable regularities within the particular empirical domain (Flood, 1987; Gell-Mann & Lloyd, 1996). Thus, I define an index of complexity, not an absolute number. Established measures of complexity from other disciplines, such as the Lempel-Ziv complexity (Kaspar & Schuster, 1987; Lempel & Ziv, 1976) are indices of complexity, not absolutes.

1.2.1.1. Complexity as a network phenomenon

In current theory, complexity arises from networks of interacting components (Kannampallil et al., 2011; Kauffman, 1993). Drawing on Simon's (1969) architecture of complexity and decades of research on complex adaptive systems, Kannampallil et al. (2011) provide a framework that embodies two key dimensions, as shown in Figure 1.1: components and relations. Components correspond to the "required acts" that Wood (1986) uses to define component complexity: a task with more "required acts" has greater component complexity.

I can interpret the axes in Figure 1.1 in network terms. Components can be represented by nodes in a network, as Wood (1986, p. 78) does when showing the sequence of actions required to land an airplane. The relatedness of the components is represented by the edges in the network. In Kauffman's (1993) influential "nk" model of complex dynamic systems, the "n" stands for the number of nodes in a network, and "k" stands for the degree of relatedness of those nodes. For a given number of nodes (components), a network with more edges (relations) is more complex.

FIGURE 1.1. COMPLEXITY AS A FUNCTION OF COMPONENTS AND RELATIONS



(Adapted from Kannampallil et al. 2011)

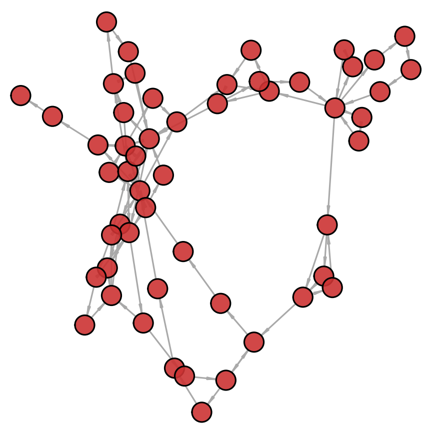
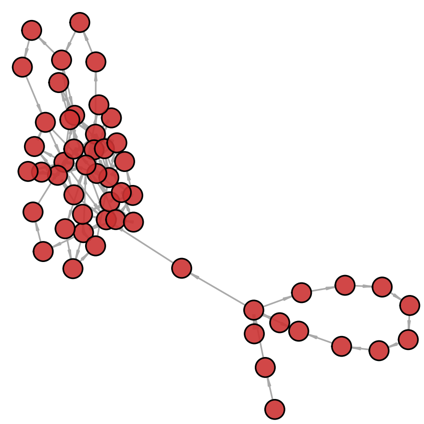
Hærem et al. (2015) build on the network representation to extend the traditional idea of task complexity introduced by Wood (1986) to include tasks performed by multiple actors. Given a network that represents a task, enacted complexity can be operationalized as the number of possible paths for getting the task done (Goh & Pentland, 2019; Pentland et al., 2020). This definition relies on the same intuition as Wood's (1986) concept of coordinative complexity, which is based on the number of paths in an idealized model of a task (not the task enactments).

This is analogous to McCabe's (1976) concept of cyclomatic complexity, in which the number of executable paths through a software module is used as an index of complexity. Fewer paths mean lower complexity; more paths mean greater complexity. Goh and Pentland (2019) note that this method is just an approximation. It does not depend on having a specific start or stop for the process. Goh and Pentland (2019) provide the following formula, which is based on McCabe's (1976) metric:

(1) $$Enacted\ Complexity = 10^{0.08*(\mathrm{edges}-\mathrm{nodes}+1)}$$

where nodes refer to the number of unique actions in the network and edges are the number of unique sequential pairs of actions in the network. Using this metric, tasks with a single execution path have complexity equal to one.

TABLE 1.1. ACTION NETWORK COMPARISON FOR TWO DIFFERENT CLINICAL VISITS

	Visit A	Visit B
# Nodes	53	53
# Edges	97	127
# Paths	926	133,484
Enacted Complexity (logged value)	8.29	13.82
Network Shape		

I visualize narrative network for two different patient visits from my data to show how nodes and edges affect enacted complexity (see Table 1.1). While visits A and B have the same number of actions (53 unique actions), they have a different number of edges (97 vs. 127). The different number of edges makes difference in the number of paths in the network. As a result, there is a huge gap in enacted complexity between the two clinical visits.

The example in Table 1.1 shows the importance of understanding complexity as a network phenomenon. In the traditional, individual-level theory of task complexity, more nodes indicate greater complexity (Wood, 1986). However, when I consider how the nodes are connected, they may or may not result in a greater number of possible paths. Although the number of nodes is the same between the two visits in Table 1.1, there is a huge gap in the number of paths as the number of edges increases. My goal in the analysis section is to understand how specialization affects the number of paths in the process.

1.2.2. Complexity in Healthcare

Complexity in healthcare has been both theoretically and practically challenging. The growth in complexity of the healthcare systems has caused a challenging environment for healthcare reform due to its own attributes of the healthcare area, characterized by intersecting biological, social, and political systems (Blanchfield et al., 2010; Long et al., 2018). As a collection of interconnected actions of individuals and technologies, healthcare systems are recognized as one of the representative complex adaptive systems (Plsek & Greenhalgh, 2001).

Many studies have warned about the growth of complexity in healthcare systems. The biggest problem of increased complexity in healthcare systems is that it increases cost and waste (Shrank et al., 2019). Blanchfield et al. (2010) find that excessive administrative complexity costs about 12 percent of net patient service revenue. As such, administrative complexity has been concerned as the largest waste in healthcare systems of the U.S. To reduce it, Shrank et al. (2019) suggest eliminating process that does contribute to quality improvement and/or access to care.

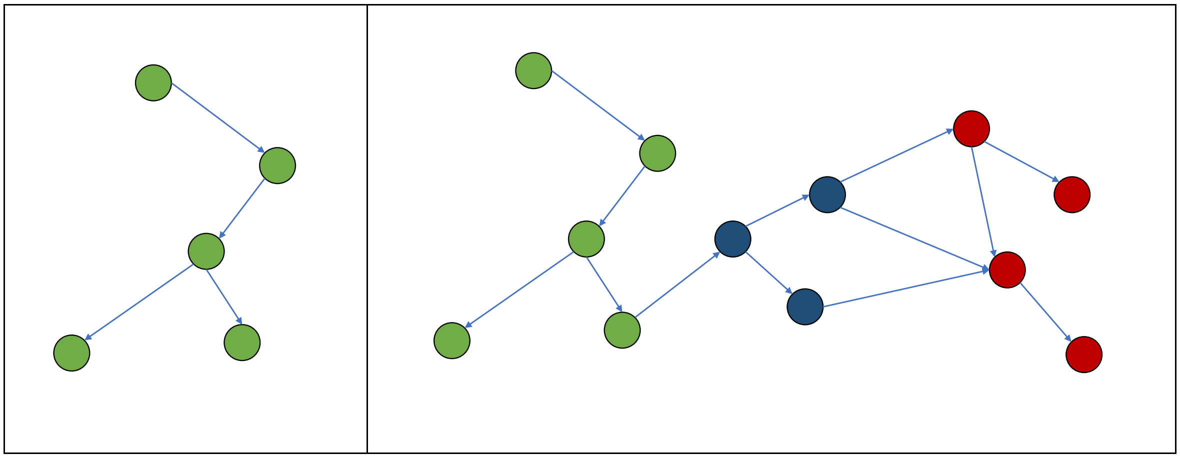
The waste of complexity is derived from the increased interconnection within and across components of systems (Simon, 1969). From network perspective, the individuals and technologies in healthcare systems are considered as nodes in healthcare systems and their interrelatedness denotes the edges of the network (Kannampallil et al., 2011). As modern healthcare systems have been developed, the work tasks have been more specified and distributed between diversified actors with new technologies. Thus, as a result of specified actors and artifacts in the healthcare process, it makes the process more complex.

As such, previous studies address complexity in healthcare system and describe the role of actors and technologies in it. However, few studies are giving much attention to the interrelatedness of contextual specifics in healthcare systems and empirically examining its impacts on complexity of process (Kannampallil et al., 2011). Previous studies have demonstrated that specialization improves performance at the organizational level under similar conditions (Clark & Huckman, 2012; Kalra & Li, 2008). For example, Clark and Huckman (2012) find that specialization in areas related to cardiovascular care has positive impacts on performance of cardiovascular patients (positive spillovers) and there are complementarities in specialization across related areas. Kalra and Li (2008) show that firms signal quality to their consumers by specialization. However, these studies have not examined the relationship between specialization and enacted complexity. Hence, in this study, I examine how the contextual factors affect the complexity of the healthcare process using the data on the clinical documentation process.

1.2.3. Number of Roles

It is easy to count the number of roles in a clinical process. Figure 1.2 shows a simple example. On the left side, I see a process with one role. On the right side, I see a process with two additional roles. New roles will always add to the number of nodes in the network. However, whether there are more (or fewer) possible paths will depend on how those nodes are connected in the network.

FIGURE 1.2. ONE ROLE VS. THREE ROLES IN A PROCESS

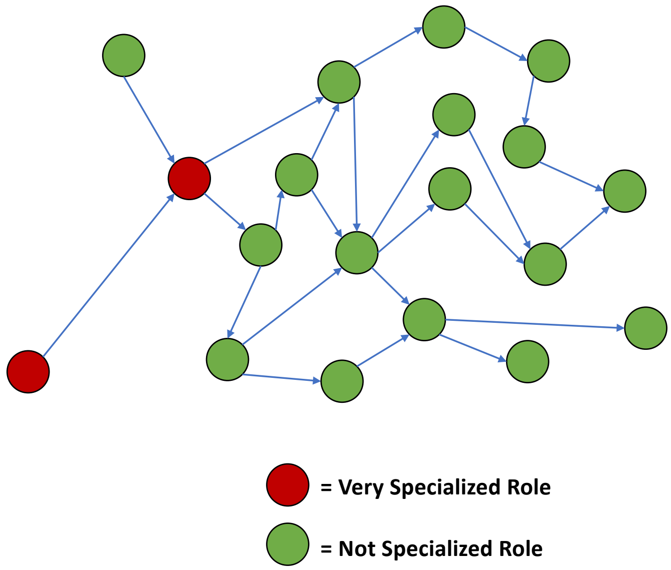


1.2.4. Role Specialization

In addition to the number of roles, I can consider how specialized the roles are. There is a consensus that specialization has played an important role in organizations. To illustrate the role of specialization, I use the concept of specialist and generalist. Prior literature shows that specialists and generalists in organizations can be conceptualized as two dimensions; 1) the extent of task concentration and 2) task variety (Fahrenkopf et al., 2020; Narayanan et al., 2009; Staats & Gino, 2012; Tyler, 1973). For example, Fahrenkopf et al. (2020) define specialists as "those who have worked in organizations with a high degree of division of work across individuals" and generalists as "those who have worked in organizations with limited or no division of work across individuals".

Specialists focus on and repeatedly execute a narrow range of tasks based on specific knowledge for those tasks, whereas generalists can cover a broader range of tasks within an organization (Vermeiren & Raeymaeckers, 2020). Figure 1.3 shows the network of events visualizing how role specialization influences the number of paths in process. Red circles in the network show tasks of a very specialized role and green ones indicate actions that a generalist performs.

FIGURE 1.3. SPECIALIST VS. GENERALIST ROLES IN PROCESS



1.3. Research Context

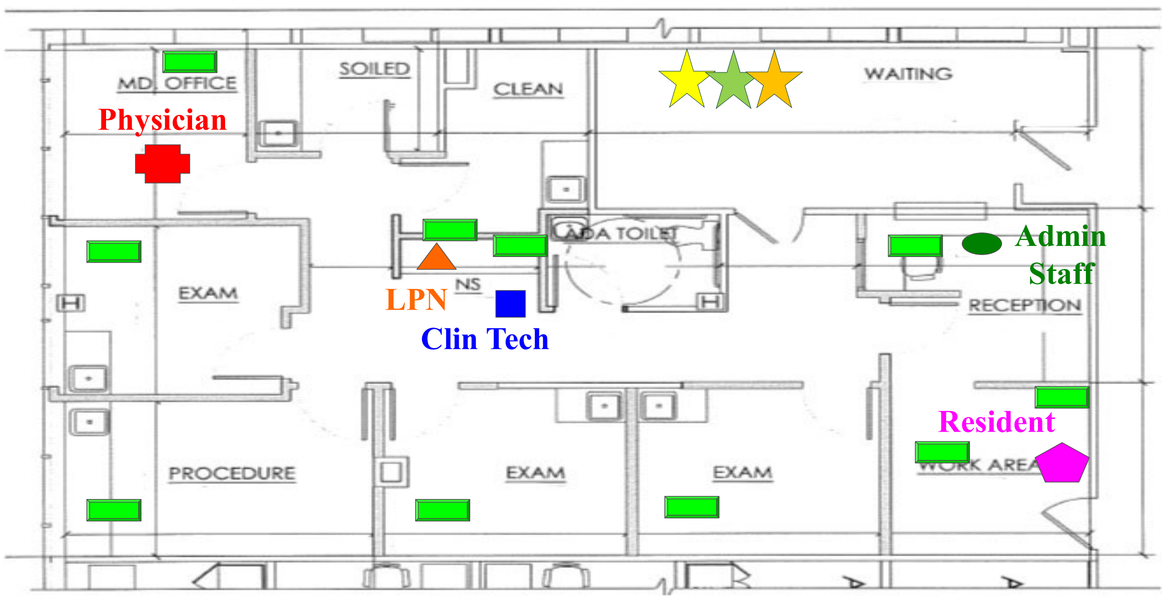
I analyze data extracted from the EPIC Electronic Medical Record (EMR) audit trail at the University of Rochester Medical Center (URMC). Clinic organization provides a clear example of a complex service organization with multiple roles with different specialties and the audit trail data shows how the clinics work. For example, when a patient visits a clinic, multiple roles are involved. Figure 1.4 is an actual layout of a dermatology clinic from my data[2]. In this layout, there are multiple roles in this layout working at different locations. The green squares are workstations where the individuals can input or access information on the patient. While the patient visits the clinic, multiple individuals input information on the patient at different locations.

In this layout, I can observe two different contextual factors in the documentation process: roles and workstations. The specialized roles are moving from one room to the others,

[2] I appreciate the layout from Dr. Julie Ryan Wolf at the University of Rochester Medical Center.

and they are creating different paths in the process by using different workstations at different locations. All workstations provide identical functions regardless of their location, but each role uses it in distinctive ways because all the roles have different specialties.

FIGURE 1.4. OUTPATIENT CLINIC LAYOUT



1.3.1. Three Kinds of Outpatient Clinics

My data is extracted from the EPIC Electronic Medical Record (EMR) audit trail from 13 different clinics with three different clinical specialties (dermatology, orthopedic surgery, and pediatric oncology) at the University of Rochester Medical Center (URMC). Table 1.2 shows brief information on three areas of medical practice in the data. The total number of roles is not the sum of each area because many of the roles exist in all clinics (e.g., physician, nurse, etc…)

