Path coherence and disruption in routine dynamics

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Abstract. We use evidence from a disruption of clinical documentation routines to propose a novel, predictive mechanism for routine dynamics based on *path coherence*. *Path coherence* refers to the continuity of situational attributes from one event to the next along a path. For example, a set of activities conducted by the same person has high actor coherence. Situational attributes include classic descriptors such as who, what, when, where, and why. To be recognized as a path, a minimal level of coherence is required, but path coherence can vary along a path. For example, in a medical clinic, typical paths flow from place to place (e.g., reception, waiting room, exam room), and involve different clinical staff (e.g., receptionist, nurse, physician). Using latent factor network models, we compare clinical documentation routines in five outpatient clinics before and after a technological disruption (an upgrade to the Electronic Health Record system). We show that coherent paths are up to 14 times more likely to persist and up to 40 times more likely to form than less coherent paths. We use these findings to theorize about the role of path coherence in routine dynamics. Path coherence in narrative networks is like homophily in social networks, but with a completely different underlying mechanism. We discuss the implications of our findings for organizational path dependence, resilience, and inertia.

Keywords**:** Disruption of routines, Routine dynamics, Network dynamics, Narrative networks, Granularity, Electronic Health Records, Latent factor models, Resilience, Inertia

Introduction

Routines come in many varieties and serve many purposes. Every standard operating procedure (Cyert and March 1963), workflow (van der Aalst and van Hee 2004), customer journey (Følstad and Kvale 2018), and job-to-be-done (Christensen et al. 2007) implies a *routine*: “a repetitive, recognizable pattern of interdependent actions carried out by multiple actors.” (Feldman and Pentland 2003, p. 95). For example, in an outpatient medical clinic, routines are carried out by combinations of receptionists, nurses, physicians, and technicians.

While routines are pervasive, so are disruptions. By *disruption*, we mean any event or circumstance that interrupts paths within a routine. *Paths* are “time-ordered sequences of actions or events in performing work” (Goh and Pentland 2019, p. 1901). Disruptions come in all shapes and sizes: missing one’s morning coffee (McClean et al. 2021), power outages (Heidenstrøm and Kvarnlöf 2018), supply chain issues (Kim et al. 2015), catastrophic hurricanes (Feldman et al. 2021), and pandemics (Richards et al. 2020). Of course, disruptions can also be intentional, as in the case of technological innovation (Schumpeter 1942, Barley 1986, Edmondson et al. 2001, Christensen et al. 2013).

In this study, we address the question: **how do minor technological disruptions influence the dynamics of organizational routines?** This builds on an emerging line of literature. Feldman et al. (2021) examined the effect of Hurricane Katrina, a disruption that shattered the lives and routines of health professionals in New Orleans. Beane (2019) and Sergeeva et al. (2020) studied the introduction of robotic technology in surgery, which disrupted many aspects of medical training and practice. Here, we examine the effect of an upgrade of the EHR system at an academic medical center in the Northeastern United States. Minor disruptions are less dramatic than hurricanes or robotic surgery, but they are frequent and pervasive and have not received much attention in the literature on routine dynamics. This theoretical blind spot is important because we expect that even minor disruptions can reshape routines. Minor disruptions encourage workarounds (Alter, 2014; Bartelheimer, Wolf, and Beverungen 2023), but leave the overall organizational context intact. Our focus on a minor disruption has advantages for theory building, as well. Major disruptions often include multiple forces and have multidimensional effects. For example, Hurricane Katrina had concurrent effects on public health, the economy, and public institutions such as schools. This makes it difficult to isolate specific mechanisms. In contrast, the upgrade of EHR was not concurrent with other major forces. Thus, it allows us to identify the effects of disruption from a focused, singular source.

We approach this question from the perspective of "routine dynamics as network dynamics" (Goh and Pentland 2019, p. 1903) by analyzing the formation/dissolution of paths that enact documentation routines in outpatient medical clinics. In a typical visit to an outpatient medical clinic, a patient moves along a path from one location to the next (reception desk, waiting room, examination room) and interacts with different clinical staff members (receptionist, nurse, physician). These paths enact (or perform) the patterns of action that we recognize as clinical routines. Goh and Pentland (2019) use network dynamics to describe and visualize changes in routines over the course of a game development project as a result of time and budget pressures. Here, our goal is to theorize about mechanisms that predict the dissolution and formation of network paths after a disruption. The effect of a disruption is difficult to predict because disrupting one path is likely to generate workarounds (Alter 2014; Bartelheimer, Wolf and Beverungen 2023) that shift the pattern of action to other possible paths. Path coherence is a good candidate because it is based on situational attributes, such as actor and location, that are known to influence the enactment of routines (Blanche and Feldman 2021, Sailer 2021).

The challenge of identifying general, network-based principles of routine dynamics is complicated by the fact that patterns of action can be analyzed at different levels of detail or granularity (Schegloff 2000, Poole et al. 2017, Kremser and Geiger in press). To describe this effect most clearly, it is helpful to think of the coarse-grained level as comings and goings: the movement of actors between locations around the clinic (Sailer 2021), as in time geography (Hägerstraand 1970), but on a smaller physical scale. Then, we can think of the fine-grained level as doings/sayings within those locations (Schatzki 2002). In other words, the comings/goings set the stage for the doings/sayings. Even a small clinic can have several distinct sites where different activities take place (e.g., waiting room versus exam room), so the comings and goings have an important role in shaping clinical routines (Sailer 2021). Kremser and Geiger (in press) argue that different levels of granularity in describing a routine can affect how we interpret patterns of action and the mechanisms that influence the patterns. For example, in healthcare routines, fine-grained patterns may be due to specific situational contingencies (e.g., a patient with an elevated pulse might need immediate attention), while coarse-grained patterns may be due to institutionalized protocols, such as formal care pathways (De Bleser et al. 2006) or the architectural layout of the clinic (Sailer 2021). In recognition of this possibility, we investigate two levels of granularity in the analysis that follows.

We apply the network dynamics perspective to analyze the effects of one minor disruption: an upgrade of the Electronic Health Record (EHR) system. While working on a larger project on the dynamics of healthcare routines, we realized that we could study this disruption. Like Goh et al. (2011), we use narrative networks (Pentland and Feldman 2007) to model the patterns of actions in medical practice. Where Goh et al. (2011) use observational fieldwork and interviews, we use digital trace data and process mining to discover and compare patterns of action pre- and post-disruption (Pentland et al. 2021). We examine network dynamics at two levels of granularity (user interface and workflow), in five outpatient clinics, encompassing thousands of patient visits. We estimate the effects of the disruption using latent factor network models (Hoff 2005, 2009) that account for dependencies in network data through information about where actions are located in a latent space (e.g., a network visualization). Our analysis shows that path coherence – defined here in terms of continuity of actor and location -- increases the odds of path persistence by up to 14 times and the odds of path formation by up to 40 times.

The main contribution of this article is a general, network-based mechanism for predicting routine dynamics based on path coherence. Based on our findings, we propose that path coherence in narrative networks functions like homophily in social networks, but with a completely different underlying mechanism. We theorize about the effects of path coherence on a range of organizational phenomena related to routine dynamics, including path dependence (Sydow et al. 2009, 2020), resilience (Vogus and Sutcliffe 2007) and inertia (Kelly and Amburgey 1991, Gilbert 2005).