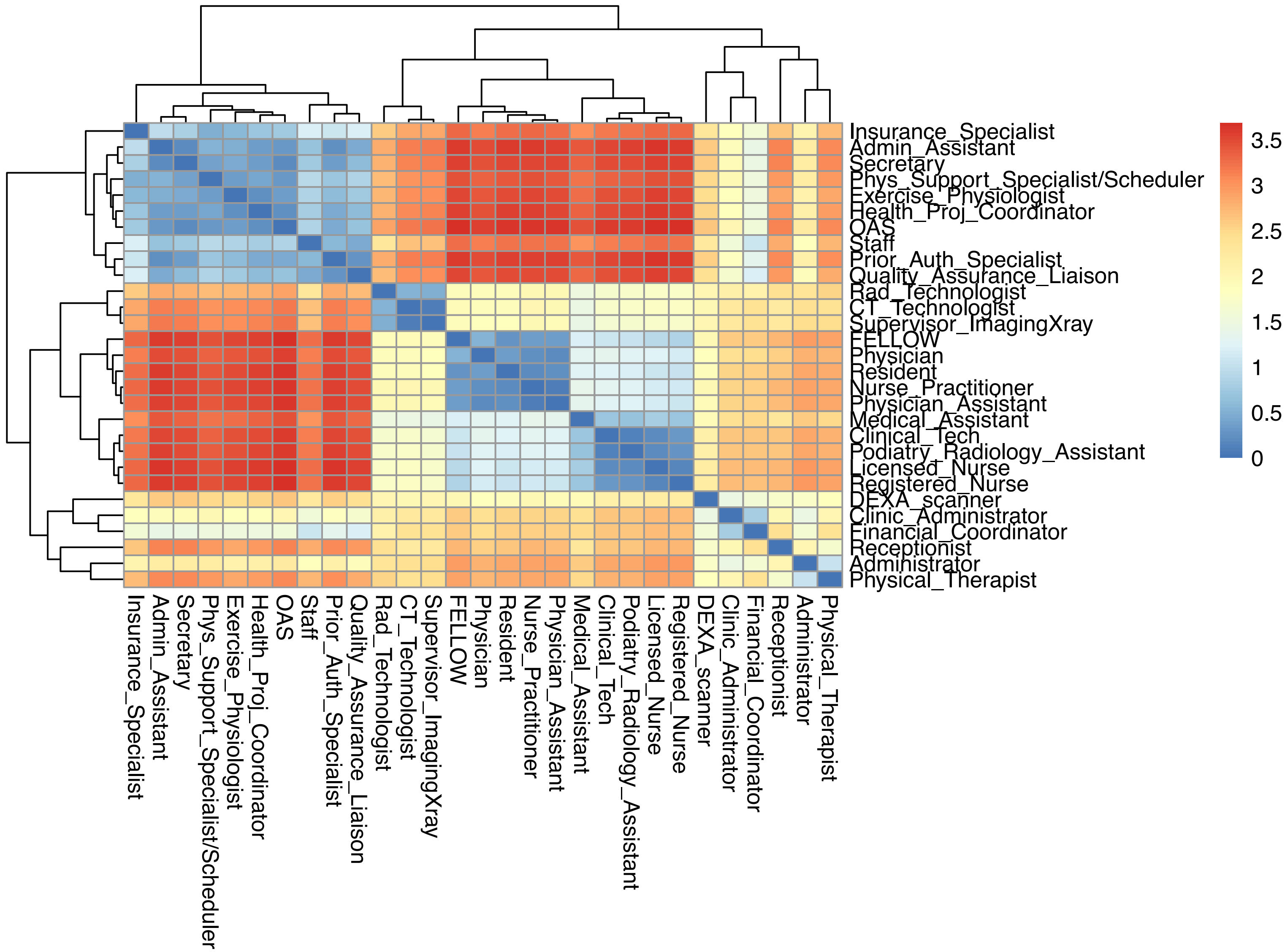
TABLE 1.2. NUMBER OF CLINICS, VISITS, AND ROLES FOR EACH SPECIALTY

Specialty	**# Clinic**	**# Visits**	**# Roles**
Dermatology	4	9,818	8
Orthopedic Surgery	8	131,345	28
Pediatric Oncology	1	6,285	22
Total	13	143,347	29

1.3.2. Clinical Roles are Specialized

As mentioned above, each clinical role has a specialized set of skills. Role specialization can be seen in the data. Figure 1.5 shows the similarity among the roles based on the frequency of actions each role performs. I compute cosine distance based on their actions to compare how similar/different action patterns each specialized role has. Red colors show that the two roles have different action patterns using workstation systems, while blue colors indicate the tendency to have similar patterns. As I assumed, there exist similarities among the specialized providers depending on the service area (e.g., administrative, technician, assistant, diagnosis, etc.) and they are clearly differentiated from each other. For example, the technologist group (Supervisor imaging X-ray, CT-technologist, and Radiology-technologist) have very similar action patterns with each other but are different from anyone else. Figure 1.5 provides a clue on how specialized the roles are in the clinical process and how the action patterns of each clinician can be differentiated/classified. The number of roles and role specialization will be the two major variables of interest in the analysis.

FIGURE 1.5. ROLES ARE SPECIALIZED



1.4. Hypothesis Development

I am concerned with the effect of roles and specialization on enacted complexity. For each independent variable (number of roles and role specialization), there are competing hypotheses about their effect on enacted complexity.

As we know from the formula for enacted complexity, there is a balancing act between nodes and edges in the network that represents the process. If there are more nodes (for a given number of edges), complexity will go down. If there are more edges (for a given number of nodes), complexity will go up. Thus, the main question is how the roles affect the number of nodes and edges in the network.

1.4.1. Effect of Roles on Enacted Complexity

As each role has a specialized set of skills, a process enacted by more distinct roles will tend to include more required acts (Wood, 1986). Medical services are typically delivered by teams of providers with differentiated roles. By role, I mean "a comprehensive pattern for behavior and attitude that is linked to an identity, is socially identified more or less clearly as an entity, and is subject to being played recognizably by different individuals" (Turner, 2001, p. 234). Intuitively, as each provider provides a differentiated service from others based on their role, adding more roles implies additional tasks in the clinical process. For example, a patient who arrives at the clinic might engage with several roles, including office staff, insurance pre-authorization, nurse, physician, and clinical technician. When the same patient returns to the same clinic a week later, the clinical process for the visit might be simpler as involving only two provider roles (e.g., office staff and physical therapist). As the increased number of actors creates more paths in the action network, it can increase enacted complexity. Figure 1.2 simply shows how additional roles can increase the number of actions in process. When the roles are added in process, nodes are added to the network, and it could increase the number of paths by generating more relations between the actions. For example, if a patient needs to see a clinical technician after seeing a physician, then it implies that the patient needs additional care service before leaving the clinic. This will generate additional steps and relations in the network for the patient visit. However, as we have seen above, the effect on enacted complexity will depend on how those steps are connected in a network. Thus, I offer two competing hypotheses

H1a: ***Processes enacted with more roles will have more enacted complexity.***

H1b: ***Processes enacted with more roles will have less enacted complexity.***

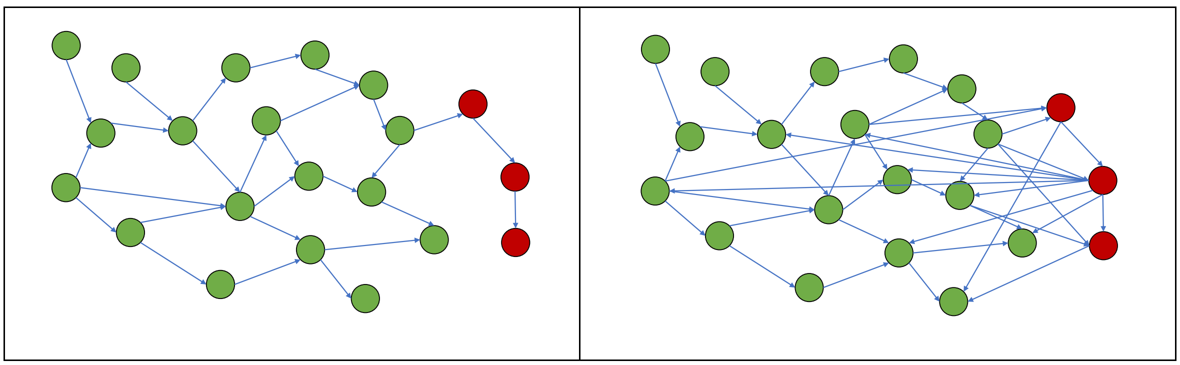
1.4.2. Effect of Role Specialization on Enacted Complexity

Next, I consider the effects of the degree of role specialization on enacted complexity. Previous studies have demonstrated that specialization improves performance at the organizational level but have not examined the effects of specialization on complexity (Clark & Huckman, 2012; Kalra & Li, 2008). Although medical settings consist of specialized tasks mostly, the depth of specialization of each role would be different depending on the roles that clinicians play in the clinical process. For example, nurse practitioners generally cover more various tasks than CT technologists and exercise physiologists have a smaller number of tasks than physicians. As such, each specialized role has a different degree of specialization and the impacts of each role on the clinical process vary depending on how specialized the roles in a clinical visit are. However, the effect of specialization will depend on whether the specialized roles add more nodes or more edges to the network. The examples in figure 1.6 suggest two possible cases. In one case, a specialized role adds three new actions that are sparsely connected to the other actions in the visit. In practice, this would mean that the new role has few handoffs with other roles (e.g., an x-ray technician). In the other case, the specialized role adds three new actions that are densely connected to the rest of the actions in the visit. In practice, this would mean that there are a lot of handoffs between the new role (e.g., a nurse) and the other roles. These two different cases lead us to two alternative hypotheses:

H2a: ***Greater role specialization causes <u>increased</u> enacted complexity.***

H2b: ***Greater role specialization causes <u>decreased</u> enacted complexity.***

FIGURE 1.6. THE SAME ROLE SPECIALIZATION COULD RESULT IN DIFFERENT NUMBERS OF PATHS



1.5. Methodology

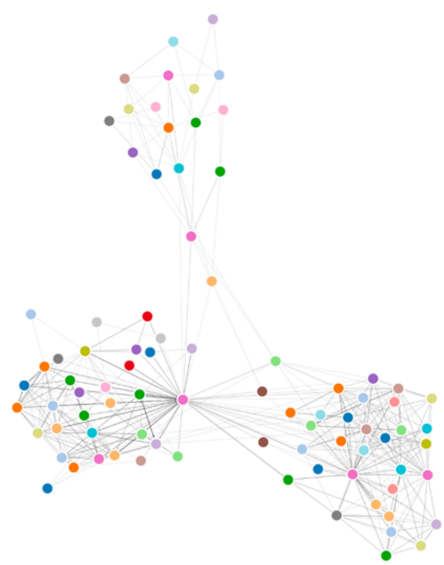
In this section, I explain how I compute each of the major variables used in testing the hypotheses. I also explain the use of Generalized Propensity Score matching, which is used for causal inference.

1.5.1. Computing Enacted Complexity

Enacted complexity is operationalized based on the actions in each outpatient visit. Each visit can be represented as a narrative network and enacted complexity is indexed by the number of paths through the network (Goh & Pentland, 2019). To operationalize, I aggregate the action trace data at the visit level. I extract unique actions with two immediate contextual specifics: roles and workstations, in each process and compute the time spent to input the data in the system for each patient visit in the EMR. The extracted actions in each visit are used as nodes in the action network for each visit.

Next, to compute the enacted complexity, I use the concept that Hærem et al. (2015) suggest. Based on conceptualizing patterns of action as directed graphs, this concept allows measuring the complexity of a task as enacted by multiple actors. To estimate enacted complexity, I use the formula in equation (1) based on the network for each visit. The nodes in the network represent the unique, contextually specific combinations of action, role, and workstation that are observed in the data for each visit. A typical example would be a nurse checking medications at a workstation in the examination room. Figure 1.7 shows how the process can be represented as a network.

FIGURE 1.7. NARRATIVE NETWORK WITH ROLE AND LOCATION



1.5.2. Computing the Specialization Index

Next, I describe the construction of a new variable, the specialization index, which captures the extent to which the roles involved in a patient visit are specialized. The specialization index is the ratio of the unique actions that each role performs to the total unique actions performed by all roles in the system. The index is constructed as follows:

$$s_i = -\frac{N(\textit{unique actions performed by role i})}{N(\textit{unique actions in the system})} \qquad (2)$$

At one extreme, $s_i = -1$ would mean that role *i* performs every action in the systems at least once. The index will be lower when the role *i* performs fewer actions. I further operationalize a weighted specialization index. The weight is given as $w_{ij} = \frac{a_{ij}}{A_j}$ where a_{ij} is the number of actions a specialized role *i* performs in the patient visit *j* and A_j is a total number of actions performed for the patient visit *j*. I place the weights on each role in the patient visits and calculate the average weighted specialization index for each patient visit as

$$S_j = \frac{1}{N_j} \sum_{i=1}^{n} w_{ij} s_i \qquad (3)$$

where N_j is the number of specialized roles in the patient visit *j*. Based on the visit level specialization index, I examine the relationship between specialization degree and enacted complexity of patient encounters.

1.5.3. Generalized Propensity Score Matching Method

I estimate causal effects using the generalized propensity score (GPS) (Hirano & Imbens, 2004). I investigate the expected outcome at different levels of two continuous variables: 1) the number of specialized roles and 2) specialization index in equation (3). To accommodate continuous variables (also called "exposures"), I use the Generalized Propensity Score (GPS), which is defined as the conditional density function of the exposure given the covariates (Hirano & Imbens, 2004; Imbens, 2000; Wu et al., 2018). GPS is widely used for causal inference and the basic idea for this method is to get the same confidence with a random assignment experiment, but with my current dataset. It has a balancing property that is conditional on observable covariates. If subjects belong to the same GPS strata, the exposure level is regarded as random. Therefore, in this study, I use a robust GPS matching approach, proposed by Wu et al. (2018), to remove bias and estimate the exposure-response function.

The main goal of the GPS matching method is to find matched observations by assessing the balance of covariates across different levels of specialization in the data. Specifically, first, I compute a GPS for each data point based on a function of the exposure and other observed covariates. Next, I find an observation that has the closest values of exposure and GPS to E and $f(E|\mathbf{X})$. I use the outcome of this observation as the counterfactual outcome of a subject with $\mathbf{X}$ and E. The matched unit is used as a valid representation of observations with the exposure level, considering the potential confounders have been adjusted. Finally, the expected outcome at a predetermined exposure level is estimated by averaging the outcomes of the matched units with such an exposure value.

1.6. Data Description

I used audit trail data from the Electronic Medical Record (EMR) at the University of Rochester Medical Center (URM). The collected data traces actions of the medical record-keeping process for each patient from 24 clinics (4 dermatology, 19 orthopedic surgery, and 1 pediatric oncology). The data includes 143,347 patient visits from April 2nd, 2018 to November 29th, 2018. Each observation contains contextual factors for patient visits: role, workstation, diagnosis group, as well as timestamps. Especially, roles and workstations are closely interrelated with the actions because some actions only can be performed by specific roles at specific locations. I consider the role and workstation as immediate contextual factors, which are directly related to actions in process (Rosemann et al., 2008). Table 1.3 describes the first five minutes of one visit as an example of the data from the first five minutes of one visit.

TABLE 1.3. EXAMPLE DATA

Time	Action	Role	WorkStation	Diagnosis	Clinic ID
2/2/15 8:53	Checkin Time	Admin Tech	W1	Neoplasm	A
2/2/15 8:53	Mr_Snapshot	Admin Tech	W1	Neoplasm	A
2/2/15 8:53	Mr_Reports	Admin Tech	W1	Neoplasm	A
2/2/15 8:53	Mr_Snapshot	Admin Tech	W1	Neoplasm	A
2/2/15 8:53	Mr_Reports	Admin Tech	W1	Neoplasm	A
2/2/15 8:55	Mr_Snapshot	Admin Tech	W1	Neoplasm	A
2/2/15 8:55	Mr_Reports	Admin Tech	W1	Neoplasm	A
2/2/15 8:56	Mr_Snapshot	Admin Tech	W1	Neoplasm	A
2/2/15 8:56	Mr_Reports	Admin Tech	W1	Neoplasm	A
2/2/15 8:56	Ac_Visit_Navigator	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Histories	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Enc_Encounter	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Vn_Vitals	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Reports	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Flowsheet	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Vn _Complaint	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Reports	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Snapshot	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:56	Mr_Reports	Lic.Nurse	W3	Neoplasm	A
2/2/15 8:57	Mr_Reports	Admin Tech	W1	Neoplasm	A
2/2/15 8:57	Mr_Snapshot	Admin Tech	W1	Neoplasm	A
2/2/15 8:58	Mr_Reports	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Ac_Visit_Navigator	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Enc_Encounter	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Histories	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Reports	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Vn_Vitals	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Flowsheet	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Reports	Physician	W4	Neoplasm	A
2/2/15 8:58	Mr_Vn_Vitals	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Histories	Lic.Nurse	W2	Neoplasm	A
2/2/15 8:58	Mr_Histories	Lic.Nurse	W2	Neoplasm	A
...	...	...	...	...	...

The shaded rows in Table 1.3 show how the role and workstation change throughout a visit at the level of individual actions. In contrast, Diagnosis and Clinic ID could be interpreted as external factors as they have the same values throughout the visit.

This data provides a unique opportunity to study the effects of specialization in a narrative network. This is because it includes fine-grained, time-stamped information about actions and roles, which vary throughout each patient visit. With two years of data, I can see how routines change over time. It provides a detailed trace of actions that are taken in the recordkeeping work for each clinic day. This allows us to analyze complex action patterns in each visit.

The number of roles is simply the number of unique roles within each patient visit. There are 30 types of specialized roles (physician, clinical tech, licensed nurse, residents, etc.). I count the number of unique roles that participated in the clinical process during each patient visit. I also count workstations and other factors that could influence the complexity of the visit. These are used as control variables in the analysis. Table 1.4 shows descriptive statistics of the variables used for the study.

TABLE 1.4. DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.
Enacted Complexity	143,663	6.86	3.41
Specialization Index	143,663	-0.12	0.06
Logged Number of Roles	143,663	1.69	1.51
Logged Number of Workstations	143,663	2.19	3.31
Logged Number of Procedures	143,663	0.41	0.98
Logged Number of Events	143,663	5.40	0.48
Logged Visit Duration	143,663	2.58	1.34

I also control for the visit level observed heterogeneity by adding the number of workstations, the number of events, performed procedures, and the duration of the visit, all of which are visit-varying variables. The complexity of the narrative network may vary depending on the procedures because the likelihood of actions on the procedures may differ. Duration time for the visit also needs to be controlled, because the required time for each visit also changes according to the patient visits. Lastly, I capture the variation by adding the number of events since longer visits (with more events) tend to have larger networks (more unique nodes and edges) and greater enacted complexity.