Background

Over the last 20 years, research on routine dynamics has emphasized the prevalence of endogenous change in organizational routines (Feldman and Pentland 2003, Feldman et al. 2021). Endogenous change arises from repetition in the face of situational contingencies that produce improvisations, workarounds, exceptions, and errors (Feldman et al. 2016). The referral routines for the dermatology provides a classic example of performing/patterning, which is a core mechanism in routine dynamics (Feldman, 2016). To work around the lengthy referral queues, primary care physicians started to contact dermatology for a consult instead of referring patients directly. Ultimately, the dermatology clinics incorporated this step (the "e-Consult") into their primary care referral process. They began performing eConsults and eventually integrated them into their routinized pattern of action. This example shows how routines are shaped by an iterative process of performing/patterning (Feldman 2016), where some paths are reinforced over time and others dissolve (Goh and Pentland 2019).

Disruptions are exogenous, but they fit neatly into the same processual model. Disruptions change which paths are performed, so they directly influence the process of performing/patterning, potentially changing the overall routine. In the following sections, we introduce the key concepts in this article: network dynamics, path coherence, granularity, and disruption.

Routine dynamics as network dynamics

Feldman et al. (2016, p. 506) state that "Routine Dynamics focuses on tracing actions and associations between actions." We can trace associations between actions (or events) in an organizational routine and represent them as a network of possible paths (Pentland et al. 2020), as shown in Figure 1.

******* Insert Figure 1 here *******

Figure 1 shows a narrative network for the patient visit routine in an outpatient medical clinic. For purposes of illustration, this network shows only some of the possible paths that can occur in a clinic. Every visit starts at the front desk, where an office assistant helps patients check-in. Then, after a brief wait, the patient moves to an examination room, where a technician takes their vital signs, a nurse asks about their medical history, and a physician conducts an examination. Some patients get sent for additional tests. At that point, two different paths are possible. For some patients, a physician enters or renews a prescription for medication. Other patients get moved to a room for an outpatient procedure, such as minor surgery. Finally, a physician adds notes to the patient's medical record and the patient checks out. Throughout a clinical encounter, some of the actions are recorded immediately in the EHR system (e.g., the vital signs), while others may be entered later (e.g., the notes might be updated after the patient leaves).

The simplified network in Figure 1 illustrates three essential concepts. First, it provides an example of a narrative network, where nodes are defined by events and edges represent sequential relations between those events (Pentland and Feldman 2007, Goh et al. 2011). In a narrative network, nodes are defined by combinations of situational attributes, such as actor, action, and location. Within the network, edges represent sequentially adjacent events, so they form the basic unit of a *path*, which we define as a coherent, temporal progression of events (Goh and Pentland 2019).

Second, Figure 1 motivates the concept of path coherence. Along the path of any clinical visit, events occur in different locations with different combinations of actors. A highly coherent path is performed by the same actor (e.g., a specific nurse) in the same location (e.g., a specific workstation).

Third, Figure 1 illustrates the concept of *process multiplicity* as a space of possible paths (Pentland et al. 2020). A possible path is simply a way of completing a clinical visit, from check-in to check-out, like a customer journey (Følstad and Kvale 2018). Figure 1 shows a simplified network with a handful of possible paths; in a real clinic, the number of possible paths can be very large.

Pentland and Feldman (2007) introduced the narrative network as a tool for describing and comparing organizational routines, and that is how it has been used in existing literature (Pentland and Kim, 2021). For example, Chao (2016) compares patterns of action before and after EHR implementation in a hospital. Sailer (2021) examined the effects of spatial layout on patterns of action in a medical clinic. Goh and Pentland (2019) identify external drivers of changes to game development routines, such as time pressure and scope changes. Other studies (e.g., Hayes et al. 2011, Yeow and Faraj 2011) use the concept of narrative network without operationalizing a specific set of nodes and edges.

While narrative networks can provide detailed descriptions, none of these studies have identified mechanisms that predict the dynamics of narrative networks based on the properties of the network, such as path coherence. In contrast, for social networks, clear mechanisms have been identified that predict and explain network dynamics, such as homophily (McPherson et al. 2001), preferential attachment (Barabási and Albert 1999), reciprocity (Wasserman and Faust 1994) , and transitivity (Davis 1970, Holland and Leinhardt 1977). The lack of any predictive mechanisms for narrative networks presents an opportunity for new theory.

Path coherence in narrative networks

The general concept of coherence has been used in several areas of organizational research, including decision-making (Hammond 2000), strategic management (Teece et al. 1994), and institutional logics (Zilber 2024). *Path coherence* is a narrower, more specific concept that we define here as the continuity of situational attributes from one event to the next along a path. In this section, we explain this concept in more detail.

Path coherence is a good candidate for a predictive mechanism because continuity of situational attributes from one event to the next implies continuity of context for the path (e.g., same actor, same location, etc.). We have known for years that routines are context-dependent (Nelson and Winter 1982, Cohen et al. 1996, Becker 2004, Howard-Grenville 2005, D’Adderio 2011). The entanglement of actions and their social/material context is axiomatic to situated action (Suchman 1987) and current theory on routines (Feldman et al. 2021). As Feldman et al. (2016, p. 506) remind us, routines “are enacted in and inseparable from the sociomaterial context.”

However, sociomaterial context has usually been used to explain stability in routines, not dynamics. For example, Pentland and Rueter (1994) argued that context defines a stable set of possible actions for a routine. In Cohen et al. (1996, p. 660), Giovani Dosi argued that organizational routines have two fundamental characteristics: "(i) their context dependence and (ii) their invariance *vis-a-vis* fine informational change, once the context has been given."

This mode of explanation makes sense if we treat context as external to the routine (Avgerou 2019). When viewed this way, context is static and unchanging (Pettigrew 2012). For example, outpatient clinical routines are performed in the context of professional standards, government regulations, and insurance industry policies. For any single patient encounter, these situational attributes do not change.

Rosemann et al. (2008) argue that the simple model of context as "out there" is a poor fit for processual phenomena. Instead, they articulate a layered model of context, like an onion. Outer layers change much slower than the time scale of the process, but the inner layers can change with every process step, as work is handed from one person or location to the next, as shown in Figure 1. For example, in an orthopedic clinic, a patient might move from the front office to the waiting area, to an examination room, to an x-ray room, back to the examination room, and so on. As the patient moves from place to place in the clinic, the set of possible actions changes (e.g., no x-rays in the waiting room). These changes occur throughout typical clinical paths, as shown in Figure 1.

Path coherence provides an indicator of these changes. Path coherence is easy to operationalize in a narrative network, where each node is described by a set of situational attributes, as shown in Figure 1. The more situational attributes (like actor and location) are consistent from one node to the next, the more the path is coherent. Consider the first network edge in Figure 1, from checking in at the front desk to taking vital signs in the exam room as shown in Table 1. In this example, some situational attributes stay the same, such as the patient and the clinic. Other attributes change, such as the specific location, the staff member serving the patient, and the specific actions being performed.

******* Insert Table 1 here *******

Following Pentland et al. (2017), path coherence can be operationalized for each edge in the network as the fraction of attributes of the edge that stay the same from one node to the next:

$$(1)\ Path\ Coherence_{Edge} = \frac{Number\ of\ unchanged\ attributes_{Edge}}{Total\ attributes_{Edge}}$$

It is worth emphasizing that path coherence is a property of an edge, not a property of an isolated action or event. It can only be computed for pairs of sequentially adjacent events. In the example in Table 1, the coherence of path from check-in to vital signs would be 1/2 because four out of eight attributes stayed the same. This calculation would depend on available data and researcher's judgment about what attributes to include. Typical choices might include who, what, when, where, and why, since these are useful ways to explain motivation and behavior (Burke 1962). In this study, we used two attributes: location and actor. When we apply equation (1) to each attribute separately, the result is a binary (0/1) variable. We provide additional explanation below.

Granularity matters

As noted in the introduction, with any kind of sequential or discursive data, researchers have some choice about granularity (Schegloff 2000, Poole et al. 2017). Kremser and Geiger (in press) argue that at different levels of granularity, we may observe different effects when describing and theorizing about patterns of action:

> Granularity is crucial for routine dynamics scholars because it influences the dynamics observed and the theories developed. … Hence, the processes of performing and patterning we unearth when we use different grain-sizes might follow very different logics and, therefore, require different explanations.

The example in Figure 1 also helps motivate the importance of granularity in narrative networks. Each of the nodes in that figure could be further decomposed into a finer-grained set of actions and paths. The first step, check-in, might involve presenting photo ID and an insurance card, confirming address information, and so on. At the other extreme, we could treat an entire clinical visit as a single node (e.g., "I went to the doctor today."). At this level of granularity, everything that happens in the clinic is hidden. Or, we could say that all of the actors are "clinical staff", and all the actions are located "at the clinic", rather than differentiating between roles and locations. But we know that roles and locations have an important influence on patterns of action in medical settings. Physicians can perform actions that other actors cannot. Certain actions are only possible in certain locations. Therefore, in the analysis that follows, nodes in the network are differentiated by actor and location.

Disruptions of paths in routines

Within a routine, paths can be disrupted for many reasons. Disruptions can be small or large, intentional or unintentional, expected or unexpected. For example, any new technology or process improvement initiative can disrupt existing routines, often with unanticipated consequences (DeSanctis and Poole 1994, Edmondson et al. 2001, Berente et al. 2016). Our view of disruption corresponds to simple, intuitive scenarios from daily life. If a road is blocked, we take the detour. Massive disruptions, like Hurricane Katrina, make normal life impossible and force people into unfamiliar contexts where they need to make new paths (Feldman et al. 2021). Minor disruptions, like software upgrades, have less devastating effects, but they happen more frequently and they can also generate new paths (Alter 2014). For example, new technology can change the way clinical records are kept (Chao 2016).

Technological disruptions are commonplace and have been an important topic in organizational research, especially in healthcare settings (e.g., Barley 1986, Edmondson et al. 2001, Beane 2019, Sergeeva et al. 2020). Technological disruptions can be complex because they can simultaneously block old paths, open new paths, and be appropriated in unexpected ways (DeSanctis and Poole 1994, Berente et al. 2016). Unlike a power outage or a hurricane, technological disruptions are often intentional, even if their effects are not.

For example, Goh et al. (2011) examine the implementation of a new EHR system in a hospital. We build on Goh et al. (2011) by using narrative networks to investigate how disruptions can reshape the space of possible paths by adding new paths and closing old ones. For example, new technology may reduce the number of steps required to access previous exam results. Pentland et al. (2022) demonstrate this idea in a computer-based simulation. In practice, with real routines, the effect of disruption can be very complex because, as Goh et al. (2011) point out, the routines are “not simply passively disrupted.” After a disruption, agents continue enacting paths to get things done.

Example: A system upgrade at a medical center

To explore the effect of disruptions and theorize about the role of path coherence in routine dynamics, we use data from a medical center in the Northeastern U.S. where there was an upgrade of their electronic health record (EHR) system. Even in a small outpatient clinic, a typical patient visit involves several healthcare staff (office admin, clinical technician, nurse, physician…) and across several different locations (front office, waiting room, exam room, procedure room, x-ray room, etc.). The electronic health record (EHR) system allows us to trace those paths.

Data source: The EHR audit trail

We analyzed data extracted from the audit trail of the EPIC EHR system. EHR audit trail data is increasingly being used to model clinical workflows (Adler-Milstein et al. 2020). The data were extracted by the technical team in the medical center. We examine the patterns of action for six weeks, three weeks before and after the upgrade. In our data, paths are defined by a de-identified ID number that is unique to each patient encounter. The EHR audit trail provides a detailed, time-stamped trace of the clinical documentation work (who did what in the medical record) from the computer system's point of view (see Figure 2, below).

The subset of records used here includes time-stamped records of EHR utilization in 4,885 patient encounters at five clinics from three different medical specialties (two from Dermatology, two from Orthopedic Surgery and one from Pediatric Oncology). The data contain over 7.8 million distinct, time-stamped actions. The data include all encounters in each of these clinics from September 16, 2019 (three weeks before the start of system upgrade) to November 10, 2019 (three weeks after), before and after the system upgrade date (October 14th). Within this time period, we excluded weekends and some weekdays for each clinic when less than 2,000 actions were performed.

Clinical documentation routines

We focus on the clinical documentation routine for two reasons: it is common to all five clinics, and it is accurately captured in the EHR audit trail. Clinical documentation work is woven into the fabric of the medical work because everything that gets done needs to get documented. EHR records are intended to facilitate handoffs within patient encounters (e.g., so the physician can see the vital signs recorded by the technician) and between patient encounters (e.g., to monitor the progress of treatment over time). In each of the clinics we studied, multiple clinical staff engage in the documentation work. All of the clinics use the same EHR system, so they were all subject to the same disruption.

The five clinics we studied involve three different areas of medical practice, as summarized in Table 2. As shown in Table 2, there are differences in terms of the number of patients they see and the typical diagnoses they treat. Even within an area of medical practice, each clinic specializes to some extent. For example, Ortho A treats patients with broken bones, while Ortho B does not.

******* Insert Table 2 here *******

For each clinic, Table 2 shows the number of actions, clinicians and locations that are involved in typical encounters. Across all five clinics, the average number of actions per encounter is 50-70. In each clinic, there are some very simple encounters; these would typically be associated with follow-up visits (e.g., to check on the progress of treatment). There are also some very complex encounters, involving as many as 29 individual staff members. On average, in all the clinics, the EHR record is accessed and updated by 4 to 8 individual actors, from 5 to 11 distinct locations.

These clinics exemplify what Cohen (2007) called the "pattern-in-variety" that is characteristic of organizational routines: you never step in the same river twice. In all five clinics, there is a great deal of repetition, but there is also a lot of variation. Most encounters follow the generic paths indicated in Figure 1 (check-in, vital signs, etc.). Within that ostensive idealization, the details of every encounter are different.

Two levels of granularity in the EHR audit trail

The EHR audit trail allows us to trace "specific actions, by specific people, in specific places and times", as suggested by Feldman and Pentland (2003, p. 101). Figure 2 shows a small part of an audit trail for one encounter. Each row is a time-stamped action, who performed the action (actor) and where it was performed (location). Because we have actor and location at each point in time, this data allows us to measure coherence of the path as it passes from actor to actor and location to location.

We can use the EHR audit trail to trace the clinical documentation routine at two different levels of granularity: a fine-grained level that represents paths at the user interface (UI) and a coarse-grained level that represents paths in the workflow.

UI Level (fine-grained). We can interpret the audit trail one row at a time, in a fine-grained narrative network, as shown on the left side of Figure 2. Each node in this network represents a unique action-actor-location. The UI level shows the sequence of actions in the user interface, as clinicians perform their clinical documentation work within the EHR system. Like clickstream research (Montgomery et al. 2004), it traces low-level user actions. It also records system events that are triggered by user actions.