1.7. Model Estimation and Results

To examine the effects of the contextual specifics on the enacted complexity of the clinical process, I specify two cross-sectional models. Two models are needed because the two aspects of specialization include overlapping information and cannot be included in the same model. In each model, the complexity of visit *i*'s network is a function of specialization and a set of control variables:

$$(4)\ \log(Y_j) = \alpha + Role_j\beta_1 + n_{Workstation_j}\gamma_1 + n_{procedure_j}\gamma_2 + duration_j\gamma_3 + n_{events_j}\gamma_4 + \delta_j + \tau_j + \varepsilon_j$$

$$(5)\ \log(Y_j) = \alpha + S_j\beta_1 + n_{Workstation_j}\gamma_1 + n_{procedure_j}\gamma_2 + duration_j\gamma_3 + n_{events_j}\gamma_4 + \delta_j + \tau_t + \varepsilon_j$$

In both models, Y_j represents the enacted complexity computed based on nodes and edges in visit j. $Role_j$ denotes the vector of a variable for specialized roles: number of roles (eq. (4)) and S_j is the specialization index for visit j. (eq. (5)). I also add the vector of control variables such as the number of workstations, events, and procedures and time duration of visits in seconds. Lastly, δ_j refers to time-invariant clinic fixed effects and τ_t are time fixed effects to capture unobserved heterogeneity of seasonality.

1.7.1. OLS Estimation

In this section, I report the results of ordinary least squares (OLS) regression. Overall, I observe strong significant effects of the number of specialists and degree of role specialization on the enacted complexity (see Table 1.5).

TABLE 1.5. RESULTS OF REGRESSIONS ON ENACTED COMPLEXITY

VARIABLES	(1)	(2)
Number of roles	-0.4604***	
	(0.0370)	
Specialization Index		-11.9598***
		(0.3141)
	(0.0087)	(0.0084)
Constant	-27.2624***	-32.8934***
	(0.2259)	(0.3134)
Observations	143,663	143,663
R-squared	0.7492	0.7655
YM Dummies	YES	YES
Workstation Control	YES	YES
Events Control	YES	YES
Procedure Control	YES	YES
Duration Control	YES	YES
Clinic Control	YES	YES

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The first column in Table 1.5 shows the effects of specialization in the clinical process: 1) the number of roles (column (1)) and 2) the degree of specialization on the enacted complexity (column (2)). I check the variance inflation factor (VIF) for the concern on multicollinearity among the variables for the explanatory variable (Belsey et al., 1980). The VIF value is less than four, which ensures that multicollinearity is not a concern. As seen in column (1) in Table 1.5, more roles are negatively associated with enacted complexity at a significant level. This result shows that more specialists tend to simplify the process, consistent with hypothesis H1b.

Consistent with the results for the number of roles, the role specialization index also shows a negative and significant association with enacted complexity. This is consistent with hypothesis H2b. Thus, both results show a negative relationship between specialization and enacted complexity.

1.7.2. Sensitivity Analysis

From the OLS estimation, I recognize there may be concerns about biased effects due to unobserved or omitted confounding variables. To prevent invalid inferences, I leverage my data and design as much as possible. Specifically, I controlled for the number of workstations, events, and procedures and the time duration of visits in seconds, clinics, and seasonality. Nonetheless, there may still be concerns about omitted variables. Therefore, I use the Konfound-it app to conduct sensitivity analysis (Frank et al., 2013). I quantify how strongly an omitted confounding variable would have to be correlated with specialization and enacted complexity to invalidate any inferences I made (Frank, 2000) and how much bias there would have to be due to the omitted variables or any other source (Frank et al., 2013).

1.7.2.1. Robustness of inference to case replacement (RIR)

First, I draw on Frank et al (2013) as in the Konfound-it app to quantify how much bias there would have to be due to omitted variables or any other source to invalidate our inference. The results indicate that 84.249% of the estimated effect of the number of roles on enacted complexity would have to be due to bias to invalidate the inference of an effect of the number of roles. Correspondingly, to invalidate the inference one would have to replace 84.249% of the observed data with null hypothesis cases of no effect of the number of roles. For the specialization index, to invalidate an inference, 94.853 % of the estimate would have to be due to bias.

1.7.2.2. Impact threshold for omitted variable

Next, I also quantify how strongly an omitted confounding variable would have to be correlated with specialization and enacted complexity to invalidate our inference. For the number of roles, the result indicates that an omitted variable must be correlated at 0.167 with the explanatory variable and with enacted complexity (with opposite signs) to invalidate the inference. Correspondingly, the impact of an omitted variable must be 0.028 to invalidate the inference. For the specialization index, the minimum impact to invalidate an inference of an effect of specialization on enacted complexity is based on a correlation of 0.309 with the outcome. This implies that the impact of an omitted variable must be 0.095 to invalidate the inference.

The results of the sensitivity analysis imply the possibility of a confounding effect, especially for the number of roles (0.167), as the correlation coefficient lower than 0.2 is normally considered a weak correlation by social science standards (Cohen & Cohen, 1983). Thus, in the next section, I adjust for any potential confounding effects using the generalized propensity score (GPS) matching method (Wu et al., 2018).

1.7.3. Causal Effect Estimation

I use the GPS matching method to adjust for the potential confounder effects and remove the endogeneity bias. I use R package *CausalGPS* for the GPS matching (Wu et al., 2018). First, I use a non-parametric, cross-validation-based *SuperLearner* algorithm to estimate the GPS of specialization (the number of roles and specialization index) conditioning on all other covariates including potential confounders. SuperLearner is an algorithm that uses cross-validation to estimate the performance of multiple machine learning models, or the same model with different settings (Kennedy et al., 2017; van der Laan et al., 2007). I implement and combine four different algorithms: 1) extreme gradient boosting machines, 2) multivariate adaptive regression splines, 3) generalized additive models, and 4) random forest, using the SuperLearner R package (Polley & van der Laan, 2010). Next, I use the caliper matching function to approximate randomized data points with the balanced pre-exposure covariates by jointly matching the units on the estimated GPS and treatment. To do this, I tune 1) the caliper parameter as the radius of the neighborhood around the exposure level and 2) the scale parameter, which assigns weight between the exposure and the estimated GPS. The specified caliper matching function is as follows:

$$m_{GPS}(e, w) = \arg \min_{i: w_i \in [w-\delta, w+\delta]} || (\lambda e^*(w_i, c_i), (1-\lambda) w_i^*) - (\lambda e^*, (1-\lambda) w^*) || \tag{8}$$

where w_i is the i^{th} exposure level, w_i^* and e^* represent the standardized Euclidean transformed exposure and GPS estimates, δ is the caliper parameter, λ is the scale parameter, and ||.|| is a Manhattan distance matching method. I rely on the data-driven method to find the best combination of the parameters that lead to the smallest absolute correlation between the covariates and exposure. The goodness of a covariate matching is quantified by absolute correlation: a value below 0.1 indicates a good balance of the covariate (Wu et al., 2018; Zhu et al., 2015). After the data-driven process, I use the caliper matching function with the scale and caliper parameters equal to 1.0 and 0.16, respectively, to match the subjects. I have assessed absolute correlations of all the covariates across different levels of exposure and the average absolute correlation is 0.87 (number of roles) and 0.67 (specialization index), indicating the covariates are well balanced. Finally, I generate the matched data by the imputed outcome values from the caliper matching function.

Next, using the matched dataset, I estimate a smooth exposure-response function by the non-parametric kernel smoothing. The kernel smoothing fits a kernel smoother on the generated matched set to get the smoothed average exposure-response function (Wu et al., 2018).

Figure 1.8 shows a negative causal relationship between the number of roles and enacted complexity. The figure shows that the magnitude of causal effects is very substantial. The analysis implies that a lower level of complexity is expected if a greater number of specialized roles are involved in the patient visit. This result demonstrates that the unexpected effect of the number of roles in OLS regression has substantial causal effects on enacted complexity.

FIGURE 1.8. CAUSAL RELATIONSHIP BETWEEN NUMBER OF ROLES-ENACTED COMPLEXITY

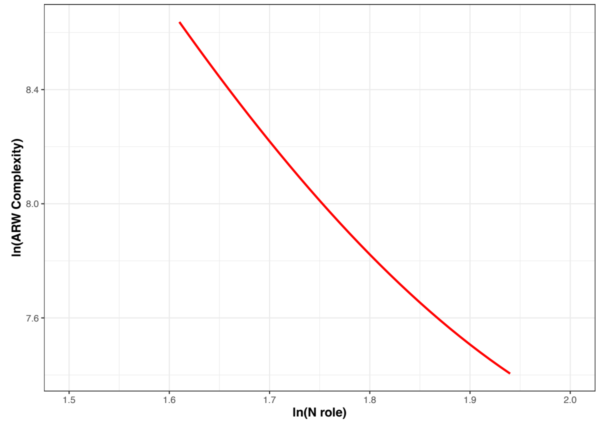
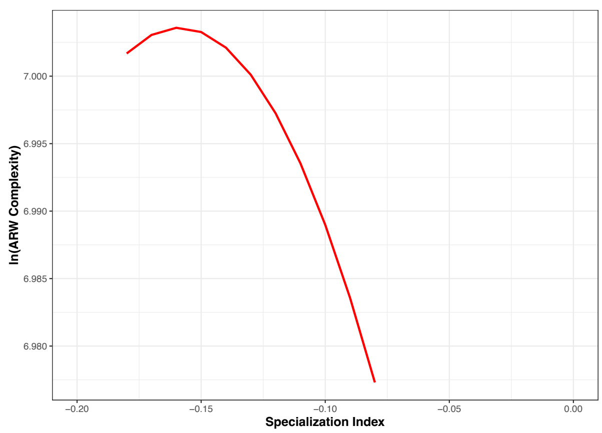


FIGURE 1.9. CAUSAL RELATIONSHIP BETWEEN SPECIALIZATION INDEX-ENACTED COMPLEXITY



The result of causal estimation for the specialization index is also consistent with the OLS regression. Figure 1.9 shows that the higher the specialization index patient visit has, the less complex process of the visit tends to be. As seen in the figure, some of the visits with lower specialization index increase enacted complexity, but mostly the magnitude of the effects is substantial. This result indicates that role specialization reduces enacted complexity even after the confounding effect is adjusted.

1.8. Discussion

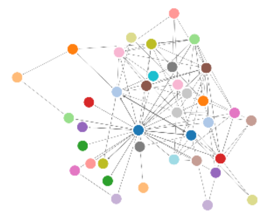
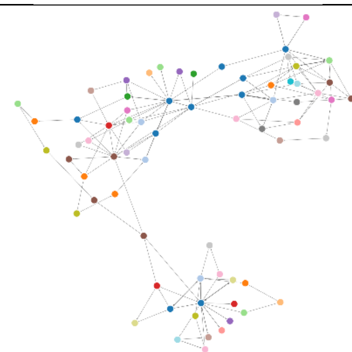
Intuitively, when more roles are involved in a process, or the involved roles are more specialized, a process seems likely to be more complex. While there may indeed be more required acts (Wood, 1986), my results show that the workflow has lower enacted complexity. This paradoxical result has some interesting implications.

1.8.1. Specialization Makes Workflows Simpler

This study points to a fundamental concept of specialization in organizational work structure. Compared to generalists, who perform a large number of actions, specialists focus on a relatively small number of distinct actions (Fahrenkopf et al., 2020; Narayanan et al., 2009). Specialists tend to reduce enacted complexity because they have a narrow and deep task range, and there are fewer relations between actions. In healthcare settings, all the provider roles are considered as specialists as every provider has their own specialty.

I visualize the effect of specialists on process enactment in terms of the narrative network (see Figure 1.10). While the graph-based only on actions has a smaller number of nodes compared to the context-aware network which considers specialized roles for nodes, it has many more edges between nodes, which increases enacted complexity. As such, contrary to intuition, adding more roles tends to simplify the graph because, in a healthcare setting, roles tend to be specialists. Specialization tends to *decrease* the enacted complexity of the clinical workflow.

FIGURE 1.10. THE VISUALIZED EFFECT OF SPECIALISTS ON ENACTMENT OF PROCESS

Representation	Visit level (1 visit)
Action only	
Context-aware (action + role)	

My analysis also leads to important substantive findings on roles and specialization. As a component of task complexity, the traditional component complexity states that a task gets more complex when there are more events (actions) because it is based on the only "content of activity" (Campbell, 1988; Wood, 1986). While it is undeniable that the number of events is an important factor to be considered, there can be also many other factors that have an impact on complexity. For example, the applied technologies in the work process affect the individuals' work practice the and structure of organizations (Orlikowski & Barley, 2001), and this change causes significant complexity and variation (Butler & Gray, 2006). I acknowledge the potential influence of social and material factors on the complexity of how the process is enacted. To address this gap, I examine the extent to which the enacted complexity is influenced by the social and material context of work. I specifically focus on the social factor, specialized workers, controlling the material context, represented as digitalized systems for the tasks. The results of this study reveal that patient visits with more specialized roles decrease enacted complexity, compared to less specialized providers.

1.8.2. Enacted Complexity as a Network Phenomenon

The results of this study show that specialists tend to decrease enacted complexity. This contradicts practitioner literature, which has argued that more touchpoints result in greater complexity (Rawson et al., 2013; Richardson, 2010). It also contradicts the traditional theory of individual-level task complexity, where more required acts indicate greater complexity (Wood, 1986). The critical difference is that I conceptualize enacted complexity as a network phenomenon. The measure of enacted complexity considers how the touchpoints (or required acts) are related (Kannampallil et al., 2011; Kauffman, 1993).

This network perspective provides a framework for managing enacted complexity in the process. To reduce complexity at the systemic level, it helps to untangle the network. Fewer edges will tend to reduce the space of possible paths. To increase complexity, it helps to add edges. The goal should be to minimize excess complexity. The contribution of this study to the practical problem is simple: the number of touchpoints (or required acts) does not tell the entire story. Enacted complexity grows exponentially as a function of the number of relations between nodes in the network.

1.8.3. Limitations

This study has several limitations. First, although I investigate the relationship between specialization and enacted complexity of process, it does not directly measure how specialization affects organizational performance. For example, there exists a big difference between specialists and generalists in terms of learning and productivity (Narayanan et al., 2009). Specialization of tasks for specialists enables a deeper understanding of concentrated tasks based on the learning curve than less specialized individuals (Dane, 2010; Flueckiger, 1976). In contrast, generalists can get impeded when it comes to learning tasks, as they are easily exposed to too much variety of tasks. For future study, studying the impact of specialization on learning and productivity of process would help us understand the quality of the organizational process. Second, this study examines the antecedents of enacted complexity in the clinical documentation process, but EMR records do not represent all the clinical processes in the clinics. It would be interesting to examine other settings of the clinical process. Second, this study examines the antecedents of enacted complexity, but I also need to examine the consequences. For future work, studying to operationalize enacted complexity could give us a better understanding of the effects of enacted complexity in process.

1.9. Conclusion

The findings provide a unique opportunity to theorize on the relationship between specialization and enacted complexity in the clinical documentation process. Using simple measurements of specialization, I find that greater specialization causes lower enacted complexity. Adding a specialized role into the process decrease enacted complexity because each role performs a set of distinct actions that are sparsely connected with the actions performed by other roles. As a result, the network as a whole becomes less densely connected and less complex.

This study deepens our understanding of the context in the organizational process. Roles and role specialization are established aspects of organizational design and structure, but their impact on process structure has not been examined. While prior works have focused on the effects of specialization or generalist experience on organizational performance, I identify the effects of specialization on enacted complexity (Fahrenkopf et al., 2020; Narayanan et al., 2009).

The results of this study suggest the potential benefit of specialization of roles and its impact on the simplification of process.

By focusing on roles and role specialization, this study examines the contextual antecedents of enacted complexity. The content of an activity affects complexity of the action patterns, but at the same time, there needs to be a consideration of the potential influence of the context of the activity. The traditional model of task complexity (Campbell, 1988; Wood, 1986) explicitly excludes the effects of context and process enactment. In doing so, it overlooks the potential influence of social factors (such as role structure) on the complexity of process enactment. This study addresses this gap and examines the extent to which the context of the work influences the complexity of action patterns in the clinical documentation process.

Lastly, I also shed light on the possibility of automation for tasks in healthcare information systems. Process mining studies have focused on automated process discovery. The complexity of workflows has been considered as one of the biggest barriers to actualizing automation of processes across industries because it is hard to anticipate potential errors (Fast-Berglund et al., 2013; Lyell & Coiera, 2017; Rojo Abollado et al., 2017; Woods, 1996). Augusto et al. (2022) show that automated process discovery can be more challenging when the event log records a small amount of process behavior that varies greatly than when the event log records a huge amount of process behavior that varies little. I can interpret this as the automatically discovering process is more difficult when there are more relations among actions. Hence, reducing the complexity is the first step toward the automation of the process. To do this, first I need to understand the structure of the process based on the contextual factors and see how much process is entangled. Considering process as sequences of actions (events) may allow us to see only the tip of an iceberg of the process because paths cannot be revealed without considering contextual specifics (Leopold et al., 2018). Even if it looks like just one action, each action has a different depth of explanation on the event because an action can be different “events” depending on who performed the action or where the action was performed. Thus, context-awareness provides a deeper level of understanding of process.