******* Insert Figure 2 here *******

Workflow level (coarse-grained). The workflow level represents the movement of the work around the clinic, from actor to actor and place to place. To represent the workflow, we can aggregate the fine-grained actions (Klijn et al. 2022) to create a coarse-grained representation of the same data, as shown on the right side of Figure 2. Event aggregation is a commonly used technique to reduce noise in process mining (Klijn et al. 2022). We refer to these aggregated units of analysis as *touchpoints* and the transitions between touchpoints as *handoffs* (Pentland et al. 2017). At the coarse-grained level, detailed actions are not represented.

The narrative networks in Figure 2 represent the trace of a single patient encounter at two different levels of granularity. The visualization provides an intuitive sense of how granularity affects the representation. A series of nine actions by the Admin_tech (at the fine-grained level) become a single touchpoint at the workflow level. At either level of granularity, each action (or touchpoint) becomes a node in the network and sequentially adjacent nodes become edges in the network. The networks have loops because some of the nodes repeat. Loops can occur anytime the same actor touches the same patient record in the same location (e.g., office assistant at the front desk).

In the analysis that follows, we aggregate these traces to create narrative networks that represent a snapshot of the paths enacted in each clinic on each day, using the same method as Pentland et al. (2021). This allows us to compare the pattern of action in each clinic day by day, before and after the disruption. We can aggregate traces within each clinic, but not between clinics. This is because the labels for actors and locations are different in each clinic. As a result, the action-actor-location combinations are different in each clinic and the networks cannot be aggregated. Thus, throughout the paper, each clinic is analyzed separately.

The disruption: A new EHR user interface

In October 2019, the medical center upgraded from EPIC v2017 to EPIC v2019. This 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; and 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) 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 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. On that date, 40 actions were added to the EPIC system that serves all clinics, while 60 actions were removed from the system.

To better describe the disruption, Table 3 provides some measures of the network before and after the disruption, as well as the overall rates of edge persistence, formation and dissolution.

******* Insert Table 3 here *******

Network size. At the UI (fine-grained) level, these networks have thousands of nodes and edges generated by tracing actions by specific actors at specific locations. Many actions can be performed by multiple actors at multiple locations; each unique action-actor-location combination that we observe in the data becomes a node in the network. At the workflow level (coarse-grained), the networks are much smaller because we have aggregated the UI-level events into touchpoints (Klijn et al. 2022), as shown in Figure 2. In all of the clinics except Ortho B, the size of the network is the same or slightly smaller after the disruption.

Network Density. These are directed networks, so density is defined by the number of observed edges divided by the total possible edges. If there are 4 actors there are 4x3 possible edges that could occur. If 3 of these do occur the density would be 25%. These networks are quite sparse, especially at the fine-grained level, where less than 1% of the possible edges were observed in any of the clinics. We interpret the low density as evidence that the clinical documentation process is highly patterned. Specific actors perform specific actions in specific locations and crucially, in specific paths. The network edges describe those paths. The density of the network is similar before and after the disruption.

Actor and location coherence. For each edge in the network, actor coherence means both actions were performed by the same person. Location coherence means both actions were performed in the same place. In Table 3, we show the percentage of edges in each network that meet this simple, descriptive test before the disruption. The upgrade to the EHR system did not have much effect on actor or location coherence in any of the clinics.

When we compare the two levels of granularity, the results are dramatically different. At the UI level, the observed actor and location coherence in each clinic range from about 70% to 82%. In other words, 70-82% of the time, sequentially adjacent actions within a patient encounter were performed by the same person (or at the same location). At the fine-grained level, the next action tends to stay with the same actor and location.

At the workflow level, the data are nearly the opposite. Average location coherence is only 2-5%, meaning that the workflow proceeds to a new location over 95% of the time. Average actor coherence is higher (12-28%, depending on the clinic), meaning that most of the time the next step in the documentation process is handed off to someone else. At the coarse-grained level, the workflow tends to jump to different actors and locations. Office assistants handle check-in, clinical technicians take vital signs, doctors write prescriptions and enter notes, and each of these actors tends to work in different locations in the clinic. These basic responsibilities were not changed by the upgrade to the EHR system.

Formation, persistence, and dissolution of edges. Most importantly, Table 3 shows that a modest system upgrade can have a large effect on the paths in the network. The fact that only 15-36% of the edges persisted underscores the scale of the disruption. This means that from one three-week period to the next, the majority of edges dissolved and new edges were formed. Also, notice that the percentage of edges that form, persist and dissolve is similar at both levels of granularity (UI and workflow). Across all five clinics, at both levels of granularity, less than a third of the edges survived the disruption.

Expectations about path persistence and formation after disruption

This example provides a rich context in which to investigate how a minor disruption affects the dynamics of organizational routines. In a network of possible paths, where there may be many alternative paths, network dynamics provides a systematic way to consider the effect of disruption on routine dynamics. We are especially interested in the role of path coherence since it has not been investigated in prior research. To put the role of path coherence in perspective, we analyze it alongside two well-established indicators of routinization: repetition and duration.

Repetition

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. 2023). At the individual level, “repetition induces a shift in the motivational control of action from outcomes to triggering stimuli.” (Wood et al. 2005). Berger and Luckmann (1967, p. 53) describe how repetition contributes to the formation of institutions: “All human activity is subject to habitualization. Any activity that is repeated frequently becomes cast into a pattern, which, *ipso facto*, is apprehended by its performer *as* that pattern.” We expect more frequently repeated edges to persist after a disruption to the network. Of course, repetition can only be used to investigate persistence; it cannot be used to predict formation of new paths because they have no history.

Operationalizing repetition. We operationalize the repetition of edges in a straightforward way, like frequency of communication in a social network (Wasserman and Faust 1994). We simply count how often each edge repeats each day.

Duration

Duration has long been recognized as an indicator of routinization (Cohen and Bacdayan 1994, Su et al. 2013). Cohen and Bacdayan (1994) use duration of response to define routinization of moves in a card game. Su et al. (2013) use duration of response to identify routines in human-computer interaction. These findings align with the idea that routinized patterns of action are important for efficiency (Nelson and Winter 1982, Becker 2004). Edges with shorter mean duration indicate faster ways of getting things done. We expect that fast edges are more likely to persist after a disruption than slower edges for two reasons. First, faster edges should be more automatic and require less conscious reflection (Cohen and Bacdayan 1994). Second, people working in the clinic are always under time pressure, so they may prefer paths that get the work done faster. Like repetition, duration can only be used to investigate persistence.

Operationalizing duration. Using the time-stamp data, we compute the mean duration of each edge in the network. For the aggregated, workflow level, we compute the mean duration from the end of one touchpoint to the start of the next.

Path coherence

Unlike repetition and duration, path coherence is not one of the classic indicators of routinization. In this study, we examine two of the most theoretically significant aspects of coherence: actor and location. This aligns with Feldman and Pentland's (2003) focus on specific people and specific places. After a disruption, we expect that more coherent paths (same actor, same location) will be more likely to persist and more likely to form.

Actor. Embodiment is essential to acting and engaging with the material world (Blanche and Feldman 2021). Individual actors embody procedural memory, habits, skills, and a host of other attributes that are known to predict the repetition or continuation of a path (Schulz 2008). Thus, retaining the same actor from one action to the next is likely to increase the likelihood of persistence of an existing path. For path formation, the rationale for actor-coherence is simple: all else being equal, the next action is always more likely to be performed by the same actor, rather than someone else.

Location. Location provides another important aspect of coherence. In social network analysis, the distance between actors as an influence on tie formation has been extensively investigated (Adams et al. 2012, De Benedictis et al. 2015). Generally speaking, closeness of location increases the chances of tie formation and persistence. Thus, to the extent that edges in an event network can be interpreted as evidence of ties in social network, we expect that location will have a strong influence on the likelihood of path formation and persistence in routines.

Operationalizing coherence. In our data, we operationalize each of these dimensions of path coherence in a straightforward way. Each actor in each clinic has a unique label (e.g., ClinTech1, ClinTech2, ClinTech3, etc.). Similarly, each workstation has a unique label that we use to identify location. If the individual actor using the EHR is the same from one action to the next, the path is coherent from an actor perspective. If the location of the action is the same from one action to the next, the path is coherent from a location perspective. We treat both as binary (0/1) variables. Rather than adding them together to create a single index of coherence, as suggested by Pentland et al. (2017), we examine them separately.

Analysis

We use repetition, duration, and path coherence to predict the persistence of existing edges and the formation of new edges after a disruption. As we explained above, this is an opportunistic study based on data that was already collected as part of a larger project. We know from experience with EHR audit trail data that there are strong associations among these variables. Therefore, rather than framing our analysis as hypothesis testing, it is more appropriate to frame it in terms of theory development or theory elaboration (e.g., Lee et al. 1999).

In the analysis that follows, repetition, duration and path coherence each potentially predict the probability of edges persisting (or forming) after the disruption, considering the rest of the changes in the network. Our methodology indicates association, not causation, but sensitivity analysis provides assurance about the robustness of the association (Frank et al. 2013, 2023).

Latent space models for edge persistence and formation

To account for interdependence of paths in the network, we use the dyadic selection model for network dynamics described by Hoff (2005, 2009). This model is ideal for our purpose because it accounts for dependencies in the edges due to sharing a node or that more broadly inhere in the overall structure of the data as represented by the location of actors in a network visualization (e.g., the right or left of Figure 2).

Persistence model. In this model, we account for the transition from the previous state of the process (at time *t-1*) to the current state of the process (at time *t*) by subsetting our data. To predict persistence, we use only those edges that occurred at *t-1* (before the disruption) and model which edges also occurred at time *t* (after the disruption). For both the UI and Workflow levels of analysis, we can use the same model of persistence:

$$\begin{aligned} Persistence_{ijt} = {} & \beta_1\left(frequency_{ijt-1}\right) \\ & + \beta_2\left(duration_{ijt-1}\right) + \beta_3\left(actor\ coherence_{ijt-1}\right) + \beta_4\left(location\ coherence_{ijt-1}\right) \\ & + \theta_i + \theta_j + u_i v_j + e_{ij} \end{aligned}$$

where $Persistence_{ijt}$ is the log odds-ratio that the path between actions *i* and *j* exists at time *t*. The independent variables, $frequency_{ijt-1}, duration_{ijt-1}, actor_{ijt-1}, and\ location_{ijt-1}$ are defined as described above, based on the network before the system upgrade. 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 the path between *i* and *j*. As we apply the model here, θ_i and θ_j reflect the change in the repertoire 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 (e.g., the right or left hand side of Figure 2) and e_{ij} is the error term.

Formation model. For formation, we use a complementary subset of the data that includes only those edges that did not exist at *t-1* (before the disruption). Then, we model which edges occurred at time *t* (after the disruption). For the formation of new edges, the model is different in two ways. First, because newly formed edges do not exist in a prior time period, we can only use information about the current time period. Second, because repetition and duration are undefined for the prior time period, the model can only include indicators of path coherence (actor and location):

$$Formation_{ijt} = \beta_3(actor\ coherence\ _{ijt}) + \beta_4(location\ coherence\ _{ijt}) + \theta_i + \theta_j + u_i v_j + e_{ij}$$

This model posits that log odds-ratio of edge formation is based on the coherence of actor and location in the current time when the new edges form.

Results of latent space models

We estimate these models for each clinic using the R package *amen* (https://cran.r-project.org/web/packages/amen/amen.pdf) which uses an MCMC (Markov Chain Monte Carlo) procedure. We use standardized variables, with log transformations for repetition and duration. At both levels of analysis, we conducted a simple meta-analysis of the results for the five clinics (Borenstein et al. 2009). A meta-analysis is needed because the data cannot simply be aggregated across clinics.

UI level results. The results at the fine-grained, UI level are shown in Tables 4-1 and 4-2. At the UI level, the effects of actor and location coherence are strong and significant across the board for persistence and formation. However, the effect of actor coherence is stronger than the effect of location coherence in path formation. The effect of repetition is also strong, but the effect of duration is weak on path formation, especially for DermB and Pedonc.

******* Insert Table 4-1 and 4-2 here *******

Workflow level results. The results at the coarse-grained, workflow level are shown in Table 5-1 and 5-2. At the workflow level, actor and location coherence are important for both persistence and formation. The effect of repetition is weak, and duration is not associated with persistence.

******* Insert Table 5-1 and 5-2 here *******

Sensitivity analysis. To examine the robustness of association between persistence, formation, and coherence, we conduct sensitivity analysis using *Konfound-it app* (Frank et al. 2013, Narvaiz et al. 2024). The analysis indicates what percentage of the observed data would need to be replaced with cases showing no association in order to invalidate the inferences. Higher percentages indicate more robust results. Table 6 presents the case replacement percentage for persistence and formation at both levels of granularity based on the data used in the meta-analyses. The results for actor and location coherence, where 35% to 40% of the data would need to be replaced to invalidate the results for actor and location. For example, the inferences for actor and location coherence on edge formation would still hold if both Dermatology clinics were removed and replaced with edges for which there was no effect of coherence. Given that the chances of observing the estimated effects in the two Dermatology clinics were very small if in fact there was no effect of coherence (with stand-alone p-values < .001), it seems unlikely that the inferences we make overall could be easily explained away by uncontrolled bias, especially noting that we already controlled for dependencies in the data through the latent space models. By comparison, the results for repetition and duration are less robust (or in the case of edge formation, not applicable), with Robustness of Inference to Replacement (RIR) values of below 11%.

******* Insert Table 6 here *******

Interpretation of results

First, it is important to emphasize that the phenomenon we are describing is inherently endogenous. Path coherence forms as a path unfolds, so the results indicate association, not causation. We use terms like *predict* and *effect* for readability, with the understanding that this terminology is not meant to imply causality.

Second, these models do not predict the next action in a specific path. Rather, they predict whether an edge that occurred in the three weeks prior to the disruption is more (or less) likely to occur in the three weeks after the disruption. Conceptually, they are more like models of *recurrence* (Webber and

Marwan 2015): what are the odds that a given edge will be repeated after a disruption? In the formation models, the edges are new, but the model predicts the formation of edges with the same actor/location, not the specific actions.

Table 7 translates the results from tables 4-1 through 5-2 into a form that allows us to compare repetition, duration, and path coherence in terms of their influence on the odds of an edge forming or persisting after a disruption. Table 7 applies the general rules for interpretation of logistic regression coefficients (Wright 1995, Hosmer Jr et al. 2013), keeping in mind that repetition and duration have been log-transformed and standardized, while actor and location coherence have not.

******* Insert Table 7 here *******

Repetition. As expected, the repetition of an edge is associated with its tendency to persist after a disruption at both levels of granularity. This finding aligns with everything we know about repetitive patterns of action: they tend to keep repeating (Schulz 2008). An increase of one standard deviation in the number of repetitions (roughly 0.66 actual repetitions) will increase the odds of persistence by 50% at the UI level and about 34% at the workflow level. This finding supports the idea that routines can form fast (Gersick and Hackman 1990) and it shows that repetition increases the odds of persistence.