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CHAPTER TWO:

DYNAMICS OF DIGITALIZATION: MECHANISMS OF STABILITY AND CHANGE IN DIGITALIZED WORK PROCESSES

2.1. Introduction

Updates, revisions, upgrades, and enhancements are pervasive aspects of digitalization. Organizations and individuals face an on-going barrage of changes in the digital artifacts I use. While many of these changes go unnoticed, some can cause significant disruption. By *disruption*, I mean changes to the ongoing pattern of action that is enabled/constrained by the artifact being upgraded. Upgrades can disrupt individual habits and organizational workflows in intended and unintended ways. While they are pervasive, they are not always visible, so their consequences are difficult to detect and analyze.

To address this problem, I build on Swanson's (2019) understanding of technology as a routine capability (p. 1008, emphasis in original):

> we argue that device-enabled routines constitute technology, in terms of capabilities achieved in human practices. Devices must, in effect, be "wrapped" in routines in the constitution of technology. *Routines are seen as integral to technology itself.*

When digital technologies are changed or upgraded, the effect is always mediated by routines. This insight is important because we know that routines can be difficult to change (Becker, 2004; Cohen et al., 1996). Information technology (IT) artifacts are constantly being upgraded, but how does this influence the routinized patterns of action that are entangled with those artifacts? The idea of technology as a routine capability provides the theoretical foundation for my main research question: what mechanisms shape the dynamics of digitalization? Does the structure of the routine itself influence the dynamics of digitalization and vice versa?

Dynamics are important because IT-induced change is not instantaneous or frictionless (Berente et al., 2016; Goh et al., 2011; Keen, 1981; Laumer et al., 2016) Technologists (re)design artifacts, hoping for new patterns of action (Pentland & Feldman, 2008), but they are often disappointed, as routines buffer the "shock" of new technology (Berente et al., 2016) and old ways of working remain in place. New technology provides an occasion for structuring (Barley, 1986), but it also provides an occasion for workarounds (Alter, 2014; Frank et al., 2011; Zhao & Frank, 2003) and appropriation (DeSanctis & Poole, 1994).

Field studies show that digitalization proceeds through a process of imbrication (Leonardi, 2011) or co-evolution (Goh et al., 2011). These are recursive, endogenous processes. Leonardi (2011) describes imbrication as the successive layering of human and material agency. Goh et al. (2011) describe a process of successive refinements of technology and routines. Like Goh et al. (2011), I model routines as narrative networks (Pentland & Feldman, 2007) and compare the network before and after a change in technology. Rather than using observational fieldwork, I use digital trace data to construct an extremely detailed picture of how routines change over time.

To better understand the mechanisms that shape these dynamics, I zoom in on one technological change, followed by one adjustment: a major upgrade of the Electronic Health Record (EHR) system at an academic medical center in the Northeastern U.S. I use process mining to discover and compare patterns of action pre- and post-disruption (Pentland et al., 2021b). Process mining provides an accurate, diachronic description of routine dynamics. The central theoretical contribution is that the structure of the routine – represented as a weighted, directed graph – influences the tendency of the routine to persist over time. I hypothesize and test the effect of three mechanisms that influence the tendency of action patterns to resist disruption and re-form quickly after disruption.

Current theory points to frequency and speed as major indicators of routinization. Routines that are fastest and most frequently repeated should be most likely to persist. However, my analysis indicates that speed is irrelevant, and coherence is the most important factor. By *coherent*, I mean that sequentially adjacent pairs of actions tend to share the same context (Pentland et al., 2017). Coherence points to the importance of materiality (rather than cognition) as an explanation for the persistence of routines after a disruption.

The theoretical contribution of this paper is made possible by the novel application of dynamic network models (Hoff, 2005; Minhas et al., 2016) to theorize about the dynamics of digitalization. Swanson's (2019) theory of technology as routine capability implies that the dynamics of digitalization are inextricably connected to the dynamics of routines. Whether we conceptualize this as imbrication or coevolution, the dynamic network framework offers a novel perspective on the dynamics of digitalization. Rather than relying on actor-centric or device-centric explanations (Swanson, 2019), it provides an explanation based on the structure of the pattern action itself. The dynamic network lens affords a variety of practical insights, as well. It provides a simple way to assess the impact of upgrades and other disruptions and it demonstrates how quickly routines can form after a disruptive event.

I begin by reviewing current research on information systems, organizational routines, and the process of digitalization. I introduce the use of network models to study change processes, such as upgrades and other disruptions. Based on the current theory, I develop a set of hypotheses about the effects of disruptions. I test these hypotheses using data from five outpatient medical clinics. I discuss the implications of this approach for research on the dynamics of digitalization.

2.2. Background

2.2.1. Information Systems and Organizational Routines

Through observational field research, information systems researchers have begun to examine the relationship between technology and routines, defined as “repetitive, recognizable patterns of action carried out by multiple actors” (Feldman & Pentland, 2003, p. 95). The entanglement of artifacts and routines is axiomatic to the current theory on routines (D’Adderio, 2011; Feldman et al., 2022), and there is a growing body of work on information systems that build on concepts and methods from research on habits and routines (e.g., Beverungen, 2014; Limayem et al., 2007; Lyytinen et al., 2010; Mendling et al., 2021; Pan et al., 2007; Polites & Karahanna, 2013; Thummadi & Lyytinen, 2020; Zhang et al., 2021). There is also a strong tradition of practice-based scholarship that examines patterns of technology-in-use without explicitly framing those patterns as routines (e.g., Orlikowski, 2000).

Within this literature, observational field studies provide the best evidence of the recursive relationship between technology and routines. This work builds on the long-standing theme of technology adaptation (Leonard-Barton, 1988; Majchrzak et al., 2000; Tyre & Orlikowski, 1994), but explicitly focuses on technology and routines. I focus on three studies that provide an especially clear picture of how changing technology is entangled with changing routines: Goh et al. (2011), Leonardi (2011), and Berente et al. (2016).

2.2.1.1. Co-evolution of routines and technology

Goh et al. (2011) conducted a detailed field study of the implementation of new healthcare information technology (HIT) system for in-patient care in a hospital. Based on their fieldwork, they "propose a dynamic, process model of adaptive routinization of HIT that explicates the mechanisms through which HIT systems are incorporated into hospital routines" (2011, p. 566). Goh et al. (2011) model healthcare routines as narrative networks (Pentland & Feldman, 2007). They compare the network before and after the implementation of new systems that include hardware and software (e.g., "computers on wheels"). Drawing on adaptive structuration theory (DeSanctis & Poole, 1994), Goh et al. (2011) conceptualize the interaction of technology and routines as a process of co-evolution:

> Methodologically, this study demonstrates that organizational routines viewed as narrative networks provide a rich and promising lens through which to understand the HIT adaptation process. We find that routines are not simply passively disrupted by technology, but rather interact through functional affordances and symbolic expressions. These interactions trigger agentic forces that actively modify the newly implemented IT artifacts. (Goh et al. 2011, p. 583)

Goh et al. (2011) focused on the initial implementation of new systems. They mapped changes in two key routines for in-patient care: consulting and rounds. They identify three phases but do not put a specific time window on adaptation and subsequent refinements. They note that after initial implementation, the technology is subject to ongoing, repeated refinement. The system upgrade I report here could be considered as a typical refinement in their framework.

2.2.1.2. Imbrication of routines and technology

Leonardi (2011) uses a field study of automotive crash testing to illustrate the idea of imbrication. Leonardi (2011, p. 147) argues that:

> Imbrication of human and material agencies creates infrastructure in the form of routines and technologies that people use to carry out their work. Routine or technological infrastructure used at any given moment is the result of previous imbrications of human and material agencies.

Through careful qualitative fieldwork, Leonardi (2011) describes this process as a series of steps where technical changes are followed by adaptation in the routines and vice versa. In this way, he breaks down the co-evolutionary process described by Goh et al. (2011) into discrete steps.

2.2.1.3. Routines as "shock absorbers"

Berente et al. (2016) studied the implementation of an enterprise resource planning systems at NASA. They documented numerous ways that routines diverged from the intent of the designers. From these observations, they theorized that routines can act as "shock absorbers" that buffer organizational structures and processes from changes in technology (Berente et al., 2016). Over time, there is mutual adjustment and alignment between the systems and routines.

Throughout these field studies, I can identify three themes that are relevant to my inquiry in this paper. First, as Swanson (2019) argues, I see that routines and information systems are integrated. Technologies are wrapped in routines; the technology only functions in the context of the routines where it is used (for treating patients, simulating car crashes, or managing budgets and inventory).

Second, I see the familiar gap between the systems *as designed* and patterns of action *as enacted* (Boudreau & Robey, 2005; Pentland & Feldman, 2008; Vaast & Walsham, 2005). As Orlikowski (2000, p. 412) notes, people "have the option, at any moment and within existing conditions and materials, to 'choose to do otherwise' with the technology at hand." Technology shapes but does not determine how people choose to use it. Thus, when technological artifacts change (as they do in a system upgrade), behavior does not necessarily follow.

Third, technology and routines change in succession as a process of repetitive, stepwise change or coevolution. This perspective adds nuance to the classic debate between technological determinism and constructivism (Leonardi & Barley, 2008). The relationship between technology and practice is mutually constitutive, but a closer look at the process reveals that changes are punctuated. In the analysis that follows, I zoom in on the dynamics of one of these punctuations.

2.2.2. The Importance of Persistence

By definition, upgrades and other disruptions happen in the context of ongoing routines. The world does not start fresh with every new version of Windows. Field studies (such as Goh et al. 2011 and Leonardi 2011) have focused on what *changes*, but they have paid less attention to what *persists*. This emphasis is appropriate because the field of information systems has an inherent interest in innovation (Yoo et al., 2010). However, work and organization can't continue unless parts of the routine persist.

When action patterns persist over time, this persistence can be interpreted in several ways, such as inertia (Gilbert, 2005), resistance (Becker et al., 2005), persistence (Howard-Grenville, 2005), regeneration (Birnholtz et al., 2007) or resilience (Grote et al., 2009). Inertia and resistance seem negative, while resilience and regeneration seem positive; but either way, the tendency of routines to persist is a crucial but under-appreciated aspect of digitalization. Researchers have examined the effect of habits on the continued use (Limayem et al., 2007; Polites & Karahanna, 2013), but this research is framed in terms of individual-level habits and choices. By definition, organizational routines embody patterns of action that engage multiple individuals (Feldman & Pentland, 2003).

Schulz (2008) offers an encyclopedic list of mechanisms that keeps routines "on track", ranging from very macro (institutional norms) to very micro (neuronal priming). Cohen and Bacdayan (1994) present evidence that routines are stored in the procedural memory of individuals performing the routine, so that routine can be considered concatenated habits.

Theoretical explanations of routine persistence have not considered the structure of the routine itself as a factor. I introduce and develop this central idea in the next section.

2.2.3. Routine Dynamics as Network Dynamics

Routine dynamics concerns understanding the mechanisms that influence stability or change in action patterns (Feldman et al., 2022). An organizational routine can be represented as a valued, directed graph where the vertices represent categories of action and the edges represent sequential relations between those categories (Pentland et al., 2017). In process mining, this is called a "directly follows graph" (DFG) (van der Aalst, 2019). Where a conventional social network represents relations between actors (e.g., people), a DFG represents relations between categories of actions. In research on organizational routines, these graphs are often referred to as "narrative networks" (Pentland & Kim, 2021).

In a narrative network, a path represents a possible way of getting something done (Goh and Pentland 2019). When a change occurs, such as a software upgrade, it may affect the structure of the network. However, some of the edges in the network need to stay the same, or else the work would cease because there would be no paths for getting things done. For this reason, persistence matters.

To model the dynamics of digitalization, I need to explain edge formation/dissolution, which is the fundamental mechanism of the network dynamics (Snijders, 2001). Pentland et al (2019) use this approach to simulate the dynamics of drift in digitalized processes. My goal is to explain why the structure of the routine changes (or persists) after an upgrade or other disruption. In social network research, models that predict edge formation or deletion are often referred to as *selection* models because they predict how people select other people as interaction partners (Steglich et al., 2010). There are well-established selection mechanisms that drive dynamics in social networks, such as homophily and preferential attachment (Snijders, 2001). My goal here is to identify and test generalizable mechanisms that drive the analogous persistence and dissolution of edges in networks of routines during the dynamics of digitalization.

2.3. Hypothesis Development

Network dynamics can be defined in terms of two basic processes: edge formation and edge dissolution (Snijders, 2001). In this paper, I focus on mechanisms that influence the persistence (or dissolution) of existing edges. I state three simple hypotheses, all of which concern how the structure of the routine before a disruption predicts the structure of the routine after a disruption. Each hypothesis involves a particular way of weighting the edges in the network. Edges indicate sequential relations between actions and each edge is part of a larger path (a way of getting things done). The weights on the edges indicate the properties of that piece of the path: How frequently is it followed? How fast is it, on average? How much does the context change from one action to the next?

2.3.1 Frequency of Edges

Repetition is definitional of routinized behavior (Becker, 2004). Edges that repeat frequently form the "ruts in the road" (Birnholtz et al., 2007) that define routinized patterns of action. Repetition is an indicator of behavior that minimizes search and cognitive effort (Hansson et al., 2021; March & Simon, 1958).

To test the effect of frequent repetition on persistence, I conceptualize the frequency of edges in a straightforward way, like the frequency of communication in a social network (Wasserman & Faust, 1994). For this hypothesis, the edges in the network are weighted according to how frequently they occur each day. I expect more frequent edges to persist after a disruption to the network:

H_1: *Frequent edges are more likely to persist after a disruption.*

2.3.2. Speed of Edges

Speed has long been recognized as an indicator of routinization (Cohen & Bacdayan, 1994; Su et al., 2013). Cohen and Bacdayan (1994) use the speed of response to define the routinization of moves in a card game. Su et al. (2013) use speed of response to identify routines in human-computer interaction. These findings align with the idea that routinized patterns of action are important for efficiency (Becker, 2004).

To test the effect of speed on the structure of a routine after a disruption, I compute the mean duration of each handoff in the network, where handoff is defined as the transition from one action to the next (Pentland et al., 2017). This definition generalizes the conventional notion of handoff (which assumes that handoffs are between two different actors) to include actions performed by the same actor at a later time, perhaps in a different location or using a different technology. For example, a nurse might enter some data for a patient on one workstation in the examination room and then review or update that data for that same patient a few minutes later on a different workstation in another part of the clinic. Thus, clinical staff can hand work off to themselves.

For this hypothesis, edges in the network are weighted according to how long they take to perform, on average, using time-stamp data from the event log. Edges with shorter mean duration indicate faster ways of getting things done. I hypothesize that fast edges (edges with shorter mean duration) are more likely to persist after a disruption than slower edges (edges with longer mean duration).

H_2*: Faster edges are more likely to persist after a disruption.*

2.3.3. Coherence of Edges

Unlike repetition and speed, coherence is not one of the classic indicators of routinization. Coherence is defined by the extent of similarity (or difference) between the context of sequentially adjacent pairs of actions (Pentland et al., 2017). Coherence can easily be computed on a narrative network where the nodes are defined by multiple contextual factors (Pentland et al., 2017). Coherence represents the number of contextual factors that remain the same across an edge. For example, are two adjacent actions in the network performed by the same actor? Do both actions occur in the same place? Do they involve the same tools or technology? Coherence provides a way to quantify the effects of materiality (embodiment and embeddedness) on the pattern of action (Feldman et al., 2022).

Coherence can be operationalized in a narrative network, where each node is defined by a number of contextual factors, such as place, actor, and technology. When more factors change, the context is less coherent. When fewer factors change, the context is more coherent. Coherence provides another way of weighting the edges in the network. The logic of this hypothesis is similar with the logic for effects of homophily in social networks ("birds of a feather…"). Thus, I expect that more coherent edges (same actor, same place, same technology) will be more likely to persist:

H_3: ***More coherent edges are more likely to persist after a disruption.***

2.4. Illustration: Upgrading an EHR System

To test these hypotheses, I use data from a medical center in the Northeastern U.S. where there was a major upgrade of their electronic health record (EHR) system. I examine the patterns of action for six weeks, three weeks before and after the upgrade.

2.4.1. Upgrading the EHR User Interface

In October 2019, the medical center upgraded from EPIC v2017 to EPIC v2019. This upgrade was considered a major system upgrade. The changes included: 1) creation of a Storyboard which rearranged the layout of patient information and activities, 2) use of sexual orientation gender identity (SOGI) and preferred name appearing for patient interactions; 3) display of cost for inpatient medications and testing at time of order for provider decision making; 4) expansion of view to widescreen mode, which can require hardware replacement to use. Two other high-impact changes influencing medical workflow, but not changing it directly included: 1) the ability of users to view data from multiple EPIC organizations and 2) online registration for Business Continuity Access (BCA) for faster downtime recovery.

A campaign to bring awareness of these widespread and high-impact changes began in April 2019 followed by detailed information sessions in July 2019. Training and practice sessions for users were implemented in August 2019. All upgrade changes were complete and live on October 14, 2019.

The impact of this upgrade on clinical activity was unclear and most likely varied by department. The widespread upgrades minimized screen jumps, consolidated important information to be viewable from anywhere in the chart, and allowed users to accomplish more on a single screen with fewer clicks and scrolling. It was anticipated that there would be minimal disruption from this upgrade if all users were prepared appropriately prior to the “go-live” date in October.