Duration. Contrary to our expectations, duration is not strongly associated with persistence. Furthermore, the direction of the association is opposite to what we would expect. At the fine-grained level, an edge that takes an extra standard deviation of time (2.4 seconds) is 21 percent more likely to persist. The association is weak, but it suggests that the upgrade of the UI interface interfered with habitual patterns of action at the UI level. After the upgrade, edges that required more conscious reflection were slightly more likely to persist. At the coarse-grained (workflow) level, duration is not associated with the persistence of edges. Clinical workflows often involve waiting for a technician, nurse, or physician to take the next step and continue the path. These handoffs are essential to the work, so the duration of the path appears to have no influence on the selection of the path.

Path coherence. The influence of path coherence is stronger and more interesting than we expected. From Table 7, we can see that path coherence has a strong, positive effect on the odds of edge formation and persistence at both levels of granularity. At the UI level, having the same actor increases the odds of persistence by 1,435%. This is roughly the same effect as 43 repetitions, assuming the effect of repetition is linear. Coherent location increases the odds of persistence by 890%. At the workflow level having the same actor increases the odds of persistence by 1,790% (as much as roughly 80 repetitions). Coherent location increases the odds of persistence by 658%. Stated differently, edges with actor or location coherence are 6 to 14 times more likely to persist.

In edge persistence, actor coherence has a stronger effect than location coherence. When performed by the same actor, sequentially adjacent pairs of actions could indicate individual habits, which are a strong factor in routinization (Becker 2004). The relatively weaker effect of location makes sense because we use workstations to indicate locations and the workstations are functionally equivalent. An actor can perform any action at any workstation, so in principle, locations are interchangeable. However, workstations are located in different parts of the clinic (offices, hallways, exam rooms, x-ray rooms, etc.) where different people work and different aspects of clinical work are performed. So, while workstations are interchangeable, clinic locations are not.

In edge formation, the story is more complicated. In path formation at the UI level, actor coherence is much stronger than location coherence (4,122% versus 165%). This is intuitive because, at the UI level, pairs of actions are most likely carried out by the same actor. At the workflow level, the situation is reversed: location is stronger than actor. The intuition here is that handoffs between actors are more common at the workflow level, even if the actions occur in the same location (e.g., in the exam room).

Alternative explanations

Many mechanisms shape organizational routines. Schulz (2008) suggests a dozen different mechanisms that keep path in routines on track, including habit, neuronal priming, reciprocal typification, institutionalization, value infusion, formalization, artifacts, concatenation of procedural memory, calculation, competency traps, escalation of commitment, coercion, and leadership. In our outpatient clinics, all these possibilities could be in the mix. Further, they would be difficult to separate out because they tend to be mutually-reinforcing (e.g., habitual behavior reinforces institutionalized behavior and vice versa, as described by Berger and Luckmann, 1967). In any case, the EHR audit trail does not contain enough information to rule out any of them.

Still, it is worth considering the types of effects that might be present that could confound our findings. For example, *actor* can be a proxy for anything that might be embodied in human individuals, including habits, skills, and beliefs (Blanche and Feldman 2021). Thus, when we say that paths involving the same actor tend to persist, it could be because of individual-level habits or other attributes. Similarly, *location* can be a proxy for a variety of technological and organizational factors (e.g., x-ray equipment stays in one location; a physician's office is different than the front desk; and so on). This is precisely what makes actor and location such powerful aspects of path coherence: they are simple, observable indicators that carry a lot of theoretical freight. And in our data, actor and location coherence are strongly associated with persistence and formation regardless of medical specialty, clinic, or granularity of observation.

Discussion

The concept of path coherence reinforces the main message from Goh and Pentland (2019): paths are an analytically important mechanism that bridges situated actions and routines. This is because actions never happen in isolation; they are always part of a path, and routines are enacted one path at a time. However, path coherence is easy to overlook. As work proceeds along a path, we naturally focus on the doings and sayings of the actors: the enactment of practices, the delivery of services, the doing of jobs to be done. Path coherence has been there all along, hiding in plain sight. To see it, we need to shift our attention away from the individual actors and their actions and trace how the actions are associated. As Feldman et al. (2016) point out, this is the foundational perspective of Routine Dynamics.

In our analysis, we have examined the disruption of paths in five outpatient medical clinics. Our results indicate that path coherence is strongly associated with the persistence and formation of paths and therefore, routines. Across the board, the effect of path coherence is unequivocal. In the discussion that follows, we consider the implications of these findings for routine dynamics, as well as organizational path dependence, inertia, and resilience.

Path coherence: A predictive mechanism for routine dynamics

In research on social networks, mechanisms like reciprocity, homophily, and preferential attachment contribute to formation and dissolution of network ties. Analogous network-based mechanisms have never been defined or investigated for patterns of action.

Our analysis of path coherence and disruption was made possible by the novel application of dynamic network models (Hoff 2005, Minhas et al. 2016) to networks of actions. In network terms, we focus on the edges (pairs of actions) rather than the nodes (individual actions). We model the effect of path coherence on each pair of actions, while taking the overall pattern of actions and other latent factors into account. These models allow us to explore the effects of specific mechanisms (repetition, duration and coherence) on persistence and formation of paths.

Mathematically, path coherence in narrative networks is like homophily in social networks, but the mechanism is entirely different. Homophily operates on social information processing (McPherson et al. 2001). One actor recognizes attributes of another actor (age, gender, dress, etc.) and initiates a social tie based on perceived shared attributes. With coherence in a path, there is no "other" and no social information processing. Furthermore, while homophily operates on the attributes of objects (the social agents themselves), path coherence operates on the attributes of actions.

In contrast, path coherence is processual; it refers to temporally adjacent actions rather than spatially adjacent places. Path coherence refers to the attributes of actions rather than properties of places. Path coherence implies that the attributes of temporally adjacent actions will tend to be more closely related than the attributes of distant actions.

Granularity matters: Comings/goings versus doings/sayings

While the analogies to homophily and spatial autocorrelation are intriguing, our results suggest that path coherence operates differently at different levels of granularity, as cautioned by Kremser and Geiger (in press). In our data, path coherence seems stronger at the fine-grained level than at the coarse-grained level. To describe this effect most clearly, it is helpful to think of the coarse-grained level as comings and goings: the movement of actors between locations around the clinic (Sailer 2021), as in time geography (Hägerstraand 1970), but on a smaller physical scale. Then, we can think of the fine-grained level as doings/sayings within those locations (Schatzki 2002). In other words, the comings/goings set the stage for the doings/sayings.

Fine-grained (UI). Research on patterns of action in routines generally starts from situated action (Suchman 1987) as the unit of observation: the doings and sayings of a given set of actors in a particular situation (Feldman et al. 2016). Situational cues from material artifacts and the other actors shape the flow of action (Suchman 1987, Lave and Wenger 1991). For example, in the exam room, a technician may take vital signs and record the numbers in the EHR. In the x-ray room, they do x-rays, and so on. Experience and habits are embodied in the actors and equipment, which provides a stable backdrop for the doings and sayings of situated practice.

Coarse-grained level (workflow). At the coarse-grained level, we can trace the comings/goings of the actors from situation to situation. In our data, actor and location change frequently because of the institutionalized division of labor in the practice of medicine. Only certain people are authorized and able to perform certain tasks, so work is passed from person to person and place to place. At the coarse-grained level, the pattern of action reflects coming and goings, rather than doings and sayings.