2.4.2. Data Source

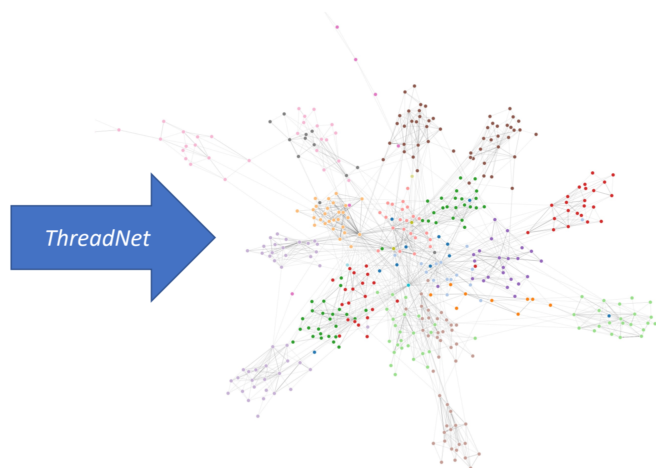
I analyzed data extracted from the audit trail of the EHR system. EHR audit trail data is increasingly being used to model clinical workflows (Adler-Milstein et al., 2020). The subset of records used here includes detailed, time-stamped records of EHR utilization in 4885 patient visits at five clinics from three different medical specialties (two from Dermatology, two from Orthopedic surgery, and one from pediatric oncology). The data include all visits to each of these clinics from September 16, 2019 (three weeks before the start of the system upgrade) to November 10, 2019 (three weeks after), before and after of system upgrade date (October 14th). Within this period, I excluded weekends and some weekdays for each clinic when less than 2,000 actions are performed.

Figure 2.1 includes a brief example of the audit trail data. Figure 2.1 shows how *ThreadNet* (Pentland et al., 2020) can be used to convert EHR audit trails into networks. Figure 2.1 shows a small part of an audit trail for one patient visit. Each row is a time-stamped action. Each unique row becomes a node in the network and sequentially adjacent nodes become edges in the network. The resulting network is a narrative network where each node is defined by the combination of action, role, and workstation.

FIGURE 2.1. CONVERTING EHR AUDIT TRAIL INTO NETWORKS

EHR Audit Trail

Time Stamp	Action	Role	Work-station
10/7/19 10:49:03	REGHARACCTCRT	Admin Tech	A
10/7/19 10:49:04	RGWKFLBEGIN	Admin Tech	A
10/7/19 10:49:05	FORM_VIEWED	Admin Tech	A
10/7/19 10:49:05	RGEPTBSCDM	Admin Tech	A
10/7/19 10:49:06	FORM_VIEWED	Admin Tech	A
10/7/19 10:49:07	MR_DEMOGRAPHICS_VIEWED	Admin Tech	A
10/7/19 10:49:09	RGEPTADDRS	Admin Tech	A
10/7/19 10:49:10	REG_SC_EPTLANGUAGE	Admin Tech	A
10/7/19 10:49:11	REG_SC_EARDEMOGRAPHICS	Admin Tech	A
10/7/19 11:16:44	AC_VISIT_NAVIGATOR	Physician	B
10/7/19 11:16:48	VISIT_DIAGNOSES_VIEW	Physician	B
10/7/19 11:16:50	MR_PROBLEM_LIST_ACCESS	Physician	B
10/7/19 11:16:51	VISIT_DIAGNOSES_VIEW	Physician	B
10/7/19 11:16:52	MR_LOS_ACCESS	Physician	B
10/7/19 11:17:01	MR_REVIEW_ENCOUNTER	Physician	B
10/7/19 11:17:04	MR_REVIEW_MEDIA	Physician	B
10/7/19 11:17:05	MR_REVIEW_ORDERS	Physician	B
10/7/19 11:17:06	MR_CHART_REVIEW	Physician	B
10/7/19 11:17:07	MR_CHART_REVIEW	Physician	B
10/7/19 11:23:14	MR_REPORTS	Clinical Tech	C
10/7/19 11:23:16	AC_VISIT_NAVIGATOR	Clinical Tech	C
10/7/19 12:23:42	SEC_FLOWSHEET_VIEW	Nurse	C
10/7/19 12:23:43	UCW_RELATED_ENCOUNTERS	Nurse	C
10/7/19 12:23:44	MR_REVIEW_ENCOUNTER	Nurse	C
10/7/19 12:23:48	MR_REVIEW_ORDERS	Nurse	C
10/7/19 12:23:57	MR_CHART_REVIEW	Nurse	C
...	...	....	...



The inclusion of contextual factors, such as role and workstation, is a departure from standard practice in process mining, which often treats actions as decontextualized. However, I include context here because routines are enacted from situated actions (Feldman et al. 2022).

Thus, I use unique combination of action-role-workstation as nodes and pairs of nodes to define the networks in this study.

2.4.2.1. Selection of clinics

The data analyzed here were collected as part of a larger study that included three medical specialty areas: dermatology, orthopedic surgery, and pediatric oncology. Where possible, I present data from two clinics in each of those specialty areas to improve the generalizability of the analysis. Pediatric oncology only had one clinic.

2.5. Descriptive Findings

Before testing my three main hypotheses, it is helpful to describe the effects of the disruption in more detail. I present two kinds of simple, descriptive analyses to help the reader build intuition about the EHR system upgrade and its effects.

2.5.1. Changes in the Narrative Networks

Table 2.1 shows the average number of visits per day in each clinic, as well as the size and density of the narrative network in each clinic before and after the upgrade. These networks have thousands of edges (between 8760 and 25,167), but the density is low. Only a tiny fraction of the possible edges was observed. With the exception of the orthopedic clinics, the networks had fewer nodes after the upgrade.

TABLE 2.1. SIZE AND DENSITY OF THE NETWORK IN EACH CLINIC

	Visits	Before Upgrade			After Upgrade		
	per day	Nodes	Edges	Density	Nodes	Edges	Density
DERM A	16.68	1,852	10,989	0.0032	1,596	8760	0.0034
DERM B	46.05	3,911	25,167	0.0016	3,494	21,281	0.0017
ORTHO A	9.73	1,247	11,800	0.0075	1,289	11,193	0.0017
ORTHO B	13.78	4,003	17,159	0.0011	4,647	19,844	0.0010
PEDONC	9.45	3,376	16,152	0.0014	2,543	11,990	0.0019

Each clinic must be analyzed separately because workstation codes (and some of the roles) are different in each clinic. As a result, the action-role-workstation combinations in each clinic have different labels and the networks cannot simply be aggregated.

2.5.2. Visualizing Diachronic Changes

Figure 2.2 shows the changes to the pattern of action over time using the network time-series visualization recommended by Pentland et al. (2021a). The figure shows three weeks before and after the upgrade on October 14th. On that date, 40 actions were added to the EPIC system that serves all of the clinics, while 60 actions were removed from the system.

This visualization addresses a simple question: how much is this network changing over time? The horizontal axis represents time measured in days; each point in the figure represents one day in one clinic. The vertical axis represents the cosine similarity of the network of each clinic on each day compared to the first day in the time series for each clinic. This similarity measure is based on the frequency of nodes or edges in the network, which change from day to day. The left side of Figure 2.2 is based on the nodes; the right side of Figure 2.2 is based on the edges. When the graph stays horizontal from day to day, the pattern of action is staying the same. For clarity, I removed a handful of outliers with very few patient visits per day.

Figure 2.2 shows the same data at three different levels of contextual specificity. Each row of the figure incorporates more situational context into the definition of the nodes in the network (Pentland et al., 2020). In the top row, the nodes are defined by actions only. In the middle row, the nodes are defined by action + role. This adds the social context of each action: *who* did what. In the bottom row, the nodes are defined by action + role + workstation. This adds the material context of each action: who did what and *where*. In each panel of Figure 2.2, I show the mean value and 95% confidence interval on the mean, before and after the upgrade. This clearly shows a significant disruption at all three levels of contextual specificity.

I show these three levels of contextual specificity for two reasons. First, it shows how situating the pattern of action in its social and material context increases the apparent variability of the routine. Second, all of my subsequent analysis is conducted on the actions situated in their social and material context (the highest level of contextual specificity) because I want to understand the effect of contextual coherence. Figure 2.2 helps convey the substantial amount of natural variability that exists in these clinical work processes. However, as expected, there is still a discernable difference before and after the upgrade. My goal in the analysis that follows is to understand how the disruption affects these fine-grained, situated patterns. To address my research question, I need to see beyond the obvious noise in Figures 2.2 (c) and 2.2 (d) and extract signals that help us understand stability.

FIGURE 2.2. DIACHRONIC VIEW OF ROUTINES

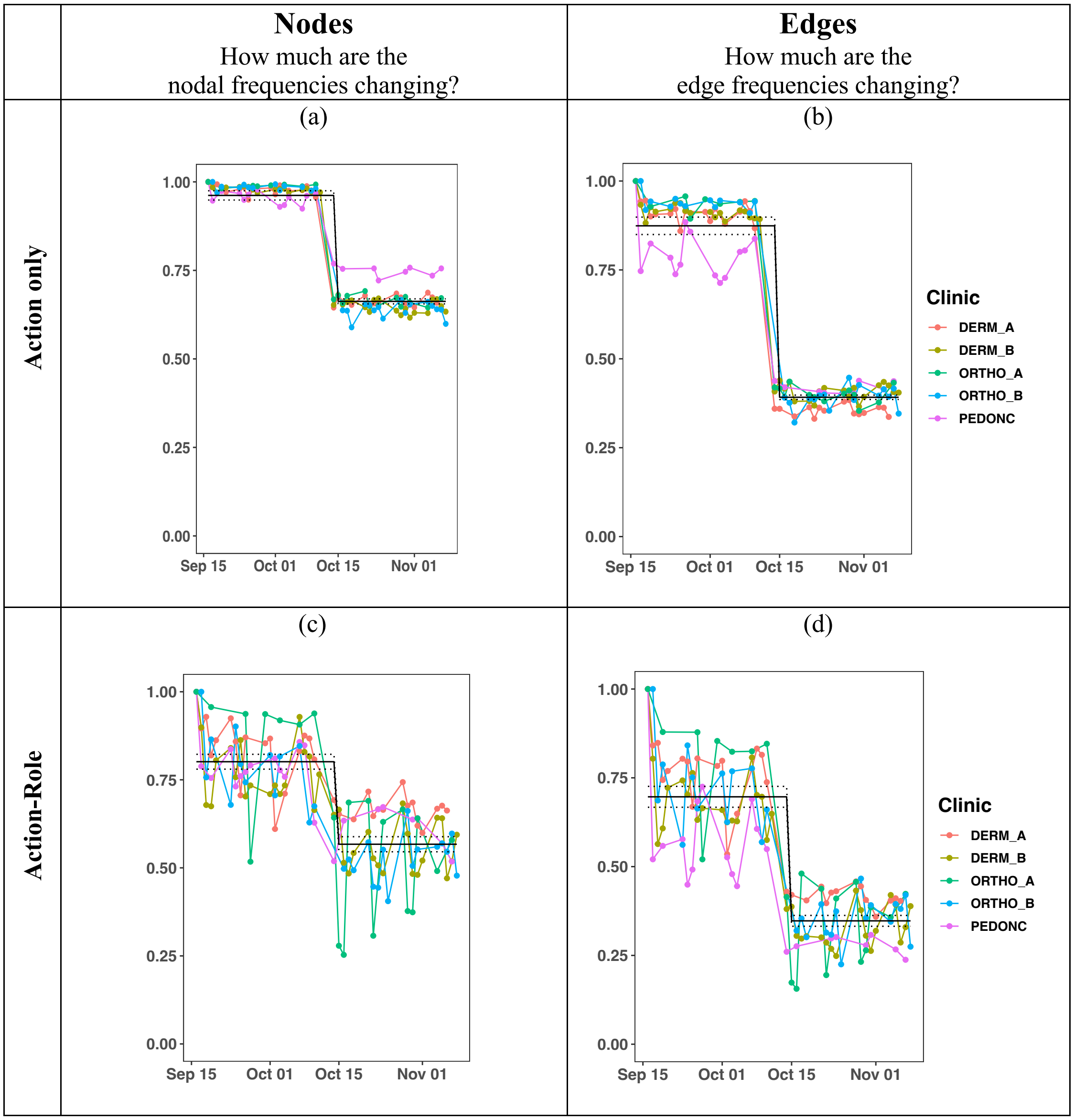
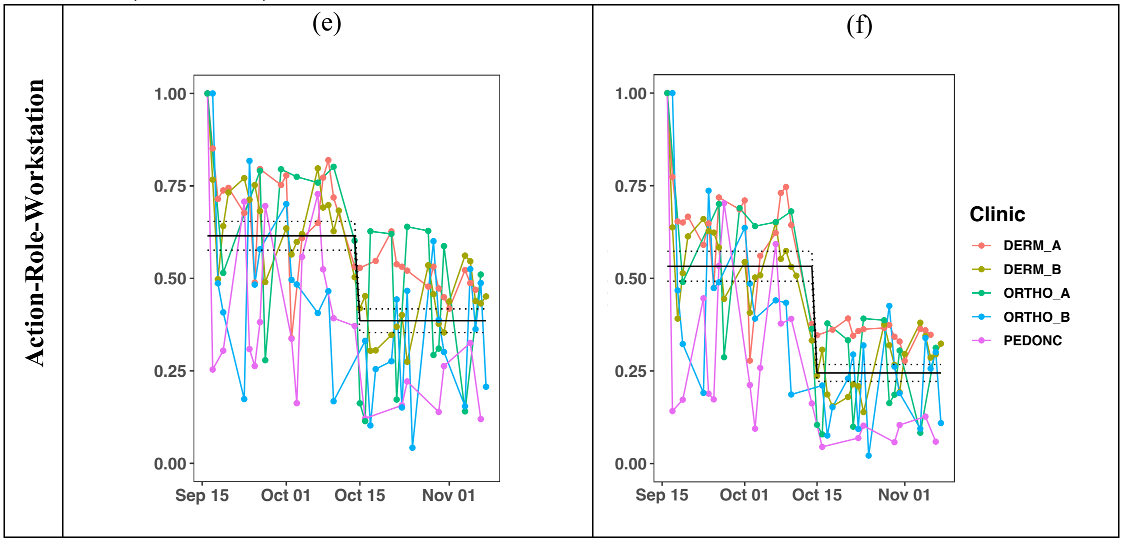


FIGURE 2.2. (CONT'D)



Contrary to the literature on information systems implementation and adaptation (e.g., Majchrzak et al. 2000), there was not an extended period of adjustment. The routines adapted to the new software immediately after the upgrade. Using a simple OLS regression, I tested the rate of change after the disruption and found that it is not significantly different than zero (see Appendix A). There is a lot of variation from day to day, but there is no trend. This implies that new routines stabilized very quickly after the new system went live.

2.6. Analysis

I examine my hypotheses in five different clinics with two kinds of models. Logistic regression provides an easy-to-interpret model of edge dissolution (Minhas et al., 2019). It also provides a simple way to test for collinearity in the independent variables. However, the standard errors from this model are naïve because they ignore dependencies in the data (Hoff, 2005). Therefore, to fully account for network effects I use the dyadic prediction model for network dynamics described by Hoff (2005, 2009) which uses latent spaces and random effects to account for dependencies in the data. Across all five clinics, with both kinds of models, the results are similar. I discuss the details of these analyses in the next sections.

2.6.1. Logit Models

I construct a logit regression model to examine evidence of the effects of edge characteristics on the structure of routines. The logit model is the simple and well-defined model to examine the relationship between the directed dichotomous relations of the edges and statistics of network characteristics (Robins et al., 1999; Wasserman & Pattison, 1996). I specify the structure as the persistence of edges. The proposed model is as follows:

$$(1)\ \mathrm{logit}\left(Persistence_{ijt}\right) = \beta_1\left(frequency_{ijt-1}\right) + \beta_2\left(\overline{speed}_{ijt-1}\right) + \beta_3\left(coherence_{ijt-1}\right)$$

In this model, the time period *t* represents three weeks before and three weeks after. The dependent variable in this model is $Persistence_{ijt}$, which is a binary variable and equals 1 if edge between actions *i* and *j* in the network exists before and after the system upgrade, and 0 if it only exists before the upgrade. Thus, the edges considered in this analysis include only those that existed before the system upgrade. $frequency_{ijt-1}$ represents the frequency of the edge from the previous time period, as in H_1. $\overline{speed}_{ijt-1}$ reflects the average speed of the edge w_{ij}, as in H_2. $coherence_{ijt-1}$ represents the extent to which actions *i* and *j* share a coherent context, as in H_3. I estimate the model for each clinic separately because they have different sets of edges. I use standardized variables so I can compare the relative magnitudes of the effects in the models.

2.6.2. Logistic Regression Results

Table 2.2 shows the result of the logistic regression in each clinic. I use standardized variables, with log transformations for frequency and speed.