We can see that path coherence is associated with persistence and formation at both levels of granularity, as shown in Table 7. These results are particularly compelling because they are strong at both levels of granularity. While path coherence has a contingent influence on the next action in any given path, it appears to have a substantial influence on persistence and formation of networks of paths. We speculate that path coherence has this effect because it sets the stage for other, more familiar mechanisms to operate. Path coherence provides the social/material continuity that is needed for situated practice. When actor and location are coherent, mechanisms like habits, artifacts, and institutions are more likely to be effective in shaping paths (Schulz 2008), and through performing/patterning (Feldman 2016), the overall pattern of the routine.

Path coherence, path disruption and path dependence

Our analysis of path coherence and disruption has implications for our understanding of path dependence, as well. We can define path dependence in the general sense that past events or decisions constrain later events or decisions (Mahoney and Schensul 2006). Path dependence takes many forms and is supported by many mechanisms. Page (2006) identifies four mechanisms that reinforce path dependence: increasing returns, positive feedback, self-reinforcement, and lock-in. All these mechanisms presuppose repetition over time. As Sydow et al. (2020, p. 727) explain, "a lock-in is not a complete standstill. It does not simply exist; it has to be practiced and continuously reproduced, whether mindfully or not, with little deviation in everyday life."

A network-based perspective that includes path coherence and multiplicity provides a more nuanced interpretation to the concept of "lock-in" that allows more variation in routine performances. In the clinics we studied, formation of new paths was crucial to the on-going capacity of outpatient clinics to deliver medical services. Only a fraction (15-36%) of the original edges in the network survived the disruption. Following the disruption, many paths dissolved, but many new paths formed. Indeed, paths were forming and dissolving all the time. Danner-Schröder and Ostermann (2022) observed a similar phenomenon in their field study of Emergency Department routines.

This finding demonstrates the basic idea from routine dynamics that people might need to do things differently (in a performative sense) in order to keep doing the same thing (in an ostensive sense) (Pentland and Feldman 2005, Berente et al. 2016, Feldman et al. 2016). It demonstrates that a disruption can reshape the space of possible paths (as performed) while maintaining the same repetitive, recognizable pattern of action (e.g., delivering medical services) that Page (2006) or Sydow et al. (2020) would describe as "lock-in". Our theory suggests that path coherence increases the chance of maintaining lock-in, even when the specific pattern of action has changed.

Inertia and resilience in organizational routines

This observation returns us to our initial question: how do minor technological disruptions influence the dynamics of organizational routines? Our answer is that those routines that are coherent in terms of consistently performed by the same actors or in the same locations are more likely persist in response to technological disruptions. By implication, as disruption will most likely affect those routines that are not coherent in terms of being performed by many different actors or across different locations. When action patterns persist or bounce back, it 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 (Vogus and Sutcliffe 2007, Grote et al. 2009). Inertia and resistance frame this phenomenon in negative terms, while resilience and regeneration frame it in positive terms.

The literature on each of these topics is too large and diverse to review in this paper. Our analysis targets the small piece of the inertia/resilience landscape that Gilbert (2005) refers to as *routine rigidity.* The network approach to disruption has been applied to phenomena at vastly different scales, from neurophysiology (Reijneveld et al. 2007) to ecosystems (Merz et al. 2023). In all these systems, the phenomena we recognize as inertia/resilience depend on the capacity of the network to adapt by adding/removing paths. Consider the example of supply chain disruptions. Severe disruptions (with large negative impact) are more likely to occur in supply networks with a small number of paths (Azadegan and Dooley 2021). Low redundancy tends to make supply networks more vulnerable. Network structure is also important. Kim et al. (2015) found that a power law structure tends to make supply networks more resilient.

In the network model we use here, process multiplicity provides a similar kind of redundancy (Pentland et al. 2020). If there is greater process multiplicity (a greater space of possible paths), then any given disruption is less likely to have consequences, good or bad. The organization can keep doing the jobs-to-be-done, even though they are doing them differently. In addition, path coherence will tend to increase the tendency for existing routines to bounce back. Paths with greater coherence -- same actor, location, technology, etc. -- are more likely to persist and more likely to form than paths with less coherence. While the current study offers only one small example, it provides a novel theory that can be tested in future research.

Limitations

This study has some obvious limitations. First, we have data from a narrow context. This is essentially a case study of one software upgrade in a few clinics within a single hospital system. While the work processes in these clinics are repetitive, they are also extremely complex. If process multiplicity and network structure do influence the effect of coherence, then subsequent studies should examine other kinds of settings.

Second, we study a single kind of disruption: a system upgrade. While this has advantages for theory development, 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 our study, the routines immediately adapted to the upgrade. With more severe disruptions, we would not expect adaptation to occur as quickly. For example, event systems theory (Morgeson et al. 2015) predicts that bigger disruptions create bigger changes. Data from different kinds of disruptions could provide additional insights concerning the influence of repetition, duration and path coherence on the persistence and formation of paths.

Third, this is an opportunistic, archival study. The data we report here was collected as part of a larger study that was not specifically focused on disruptions. As a result, we don't have interviews or observational data that would add richness to the story. Other studies of technological disruptions have used ethnographic fieldwork to examine patterns of action that change repeatedly over time (e.g., Goh et al. 2011, Leonardi 2011, Berente et al. 2016). 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. Future studies would undoubtedly benefit from a combination of fieldwork and archival methods.

Fourth, we could have a better measure of location. Our measure reduces distance to a categorical variable with two values: "same place" or "somewhere else." Multiple studies have shown that geographic distance tends to influence network structure (Rothenberg et al. 2005, Lee et al. 2011, Parreira et al. 2017). For some kinds of paths, actual geographic distance could be an important aspect of coherence.

Finally, our use of latent factor models (Hoff 2005) constrained us to focus on the persistence and formation of single edges, the shortest unit of a path. We could also use pattern mining (Hansson et al. 2023) to find the most common paths of intermediate length and directly investigate which paths became more or less common. That approach would be more viable in a less complex setting. In our data, each clinic is different, so they have different paths that are idiosyncratic to the way they use the EHR. Focusing on single edges provides a rigorous way to compare the effects of path coherence across clinics. Also, it allows us to account for systemic interdependence within the network which will affect all edges, not just the most common combinations. Still, in a less complex setting, a pattern mining approach might provide a more relatable set of results.

Conclusion

This paper introduces the concept of path coherence and demonstrates its role as a predictive mechanism in routine dynamics. Viewing routine dynamics as network dynamics provides a rigorous new way to analyze stability and disruption, even in a setting that has a great deal of variability. In practice, paths get things done, as they pass from person to person and place to place. Path coherence provides a way to explain both the persistence of existing paths and the formation of new paths, both of which are essential to the on-going enactment of routines after a disruption.