TABLE 2.2. LOGISTIC REGRESSION RESULT ON EDGE PERSISTENCE

Variables	(1) DERM_A	(2) DERM_B	(3) ORTHO_A	(4) ORTHO_B	(5) PEDONC
H_1: Frequency	0.7031***	0.7823***	0.6651***	0.6943***	0.6090***
	(0.0291)	(0.0219)	(0.0300)	(0.0258)	(0.0233)
H_2: Speed	- 0.0213	0.0525**	0.0343	- 0.0238	0.0092
	(0.0255)	(0.0187)	(0.0286)	(0.0226)	(0.0290)
H_3: Coherence	0.1834***	0.4296***	0.5580***	0.4944***	0.7493***
	(0.0280)	(0.0217)	(0.0334)	(0.0270)	(0.0467)
Constant	-1.8727***	-2.6562***	-3.3371***	-3.1807***	-4.3291***
	(0.0874)	(0.0697)	(0.1107)	(0.0874)	(0.1570)
Observations	10,906	24,886	10,300	16,999	16,046
Pseudo R2	0.0906	0.131	0.124	0.127	0.114

Naïve robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05

In Table 2.2, I observe that in all clinics the probability of edge persistence increases with the frequency of edges from the previous period. I can interpret this as two actions tend to persist more after the system upgrade the more frequently they were performed before the upgrade. In contrast, the magnitudes of the estimates for speed are typically less than their naïve standard errors, with the exception of one Dermatology clinic (DERM_B) whose estimate is positive and more than three times its naïve standard error. I infer that in contrast to my hypothesis, speed of the edges does not increase their tendency to persist. Lastly, I infer that coherence has significant and positive coefficient on persistence. This indicates that the probability of edge persistence after the system upgrade increases when the actions are performed by the same role and at the same workstation.

From the results of the logit regression models, I infer that the edge characteristics, frequency (H_1) and coherence (H_3), have positive effects on edge persistence. However, the speed of the edge (H_2) does not seem to affect persistence. As explained above, the results from logistic regression may be biased because of unobserved random effects due to the interdependence between the nodes. Thus, I use the dyadic prediction model for network dynamics described by Hoff (2005, 2009).

2.6.3. Dyadic Prediction Model for Network Dynamics

The dyadic prediction model is introduced to account for the interdependent patterns in network and make predictions about the paths based on not only the observed characteristics of the nodes and edges but also unobserved random effects on the base rate of edges (Minhas et al., 2019). Considering the interdependence between actions is especially important because the actions and edges are not independent.

In social networks, to estimate how actors choose others with whom to interact, the logistic selection model is generally considered as

$$\log\left[\frac{p(w_{ij})}{1-p(w_{ij})}\right] = \beta_0 + \beta_1|x_i - x_j| \quad (2)$$

where w_{ij} is interactions, edge persistence, between *i* and *j*, x_i is a characteristic of node *i* such as weight, and β_0 is odds of tie occurring when $|x_i - x_j| = 0$. Lastly, β_1 represents the change in log odds of a tie occurring for a one unit increase in $|x_i - x_j|$. In this context, if each of the interactions is conditionally independent, I can write the joint likelihood function as

$$P(\mathrm{W}|\beta, \mathrm{X}) = \prod_{i\neq j} \log\left[\frac{p(w_{ij})}{1-p(w_{ij})}\right] \quad (3)$$

Where I write W as the network matrix of w_{ij}, X as the array of *x,* and β as the regression coefficient. However, there exist random effects representing potential interdependence in the process network. As a directed network, the event in the process is selected based on the previous paths, and it also influences the next event. Amis-specified model without considering the potential dependencies can have simultaneous dependencies for reciprocity between events

(Hoff, 2009; Holland & Leinhardt, 1981). Thus, it is important to specify a model that considers potential dependencies in the data. The suggested random effect model is as follows:

$$\log\left[\frac{p(w_{ij})}{1-p(w_{ij})}\right] = \beta_e^T \mathrm{x}_{e,i,j} + \beta_s^T \mathrm{x}_{s,i} + \beta_r^T \mathrm{x}_{r,j} + \theta_i + \theta_j \quad (4)$$

$$\theta_i = \gamma_0 + \gamma_1 x_i + u_i \quad (5)$$

$$\theta_j = \gamma_0 + \gamma_1 x_j + v_j \quad (6)$$

Where $\mathrm{x}_{d,i,j}$ refer to edge covariates, $\mathrm{x}_{s,i}$ and $\mathrm{x}_{r,j}$ represent covariates for sending and receiving nodal attributes, and θ_i and θ_j are the random effects of senders and receivers. In my model, I interpret senders as predecessor actions and receivers as successor actions.

There is another potential dependence associated with transitivity and clusterability of nodes in the network (Hoff, 2005). This third-order dependence pattern can be accounted for with the similarity of relational patterns of two nodes (Minhas et al., 2019). Each node has unobserved attributes which can affect the ties between nodes. In the latent factor model, these unobserved factors of nodes are considered an unobserved vector of factors based on similar relational patterns. Hoff (2005), 2009) suggests adding $u_i v_j$ term in the model, which represents the similarity between pairs of nodes on each dimension based on the latent nodal attributes of sending and receiving nodes. Thus, the final model proposed by Hoff (2009) is as follows:

$$y_{ij} = \beta_e^T \mathrm{x}_{e,i,j} + \beta_s^T \mathrm{x}_{s,i} + \beta_r^T \mathrm{x}_{r,j} + \theta_i + \theta_j + u_i v_j + \epsilon_{i,j} \quad (7)$$

2.6.4. Application of the Latent Space Model

My goal is to predict the frequency of all edges in the narrative network that represents the clinical documentation process. To do so, I use the previous state of the process (at time *t-1*) to predict the current state of the process (at time *t*). Using this approach, I can test my three hypotheses within the model as follows:

$$(8) \qquad Persistence_{ijt} = \beta_1(frequency_{ijt-1}) + \beta_2(\overline{speed}_{ijt-1}) + \beta_3(coherence_{ijt-1}) + \theta_i + \theta_j + u_i v_j + e_{ij}$$

where θ_i and θ_j are random effects relating to the base rate of actions i and j. If i and j occur more or less often, that will directly influence how often w_{ij} occurs. As I apply the model here, θ_i and θ_j reflect the change in the repertoire of actions. I am interpreting random effects (θ_i and θ_j) as control variables: Controlling for changes in base rates of the actions, what drives changes in the pairs of actions? Lastly, $u_i v_j$ represents the similarity between pairs of nodes on each dimension (action *i* and *j)* of a latent space and e_{ij} is the error term.

2.6.5. Results of Dyadic Prediction Models

To estimate the latent space models, I use the R package *amen* (https://cran.r-project.org/web/packages/amen/amen.pdf) which uses an MCMC (Markov Chain Monte Carlo) procedure. As with the logistic regression, I use standardized variables, with log transformations for frequency and speed. Table 2.3 shows the results for each of the clinics in my data. The results show that standard errors of the variables are significantly decreased compared to the result of logit regression, as a lot of the variance is explained by the random effects and latent factors.

TABLE 2.3. RESULTS OF ANALYSIS FOR EDGE DISSOLUTION

	DERM A	DERM B	ORTHO_A	ORTHO_B	PEDONC
H_1: Frequency	0.516***	0.968 ***	0.559***	0.573***	0.573***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)
H_2: Speed	0.101***	0.122***	0.026	0.077**	0.015
	(0.003)	(0.0006)	(0.044)	(0.003)	(0.003)
H_3: Coherence	1.229***	1.675***	1.353***	1.300***	1.348***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Constant	-6.105***	-5.833***	-6.727***	-6.246***	-6.649***
	(0.020)	(0.027)	(0.037)	(0.032)	(0.004)
Random Effect: a_i	0.926	0.709	1.116	0.710	0.846
	(0.012)	(0.012)	(0.016)	(0.011)	(0.035)
Random Effect: b_j	0.805	0.557	0.819	0.517	0.553
	(0.018)	(0.019)	(0.025)	(0.017)	(0.019)
# nodes	1,851	3,910	3,090	4,002	3,375
# edges	10,906	24,886	16,503	16,999	16,049

2.6.6. Summary of Results

Table 2.4 summarizes the results of the analysis for both kinds of models.

TABLE 2.4. SUMMARY OF RESULTS

Hypothesis	Logistic Regression Model	Dyadic Prediction Model	Overall
H_1: Frequency	Strong, significant in all clinics	Strong, significant in all clinics	Supported
H_2: Speed	Weak, opposite direction in all clinics	Weak, opposite direction in all clinics	Not supported
H_3: Coherence	Strong, significant in all clinics	Strong, significant in all clinics	Supported

2.6.6.1. Frequency (H_1)

As expected, the frequency of an edge is a strong predictor of its tendency to persist after a disruption. This finding aligns with everything I know about repetitive patterns of action: they tend to keep repeating (Schulz, 2008). However, this is the first time this hypothesis has been tested in empirical research.

2.6.6.2. Speed (H_2)

The hypothesized effect of speed is not supported by the data. Contrary to existing theory, it would appear that *slower* edges are slightly *more* likely to persist than faster edges. This effect is small and not always statistically significant, so I should not overstate its implications. Nevertheless, it is interesting because it seems to contradict the idea that speed indicates routinization, which was introduced by Cohen and Bacdayan's (1994) pioneering lab experiment.

2.6.6.3. Coherence (H_3)

The hypothesized effect of coherence is also supported by both models in all of the clinics. In the dyadic prediction model, where the coefficients and standard errors are less subject to bias, the magnitude of this effect is consistently much larger than the effect of frequency. This suggests that relations between actions are strongly shaped by contextual factors, accounting for *the effect of repetition.* In my data, edge persistence is shaped by the role of the person performing the action and the workstation where it is performed.

2.6.7. Which Edges are Most Persistent?

Contrary to the stereotype of routines as fixed patterns of action (March & Simon, 1958), these outpatient clinical routines are quite variable. Any given edge has a substantial probability of disappearing (or reappearing) from one time period to the next, especially after a disruption. Nevertheless, it is interesting to examine which edges are most nearly locked in.

The dyadic prediction model estimates the probability of each edge persisting after the upgrade. Using this result, I can identify the edges in each clinic that are most likely to survive

($Persistence_{ij} \geq 0.95$). In Figure 2.3, I use a simple 3-D scatter plot to show how these highly persistent edges compare to the others. In Figure 2.3, larger red points represent edges with more than or equal to 95% probability of persistence. In contrast, smaller blue dots represent the edges with less than 95% probability of persistence after the upgrade. The results are similar in all of the clinics, so to save space I present one clinic from each medical specialty.

FIGURE 2.3. WHICH EDGES ARE MOST LIKELY TO PERSIST?

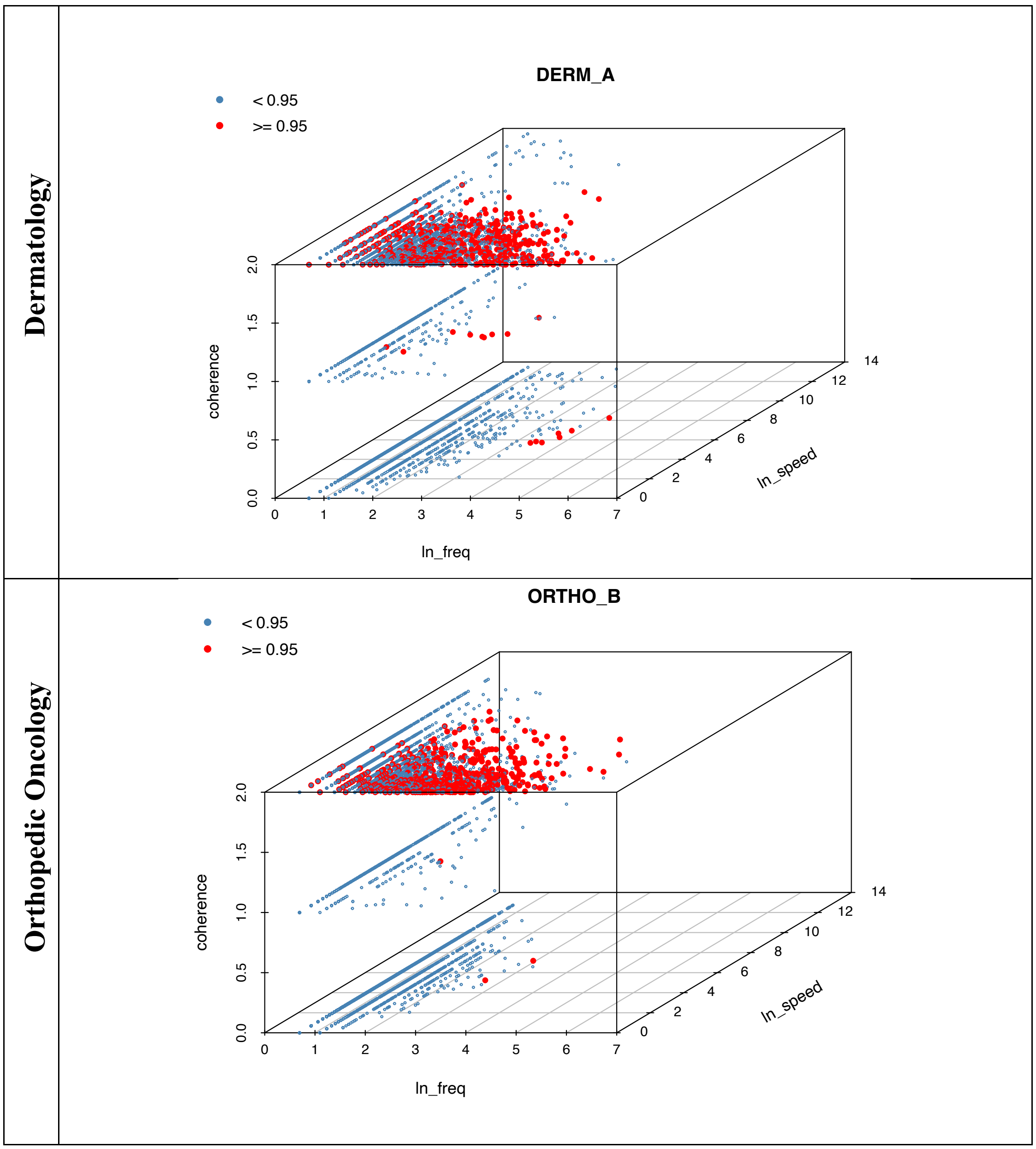
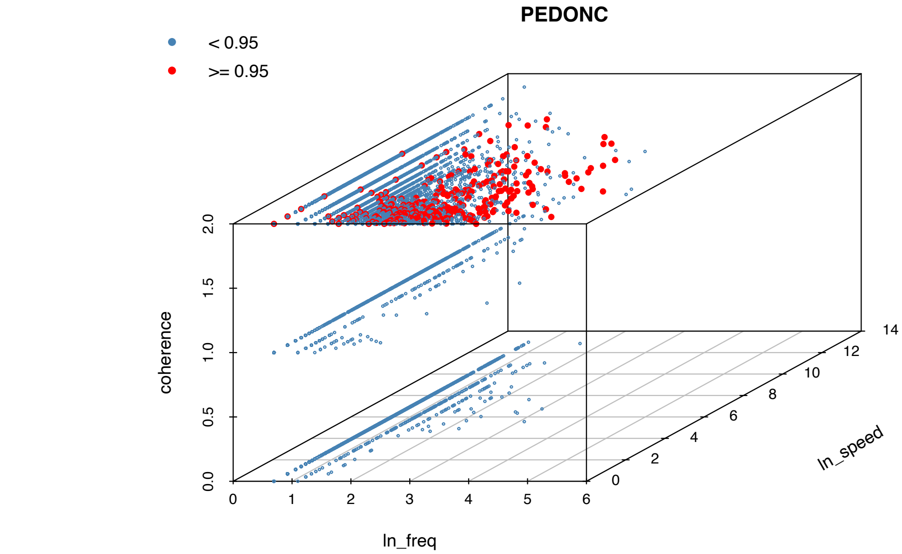


FIGURE 2.3. (CONT'D)

Pediatric Clinic	

Clearly, coherence dominates the picture. For all clinics, most of the persistent edges are at the highest level of coherence. This implies that having the same/similar contextual factors correlates with lock-in. What this means, in concrete terms, is that the most persistent pairs of sequentially adjacent actions are performed by the same person at the same workstation. In other words, materiality dominates the picture. Although it is based on the top 5% of persistence, the visualization in Figure 2.3 reinforces the findings from the models. The edges that are most likely to persist have the highest frequency and coherence. In contrast, speed does not have a clear relationship to persistence probability.

Notice, however, that in the Dermatology clinic, 16 edges persisted with lower coherence. When coherence is zero, the pairs of actions are performed by a different person at a different workstation. The most persistent handoffs in DERM_A are between the clinical coordinator and the nurses or clinical technicians. At the next level of coherence, the most persistent pairs of actions are performed and transferred to each other at the same workstation mostly or the same role tend to take different actions at different locations.

2.7. Discussion

This paper provides a novel perspective on the dynamics of digitalization. The empirical foundation for this theory is generated through process mining, which is usually used to discover a stationary model of a process (van der Aalst 2012). Here, I am using process mining to help build theory about stability and change in routines, as suggested by Pentland et al (2021). The contributions here go beyond the specific findings in these particular clinics. The main methodological contribution concerns the use of dynamic network models to analyze routine dynamics. I borrow a foundational idea from social network analysis (that network structure influences network dynamics) and apply this idea to routine dynamics. The theoretical contribution concerns the extension of Swanson's (2019) concept of technology as routine capability and the use of routine dynamics to develop a new theory about the dynamics of digitalization. In the following sections, I discuss these contributions in more detail.

2.7.1. Putting Action into Context

The essential conceptual move in this research is to locate actions in context. In a recent review, Avgerou (2019) examines the role of context in IS research. Her key message is that context is crucially important and enters IS-related phenomena in a host of different ways. Typically, I think of context as outside, in the background, like the weather. However, as Rosemann et al. (2008) point out, context can permeate to the finest-grained level of description. At this fine-grained level, context can change constantly throughout the execution of a process or routine as work is handed from one person to another, one place to another, one system to another, and so on. Explicitly locating actions in their immediate context aligns with the emphasis on *situated action* that has been the driving for the last 20 years of research on organizational routines (Feldman et al., 2022).

In this paper, I put action into context at this fine-grained level in two different ways. First, I put actions into sequential context. I do this by defining sequentially adjacent pairs of actions as the unit of analysis. These pairs of actions are the edges in the narrative network that represents a routine. This constitutes a departure from more familiar research traditions that emphasize isolated decisions by individual actors (e.g., psychology, behavioral economics). Actions are never isolated; they are always part of a larger trajectory, path, or line (Ingold, 2015).

Second, coherence puts actions into context by taking the actor (role) and location (workstation) into account. Without a doubt, there are many other contextual factors that could be included, but the combination of action+actor+location is indicative of the technology-in-use (Orlikowski, 2000). When I take the technology out of context (as suggested by Figures 2.2 (a) and 2.2 (b), the effects of change seem straightforward and perhaps even deterministic. When I examine actions in context, I see an entirely different picture, where the changes on October 19 are situated in a stream of continually changing networks.

2.7.2. Imbrication and Evolution

Where Goh et al. (2011), Leonardi (2011), and Berente et al. (2016) used ethnographic fieldwork, I have used archival trace data to zoom in on one particular technological change. As a methodology, fieldwork is well suited to the analysis of innovation and change because it can provide a more holistic perspective. The influence of culture, power, emotion, and conflict are all potentially on display and available for analysis. There is no way that an archival method, based on digital trace data, can offer those kinds of insights. What trace data and process mining can offer, however, is a complementary perspective that is not available to any human observer.

Imbrication and evolution are conceptualized as an ongoing series of changes, so I zoom in on one of those changes in detail. I examine the mechanisms that influence the tendency of routines to persist. Persistence can be interpreted as an indicator of a resilience (Grote et al., 2009), or resistance (Becker et al., 2005). Either way, persistence is an essential, take-for-granted aspect of digitalization. As routines evolve (Goh et al., 2011) or undergo successive refinements, changes, and re-alignments, significant parts of the overall pattern of action remain the same. Where IS research has generally put the changes in the foreground, I have put continuity in the foreground, as in Figure 2.3. In doing so, I see that only a small fraction of the overall pattern of action is truly locked in. At the level of situated action, there is a great deal of variability in the networks of action that are constitutive of this technology-in-use.

2.7.3. Routine Dynamics as Network Dynamics

In research on social networks, mechanisms like reciprocity, homophily, and preferential attachment contribute to the formation and dissolution of network ties (Snijders, 2001). Until now, analogous network-based mechanisms have never been defined or investigated in the context of digitally enabled routines. It is important to recognize that hypotheses 1-3 represent a first attempt at defining network-based mechanisms that influence the dynamics of routines and therefore, the dynamics of digitalization. These mechanisms may seem simple, but so are the key mechanisms that drive the dynamics of social networks: homophily ("birds of feather..."), preferential attachment ("the rich get richer...") and transitive closure ("the friend of my friend..."). In theory, simplicity is a virtue.

My analysis suggests that routines persist for structural reasons, such as frequency of repetition and coherence of context. The effect of coherence is particularly strong in these five clinics: roughly twice as strong as the effect of repetition. In Figure 2.3, coherence is strongly associated with the most persistent edges. As it is defined in my data, coherence refers to the continuity of the actor and the location from one action to the next. Thus, pairs of actions with the highest coherence are performed by the same actor in the same location. For this reason, I can interpret the effect of coherence in terms of materiality. The metaphorical "ruts in the road" that make routines recognizable are embodied in the actors and places where they are performed.

2.8. Limitations

This study has some obvious limitations. First, I have data from a narrow context. This is essentially a case study of one software upgrade in a few clinics within a single medical system. The findings would be more generalizable if they were reproduced in a broader range of settings.

Second, I study a rather simple disruption: a system upgrade. It would be helpful to study a broader range of disruptions. For example, the COVID epidemic disrupted medical services in a variety of ways, from interruptions (e.g., lockdowns) to new technology (e.g., telemedicine). In this study, the routines immediately adapted to the upgrade. With more severe disruptions, I would not expect adaptation to occur as quickly. Data from different kinds of disruptions would provide additional tests of my hypotheses concerning the influence of frequency, speed, and coherence on the persistence of routines.

Third, I don't have measures of other variables (such as attitudes or incentives), nor do I have an interview or observational data about this upgrade. These variables would add richness to the story and allow us to discuss alternative explanations and consequences. The data I report here was collected as part of a larger study that was not specifically focused on upgrades or disruptions. Future studies would undoubtedly benefit from a combination of fieldwork and archival methods.

Fourth, I only address the dissolution of existing edges, not the formation of new edges. As a result, my analysis is limited to existing paths, not new paths. In future studies, it may be possible to use the attributes of actions to predict edge formation, as well.

2.9. Conclusion

The entanglement of technology and human behavior has been a central concern of information systems theory and practice for decades (Bostrom & Heinen, 1977; Mumford & Weir, 1979; Orlikowski, 1992) and remains a central "axis of cohesion" for the IS discipline (Sarker et al., 2019, p. 695). The theory and method I employ here offer a way to reinvigorate the sociotechnical foundations of the information systems field by explicitly examining the systemic connections between technology and patterns of action. As my analysis shows, this relationship can be noisy and complex. This is especially true when I examine it with fine-grained trace data.

The tools I demonstrate here provide a rigorous new way to analyze stability and change, even in a setting that has a great deal of variability. As a discipline, information systems scholars tend to focus on innovation and change (Yoo et al., 2010). In most of my research, change is the figural part of the picture. But change always happens against a background of stability. As digitalization continues to progress, I need to see figures and ground if I want to understand the whole picture.

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CHAPTER THREE:

PREDICTING NEXT ACTION BASED ON CONTEXTUAL SPECIFICS: EVIDENCE FROM ELECTRONIC MEDICAL RECORDS

3.1. Introduction

As the increased number of paths makes a process more complex, it becomes difficult to predict what happens next. The increased complexity in the process makes monitoring and predicting process a significant factor in both industries and disciplines related to organization and business process (Allen & Varga, 2006; Augusto et al., 2022; Rettig, 2007; Russell et al., 2006).

In process mining, the sequence of events is essential in determining the "flow of control", which provides a model for the expected sequence of actions in a process (Bozkaya et al., 2009; van der Aalst et al., 2005; van der Aalst & Weijters, 2004; van der Werf et al., 2008). However, relying only on the sequence itself may not provide enough clues for prediction when organizational processes are more complex. It is especially hard to understand contextualized processes, where the control flow may depend on contextual factors. When a firm tries to adopt a new business process, it often fails when there is no consideration of contextual factors (vom Brocke et al., 2016). Prior studies discuss the importance of contextual factors in the design of the business process (Ploesser et al., 2009; Rosemann et al., 2008; van der Aalst & Dustdar, 2012), but few studies focus on contextual factors in process prediction.

Context is particularly important in healthcare, where very specific procedures and specialties exist. For example, when clinical employees input patient information at a workstation for electronic medical record (EMR) systems for the recordkeeping process, taking a particular action (e.g., *check_meds*) takes on a different meaning depending on who performs it and where it is performed. The office staff can *check_meds* at the workstation in the front office.

This might be in response to a patient question (e.g., can I refill this prescription?). This might occur as the patient is checking in or checking out. Alternatively, a nurse, resident or doctor might *check_meds* in the examination room, or outside the examination room, in order to confirm the dosage, look for conflicts, or write a new prescription. These examples point out that when the physician checks the patient's medication, it has a different significance than when the office staff does so. It looks like the same action in the event log, but it is not, because the immediate context is different.

As such, while the adoption of EMR systems is intended to make recordkeeping processes more efficient, studies argue that EMR systems cause entanglements of processes that can increase process complexity (Frankel et al., 2005). Thus, to understand the entangled process, it needs to be understood based on the sequence of events with its context. Without consideration of context, the entangled process cannot be grasped clearly.

To address this, I investigate prediction models based on contextual specifics as well as the sequence of actions, using clinical documentation process data. Specifically, I examine if context can help to get better prediction results with fewer parameters / simpler models / or less training. The research questions I address here are as follows; **1) Can contextual specifics make patterns more recognizable and predictable? 2) Can we use context to get better results with fewer parameters/ simpler models?**

To address these questions, I use Long Short-Term Memory Networks (LSTM) (a kind of Recurrent Neural Network (RNN)) which models both the observed sequence of actions and their contextual factors in process. I build on work by Camargo et al. (2019), who trained LSTM networks to predict sequential process patterns. In this study, I extend the idea of Camargo et al.

(2019) on associated resource pools as contextual factors to see the importance of context in the business process prediction.

For the analysis, I compare models using different types of variables: 1) sequence of actions, and 2) contextual specifics with the action sequence. First, I predict the action in the clinical documentation process based on the sequence of actions only. Next, I add different contextual factors; role, workstation, diagnosis group, and others, and see how the prediction level changes with the factors. Lastly, I examine how the results could be changed depending on the different settings of hyperparameters. This analysis provides important findings as the results show that some contextual specifics improve the process prediction more than others. I show that the more relevant contextual information is included, the more accurate prediction is feasible.

I organize the rest of this study as follows. In the next section, I review the literature on how RNN has been used for process prediction and the relations between actions and their contextual specifics. Then I describe the data sources used for the study in section 3. In section 4, the model is developed to predict actions in the clinical documentation process. I report the results of the estimates in the subsequent section and conclude the paper by discussing the contribution of the results and limitations of the study.

3.2. Theoretical Background

Predicting what happens next is not an unrealistic and future technology anymore. Imagine that you have a friend who has dinner with you often and you are about to text him again to ask to join dinner tonight. You have added dinner events with your friend in the calendar on your phone for a few weeks. Based on this "context", when you text, your phone will automatically suggest words on asking to join dinner tonight, such as time, location, or even menu. This is a very common example that shows the convenience of prediction. As such, it is obviously possible to predict the next event more accurately based on context. In this section, I explain what role contextual factors play in the organizational process and introduce prediction models in process management.

3.2.1. Process and Contextual Factors

Recognizing patterns in business processes is not a new rising domain. Numerous studies in the business process discipline have investigated business process mining to decompose entangled patterns of business processes (Gacitua-Decar & Pahl, 2009; Mejia Bernal et al., 2010; van der Aalst et al., 2007). However, the importance of context in process management was overlooked in many process mining analyses (Kronsbein et al., 2014; Li et al., 2010; van der Aalst & Dustdar, 2012). Even after the importance of contextual factors is discussed, many studies neither reflect the factors for the prediction model nor consider with a narrow perspective. Prior studies show how to classify contextual factors based on the characteristics of each. Contextual factors are largely divided into two dimensions; internal and external factors (Kronsbein et al., 2014). While internal factors are important to recognize the patterns because these factors are directly related to events (i.e: particular roles or location in the process), external elements influence the occurrence of events from outside of the process. In the onion model for contextual factors (Rosemann et al., 2008), these two factors are segmented into more specific types of contexts, depending on how frequently the factors are changed during the execution of the process. For example, while suppliers and customers are somewhat controllable in the organizational process, climate or seasonality cannot be controlled but its impact on the patterns of actions can be substantial (vom Brocke et al., 2016). Extending the internal and external contextual factors to the more specific types of context helps figure out which types of contextual factors influence the prediction levels in process.

Many studies on monitoring and managing processes discuss the importance of contextual specifics, but those factors are seldomly used for the predictive process models. For this study, following Rosemann et al. (2008), I use immediate and external contextual factors for the prediction. As the immediate layers, I use actors (who), workstation as location (where), and diagnosis group of patients for each visit as immediate context. As the external factors, I use flu season information and if the system is upgraded

3.2.1.1. Prediction models in process management

Prior to the introduction of RNN, predictive process models were generally based on diverse probabilistic models (Breuker et al., 2016; Pravilovic et al., 2013; van Dongen et al., 2008). However, since RNN was introduced, most of the studies on process prediction models have depended on it because of its enhanced features in processing sequential data (Lipton et al., 2015).

Compared to Convolution Neural Network (CNN), RNN can handle and model sequence data (Graves et al., 2006). Simply put, RNN helps predict what comes next in one thing following another. RNN architecture applies to the predictive model for process monitoring because RNN can learn order dependence in the input sequence. In other words, RNN can encode information from all the events in previous steps so that it is proper to construct the predictive model for the next actions in the clinical documentation process. However, RNN has a fatal challenge of the vanishing gradient problem which does not capture long-term dependencies in sequences. To alleviate, there have been many alternative approaches with modified RNN, such as LSTM, which utilizes forget gate to complement short-term memory and vanishing gradient of the RNN (Gers et al., 1999; Hochreiter et al., 2001).

In the business process management (BPM) discipline, studies show how deep learning techniques allow us to predict the next events in the business process (Becker & Intoyoad, 2017;

Camargo et al., 2019; Tax et al., 2017; Tello-Leal et al., 2018). RNN, especially the LSTM network, is frequently used for business process monitoring because it has been developed to deal with sequential data (Gers et al., 1999; Gers et al., 2002). Using the LSTM network, numerous studies propose approaches for predictive business process monitoring (Di Francescomarino et al., 2017; Evermann et al., 2017; Tello-Leal et al., 2018). For example, Tax et al. (2017) model a predictive process monitoring function. This approach predicts the next activity and its timestamp based on the event logs. Mehdiyev et al. (2020) propose a multi-stage business process prediction model for a loan application process and show the improvement of the prediction performance for rare case events.

Previous studies used a history of events and its related information to predict the next event, but few studies focus on how contextual information influences the prediction level.

TABLE 3.1. REPRESENTATIVE PROCESS PREDICTIVE MODELS

Authors	**Prediction Object**	**Predictive Model**	**Dataset**	**Inputs**
van Dongen et al. (2008)	Cycle Time prediction	Non-parametric Regression	bezwaar WOZ	Occurrences of events, case attributes, duration
Pravilovic et al. (2013)	Next event log and its attributes	Predictive clustering trees	Event logs in Process Mining book	Events, resource, lifecycle, time
Breuker et al. (2016)	Next event	RegPFA predictor	2012, 2013 BPI challenges	Events
Choi et al. (2016)	Next Clinical Events (Diagnosis and Medication Categories)	LSTM	Historical HER data	Diagnosis, Medication codes, and procedure codes
Evermann et al. (2016, 2017)	Next event with resources or organizational group in a process	LSTM	2012, 2013 BPI challenges	Events, event life cycle, resource name, Organizational Group
(Tax et al., 2017)	Next event and its timestamp	LSTM	Helpdesk, 2012 BPI challenge	Events, timestamp
Tello-Leal et al. (2018)	Next activity in manufacturing process	LSTM	Executed production process data	Events, resources, time-stamp
Mehdiyev et al. (2020)	Next activity process	LSTM and CNN	Helpdesk, 2012, 2013 BPI challenge	Events as n-gram, organizational information

Process predictive models from previous studies generally have high accuracy (0.6-0.8) without consideration of contextual factors. If I use the suggested models in Table 3.1 for prediction, the high performance of the predictive models may be assured. However, previous studies train and test the models using the event log data that are extracted from relatively simple processes. These processes have a relatively small lexicon and a small number of possible paths. In process mining, process complexity correlates with the quality of the automated process discovery (Augusto et al., 2022). This implies that simple event logs make it easy to find patterns and predict the next events. However, a complex process like clinical documentation has a large lexicon and billions of possible paths (Pentland et al., 2020), so it is harder to discover and model the process.

In this study, I show that even with complex event logs, the quality of the predictive models can be improved with contextual factors. By adding diverse types of contextual factors, I expect to see a more accurate prediction level in complex processes in the neural network. Hence, I compare the network based on the sequence of action only and the neural network of sequential actions with its contextual factors.

3.3. Data Description

For the analysis, I use the EMR audit trail data. It lists sequential touchpoint event logs for the clinical documentation process. Each touchpoint refers to an event that occurs when a “specific clinic staff” member accesses a “specific patient record” at a “specific workstation”. An event represents the execution of specific actions. The event logs include 529 distinct actions of the clinical documentation process. Each event includes attributes on event timestamp, role, workstation, flu season, system upgrade, and clinic information.

TABLE 3.2. SAMPLE OF RAW DATA

Tstamp	Flu Season	VISIT ID	Workstation_ID	Role	Action Code
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Regharacctcrt
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Rgwkflbegin
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Form_Viewed
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Rgeptbscdm
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Form_Viewed
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Mr_Demographics_Viewed
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Rgeptaddrs
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Reg_Sc_Eptlanguage
4/2/18 10:49	Non_Flu	1	Bcabrkderm	OAS	Reg_Sc_Eardemographics
4/2/18 12:16	Non_Flu	1	Brkdermdt6	Physician	Ac_Visit_Navigator
4/2/18 12:16	Non_Flu	1	Brkdermdt6	Physician	Visit_Diagnoses_View
4/2/18 12:16	Non_Flu	1	Brkdermdt6	Physician	Mr_Problem_List_Access
4/2/18 12:16	Non_Flu	1	Brkdermdt6	Physician	Visit_Diagnoses_View
4/2/18 12:16	Non_Flu	1	Brkdermdt6	Physician	Mr_Los_Access
4/2/18 12:17	Non_Flu	1	Brkdermdt6	Physician	Mr_Review_Encounter
4/2/18 12:17	Non_Flu	1	Brkdermdt6	Physician	Mr_Review_Media
4/2/18 12:17	Non_Flu	1	Brkdermdt6	Physician	Mr_Review_Orders
4/2/18 12:17	Non_Flu	1	Brkdermdt6	Physician	Mr_Chart_Review
4/2/18 12:17	Non_Flu	1	Brkdermdt6	Physician	Mr_Chart_Review
4/2/18 12:23	Non_Flu	2	Brkdermproc	Admin Tech	Mr_Reports
4/2/18 12:23	Non_Flu	2	Brkdermproc	Admin Tech	Ac_Visit_Navigator
4/2/18 12:23	Non_Flu	2	Brkdermproc	Clinical Tech	Sec_Flowsheet_View
4/2/18 12:23	Non_Flu	2	Brkdermproc	Clinical Tech	Ucw_Related_Encounters
4/2/18 12:23	Non_Flu	2	Brkdermproc	Clinical Tech	Mr_Review_Encounter
4/2/18 12:23	Non_Flu	2	Brkdermproc	Clinical Tech	Mr_Review_Orders
4/2/18 12:23	Non_Flu	2	Brkdermproc	Clinical Tech	Mr_Chart_Review
4/2/18 12:23	Non_Flu	3	Brkdermproc	Nurse	Mr_Reports
4/2/18 12:28	Non_Flu	3	Brkdermproc	Nurse	Mr_Reports
4/2/18 12:33	Non_Flu	3	Brkdermproc	Nurse	Mr_Reports
4/2/18 12:38	Non_Flu	3	Brkdermproc	Nurse	Mr_Reports
…		…	…	….	…

Table 3.2 shows a sample subset of raw data for the clinical documentation process. The raw dataset consists of a list of actions with its specific attributes as described, but the data shape

needs to be processed to analyze. Thus, prior to analysis, I conduct data pre-processing by transforming data from individual action levels to consecutive actions with contextual factors (Table 3.3). Each of the rows in Table 3.3 shows a series of actions that are performed at each touchpoint (Visit ID + Role + Workstation) with the contextual information.

TABLE 3.3. EXAMPLE OF TOUCHPOINTS

Visit ID	Role	Workstation	Diagnosis Group	Flu Season	Action
1	Clinical_Tech	Bcabrkderm	Uncertain Neoplasm	No_flu	As_Appt_Desk
1	Physician	Brkdermproc1	Actinic Keratosis	No_flu	Mr_Review_Encounter, Mr_Chart_Review_Viewed…
1	Clinical_Tech	Haikugenericw	Seborrheic Keratosis	No_flu	Rgwkflbegin, Form_Viewed, Rgeptbscdm…
2	Clinical_Tech	Brkdermproc1	Dermatitis	Flu	Mr_Reports, Mr_Synopsis, Ac_Visit_Navigator…..
2	Clinical_Tech	Clisup	Rosacea	Flu	As_Appt_Desk
2	Clinical_Tech	Dermfromisdt5	Psoriasis	Flu	Mr_Reports, Mr_Reports, Sec_Flowsheet_View….
2	Physician	Dermfromisdt5	Nevi	Flu	Ac_Visit_Navigator, Ucw_Related_Encounters….
3	Physician	Bcabrkderm	Nevi	No_flu	Ac_Visit_Navigator, Sec_Flowsheet _Report
…	…	…	…	…	…

Table 3.4 summarizes the characteristics of attributes for this study. The number of identified roles and workstations is 47 and 1,343. In this essay, I use only categorical contextual factors for the comparison.

TABLE 3.4. VARIABLE DESCRIPTION

Variable Name	Variable Type	# of Values (Mean for Numeric)
Actions	Categorical	529
Role	Categorical	47
Workstation	Categorical	1,343
Diagnosis Group	Categorical	160
Clinic	Categorical	12
Flu Season	Dummies (Categorical)	
System Upgrade	Dummies (Categorical)	

In the next stage, I eliminate consecutively duplicated actions because I regard them as un-informative. After removing the duplicates, I list all the events in one column for each touchpoint and create data points that consist of five consecutive sequential actions[3]. For example, if an event chunk contains six sequential actions e = [A,B,C,D,E,F,G], it generates three observations [A,B,C,D,E], [B,C,D,E,F] and [C,D,E,F,G], which consist of four input variables and one target variable.

Next, I add contextual factors as additional attributes to train the model. To add the factors to the model, I set the contextual factors before the sequence of actions (e.g., [factor 1, factor 2, …, A,B,C,D,E]). In this way, the context sets the stage for each sequence of actions. Next, I encode the input sequences. This step is required to convert the character strings, the specific actions in this study, into a unique integer. For the encoding process, using tokenizer, I find all the unique values from the entire dataset and convert them into a numeric feature. Based on the dataset of sequential event logs, I split the inputs into two types; training and target variable. The first four actions and contextual factors are regarded as input datasets to train the

[3] Predicting sequence within touchpoints represents an important simplification in the analysis. If we tried to predict the sequence between touchpoints, we would need to include contextual factors for each action, so there would be a combinatoric explosion in the size of the lexicon (529 actions * 47 roles * 1343 workstations…) It would be impossible to train a model of this complexity with the available data.

model and the last action is set as the expected value that corresponds to input variables. In other words, the model is trained using the training dataset to predict the target variable.

3.4. Model

3.4.1. Long Short-Term Memory Network

A recurrent neural network (RNN) is a class of deep artificial neural networks based on a sequential process (Baziotis et al., 2017). The state output at each time consists of the hidden state as well as the old state with the outputs of previous steps as follows.

$$h_t = f_w(h_{t-1}, x_t) \tag{1}$$

In eq (1), h_t denotes a new state at time *t* founded on a function with parameters W and x_t, an input vector at time *t*. The model learns the name of the actions embedding at each step and only passes useful information as weighting vector W makes a prediction on the label assigned to the current action name.

However, a standard RNN has a vanishing gradient issue over long sequences that makes the RNN difficult to train (Pascanu et al., 2013). Applying RNN to text analysis requires overcoming this issue because long sentences/lists of the words are loaded as the dataset. To overcome the gradient issue, Long Short-Term Memory (LSTM) network is used by including three types of gates (input gate, output gate, and forget gate) and a cell memory state.

The word vector (a type of action in this study), w_N, in a sentence with length *N* (sequence of actions in this study) is generated from word embeddings as dense vector representations of words (Nakov et al., 2019). Each LSTM unit contains an input gate i_t, a forget gate f_t, an output gate o_t, a memory cell c_t, a hidden state h_t, and the word embedding input, x_t, at time step *t*.

(2) $$X = \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix}$$

(3) $$f_t = \sigma(W_f \cdot X + b_f)$$

(4) $$i_t = \sigma(W_i \cdot X + b_i)$$

(5) $$o_t = \sigma(W_o \cdot X + b_o)$$

(6) $$u_t = tanh(W_c \cdot X + b_c)$$

(7) $$c_t = f_t \circ c_{t-1} + i_t \circ u_t$$

(8) $$h_t = o_t \circ \tanh(c_t)$$

Each gate consists of the weighted matrices (W_i, W_f, W_o) and biases of LSTM (b_i, b_f, b_o) in the training process. The weighted matrices and biases parameterize the transformations of three gates with the embedding inputs respectively (Xu et al., 2016). σ is the sigmoid function and the operator $\circ$ denotes element-wise multiplication.

In LSTM, each gate plays important role in the process. In the input gate, I first decide how to update each unit. Next, forget gate controls the extent to which the previously stored information in the memory cell is forgotten. Lastly, the output gate controls the exposure of the internal memory state. Through this process, the hidden state captures and stores both past and future required information. For the prediction model, I use LSTM and train the sequence of actions list in clinics.

For the analysis, I implement parameters of LSTM network using Keras framework, since it provides the required functionalities to model LSTM network (Keras-team, 2019). First, I set the embedding dimensionality as 529, the number of unique actions in the clinical documentation process, and the length for the sequence set as 5, implying four sequential actions for training and one for predicted action. The basic model is trained for 50 epochs in batches of size 128. To encode input vectors to the hidden layer, I adopt the Rectified Linear unit (ReLU) as an encoding activation function (Ketkar & Santana, 2017). Compared to other activation functions, ReLU, as one of the most popular activation functions, has several advantages in terms of computation time and efficiency of gradient propagation (Xu et al., 2016). The ReLU activation function is defined as follows;

(9) $$h = f_{ReLu}(x) = \max(0, x) \qquad h \in [0,1]$$

This activation function produces a linear function only if $x \geq 0$, otherwise it outputs only 0. For the classification, I employ Softmax activation function as last layer. Softmax is generally used for a multi-class classification (Mehdiyev et al., 2020). To estimate a discrete probability of class i, Softmax layer is defined as:

(10) $$p(y = i|x) = \frac{\exp(w_i x)}{\sum_i \exp\,(w_i x)}$$

where *w* is a weighted parameter and *x* indicates the input vector. Based on the probability distribution of classes, a class with the highest probability of prediction is selected. Table 3.5 shows the hyperparameter configurations for this study.

TABLE 3.5. CONFIGURATION PARAMETERS OF THE LSTM NETWORK

Parameters	Value
Sequence length of actions for prediction	4
Embedding dimension	50
Epoch	50
Batch size	128
Activation	ReLU
Activation for classification	Softmax
Loss	Categorical_Crossentropy

3.5. Results

Table 3.6 summarizes the overall performance for the next action prediction task in the clinical documentation process. I use weighted average accuracy, precision, recall, and F-score value for the comparison. Overall, the suggested approach with contextual factors has better performance than the model with a sequence of action only, and each of the factors has different impacts on the prediction level. The initial result of the study shows the capacity to predict the next action in the clinical documentation process. I have tested four different types of models; 1) the sequence of actions model, 2) the model with the internal contextual factors, 3) the model with the external contextual factors, and 4) the model considering all the contextual factors.

TABLE 3.6. RESULTS FROM PROPOSED APPROACH

		Accuracy	Precision	Recall	F-score
No Contextual Factor					
	One Action	0.283	0.26	0.04	0.05
	Two Actions	0.373	0.57	0.14	0.20
	Three Actions	0.423	0.61	0.22	0.30
	Four Actions	0.454	0.66	0.26	0.36
Internal Contextual Factors	Four Actions +				
	Role	0.461	0.68	0.27	0.37
	Workstation	0.471	0.69	0.29	0.38
	Role + Workstation	0.478	0.69	0.30	0.40
External Contextual Factors	Four Actions +				
	Diagnosis Group	0.458	0.68	0.27	0.36
	Flu Season	0.455	0.67	0.29	0.36
	System Upgrade	0.469	0.67	0.29	0.38
	Diagnosis Group + Flu Season + System Upgrade	0.475	0.69	0.29	0.39
All Contextual Factors		0.494	0.70	0.32	0.42

In the first model, I predict the next action only based on the sequence of actions for the base model. To examine the effects of sequence of actions, I run the models including different number of actions. For the internal contextual factors, I add a role and workstation as those immediate contexts are the attributes that directly facilitate the execution of process (Rosemann et al., 2008). Next, I use the diagnosis group of patients, flu seasons, and system upgrade as external contextual-specific covariates since they are impactful factors on the process, but beyond the controllable boundary of the organization. Lastly, I include all the factors for the prediction to see the extent to which contextual factors affect the prediction level.

The average validation accuracy for all learning rates of each model shows that as I assumed, the action is the most important factor for the process predictive model. However, the margin of increase is reduced when more action sequences are added, so I added the contextual factors as additional attributes in the model. The internal contextual factors generally have slightly higher predictive power than the external factors (0.478 vs. 0.475). Specifically, the workstation works better than the role (0.471 vs. 0.461), but the combination of role and workstation does not show much difference with workstation (0.476 vs. 0.471). This result implies that workstation as location (where) is more informative because clinicians perform specific tasks at a specific location. Although the role as the actor provides information on what role each clinician performs, the location information could provide much more detailed information.

In case of the external factors, whereas most of the factors do not boost accuracy a lot (Diagnosis group = 0.458 and flu season = 0.455, system upgrade does increase accuracy as much as workstation (0.469). This makes sense because the system upgrade changes the lexicon of the actions. After the system upgrade, some of the actions are no longer available and new actions are added. These new and removed actions could create new habits for the system use. Thus, the system upgrade attribute is informative to predict the next events, as it infers that new pattern of actions are created or some paths are removed from the process. In case of diagnosis group and flu season, in contrast, there is no dramatic change in accuracy for both models. I expected that the system usage patterns of the users might change depending on whether or not it is the flu season or patients' diagnosis, but they don't seem to be very informative. These results show that although the internal contextual factors generally boost accuracy more, there are still important external factors that may affect the quality of the process predictive model.

3.6. Discussion

This essay represents a first step toward revealing the importance of contextual factors in process prediction. I use RNN to model the observed sequence of actions and their contextual factors together in the process. Specifically, I use Long Short-Term Memory Networks (LSTM) to find recognizable patterns and predict events (Gers et al., 2002; Tello-Leal et al., 2018).

The main contribution of this study concerns the idea of contextual information on process prediction. There is no doubt that the most essential attribute of the predictive process model is the sequence of actions. However, adding more actions does not fully reflect the structure of complex process because there is no consideration of context. The result of this study shows that the internal contextual factors increase the prediction level more than the external contextual factors.

From the internal contextual factor, the influence of the workstation is very interesting. In the EPIC EMR system, every workstation provides the same function for users. So, the workstations can be regarded as identical from the point of view of the users. However, every workstation is located in a different place, so the workstation indicates the location of the work (e.g., in the examination room, at the nurses' station in the hall, in the front office, etc.). In this perspective, the effect of the workstation may not be surprising because the physical environment of a hospital could determine its influence. A busy hallway is different from a private office. Of course, these contextual differences are not generally conceptualized as relevant to process execution, but this study suggests that they can be.

The system upgrade, on the other hand, is an important external factor that increases the prediction accuracy. This variable provides a simple indicator of whether the system is upgraded when a patient visits a clinic, but it seems to play an important role in the prediction model. This implies that the patterns of the system use may change when the system is upgraded. Habitual patterns of actions can be changed depending on the system the users use, and it affects the prediction level considerably. This points out that although the external contextual factors are not controllable as much as the internal factors are, they still need to be considered when it comes to predicting the next events in process.

This study extends our understanding of the entangled relationship between contextual factors (features of nodes) and actions (nodes) and the extent to which the factors could impact predicting the next actions in EMR settings. Currently, the clinical process has been more complex because of entangled relationships among numerous stakeholders and new technologies. Complexity of the process influences the quality of the model, so the understanding of the relationship could provide clues to disentangling complex relationships and finding recognizable patterns (Augusto et al., 2022). The recognizable patterns are useful for organizing actions in the clinical documentation process.

My results show relatively less accuracy and precision than studies that use simpler event logs for training and testing (e.g., the studies in Table 1). However, the purpose of this essay is different from other process predictive frameworks in two ways. First, my analysis shows that the suggested approach can be applied and worked in real process datasets that are extremely complex. Second, I extend the idea of a process predictive model based on LSTM. To the best of my knowledge, prior studies suggest a predictive model based on the previous events only or with a few contextual factors, but there are few studies to see the effects of contextual factors. The main goal of the study is to see how the contextual factors affect the prediction, rather than introducing a higher performance prediction model using LSTM.

Another contribution of this study is its practical implication in the clinical documentation process in terms of text suggestion. Currently, clinical documentation is regarded as a process that requires considerable time consumption (Friedman et al., 2004; Lin et al., 2018). Predicting the next actions suggests what comes next and it helps input the documentation process faster. The application of my approach with contextual factors could reduce the number of suggested actions and increase human accuracy. In other words, using suggested actions in the documentation process could even reduce the chance that clinical practitioners may input wrong information by mistake. I assume that considering contextual factors in the prediction model for the process could help the interdependent organization process be efficient and effective.

3.7. Conclusion

This essay uses a deep learning approach to predict the next actions in the clinical documentation process and investigates the effectiveness of contextual factors in predicting events. To examine the effects of contextual factors on predictive performance, I apply the deep learning model using LSTM recurrent neural networks and compare different models with different combinations of attributes. This paper shows how the LSTM-based approach performs for predicting the sequence of actions in the clinical documentation process. As expected, the results show that context can improve predictive models. In the case of outpatient medical clinics, the strongest improvement in accuracy comes from two attributes: 1) the workstation (location) where work is performed and 2) whether or not the system has been upgraded. This result implies positive potential to demonstrate the significance of contextual factors in the predictive model for the clinical documentation process.

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