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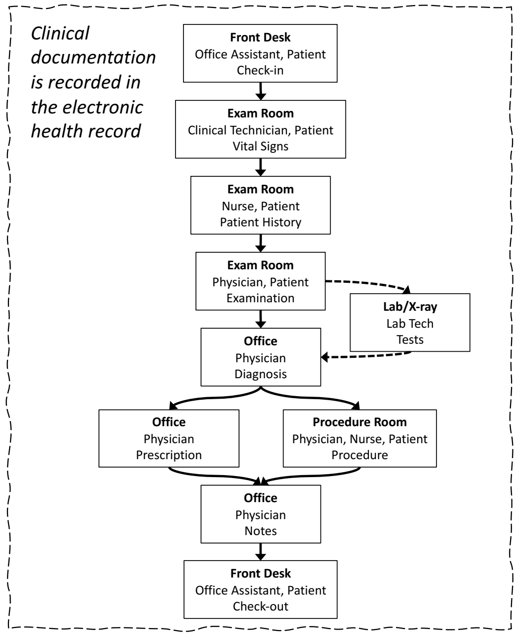
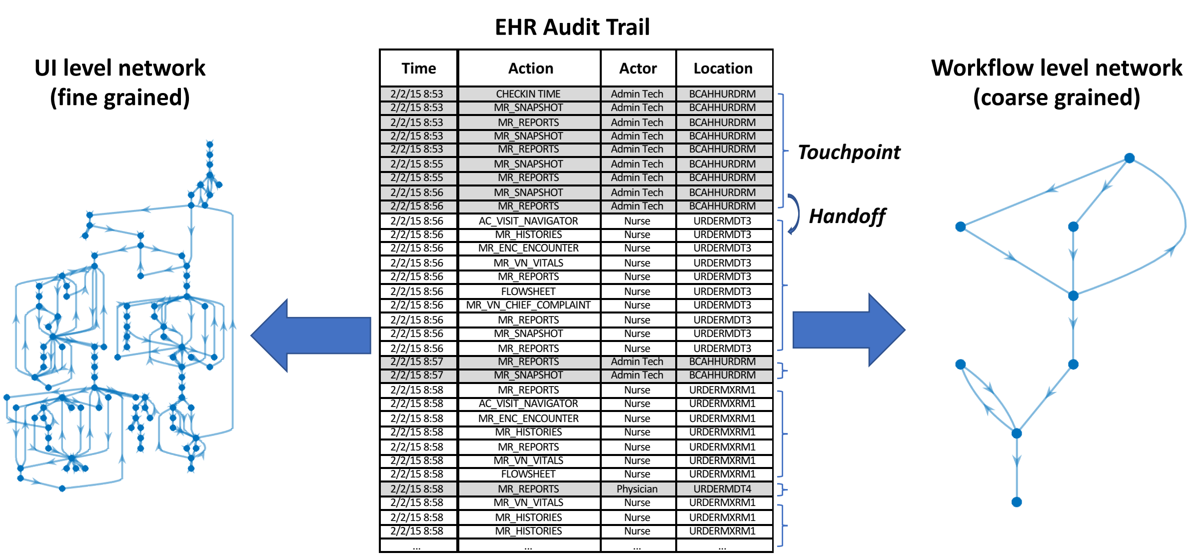


Figure 1. Simplified narrative network for an outpatient medical clinic



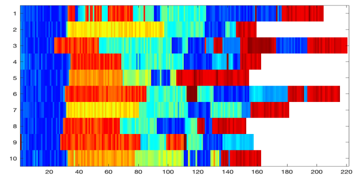
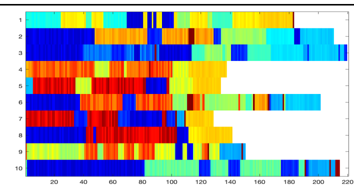
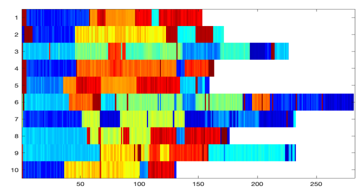
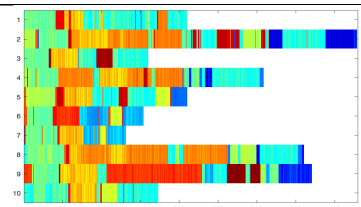
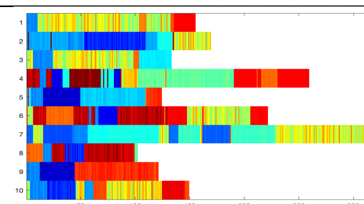
Time	Action	Actor	Location
2/2/15 8:53	CHECKIN TIME	Admin Tech	BCAHHURDRM
2/2/15 8:53	MR_SNAPSHOT	Admin Tech	BCAHHURDRM
2/2/15 8:53	MR_REPORTS	Admin Tech	BCAHHURDRM
2/2/15 8:53	MR_SNAPSHOT	Admin Tech	BCAHHURDRM
2/2/15 8:53	MR_REPORTS	Admin Tech	BCAHHURDRM
2/2/15 8:55	MR_SNAPSHOT	Admin Tech	BCAHHURDRM
2/2/15 8:55	MR_REPORTS	Admin Tech	BCAHHURDRM
2/2/15 8:56	MR_SNAPSHOT	Admin Tech	BCAHHURDRM
2/2/15 8:56	MR_REPORTS	Admin Tech	BCAHHURDRM
2/2/15 8:56	AC_VISIT_NAVIGATOR	Nurse	URDERMDT3
2/2/15 8:56	MR_HISTORIES	Nurse	URDERMDT3
2/2/15 8:56	MR_ENC_ENCOUNTER	Nurse	URDERMDT3
2/2/15 8:56	MR_VN_VITALS	Nurse	URDERMDT3
2/2/15 8:56	MR_REPORTS	Nurse	URDERMDT3
2/2/15 8:56	FLOWSHEET	Nurse	URDERMDT3
2/2/15 8:56	MR_VN_CHIEF_COMPLAINT	Nurse	URDERMDT3
2/2/15 8:56	MR_REPORTS	Nurse	URDERMDT3
2/2/15 8:56	MR_SNAPSHOT	Nurse	URDERMDT3
2/2/15 8:56	MR_REPORTS	Nurse	URDERMDT3
2/2/15 8:57	MR_REPORTS	Admin Tech	BCAHHURDRM
2/2/15 8:57	MR_SNAPSHOT	Admin Tech	BCAHHURDRM
2/2/15 8:58	MR_REPORTS	Nurse	URDERMXRM1
2/2/15 8:58	AC_VISIT_NAVIGATOR	Nurse	URDERMXRM1
2/2/15 8:58	MR_ENC_ENCOUNTER	Nurse	URDERMXRM1
2/2/15 8:58	MR_HISTORIES	Nurse	URDERMXRM1
2/2/15 8:58	MR_REPORTS	Nurse	URDERMXRM1
2/2/15 8:58	MR_VN_VITALS	Nurse	URDERMXRM1
2/2/15 8:58	FLOWSHEET	Nurse	URDERMXRM1
2/2/15 8:58	MR_REPORTS	Physician	URDERMDT4
2/2/15 8:58	MR_VN_VITALS	Nurse	URDERMXRM1
2/2/15 8:58	MR_HISTORIES	Nurse	URDERMXRM1
2/2/15 8:58	MR_HISTORIES	Nurse	URDERMXRM1
...	...	...	...

Figure 2. EHR audit trail can be interpreted at two levels of granularity

Table 1. Coherence in a clinical path

	Check-in	→ Vital Signs	
What	Check-in	Enter Vital signs	Different
When	9:30 am	9:40 am	Different
Where	Front desk	Exam room	Different
Who	Office assistant	Tech	Different
Who	Patient X	Patient X	Same
Where	Derm Clinic	Derm Clinic	Same
Why	Skin rash	Skin rash	Same
How	EHR system	EHR system	Same

Table 2. Five outpatient clinics

	Visits per day	Most common diagnoses	Ten typical encounters[1]	Descriptive measures
DERM A	17.10	Seborrheic keratosis Polycythemia Acne		41 ≤ Actions ≤ 90 3 ≤ Clinicians ≤ 13 3 ≤ Locations ≤ 18
DERM B	46.05	Psoriasis Polycythemia Dermatitis		6 ≤ Actions ≤ 93 1 ≤ Clinicians ≤ 17 1 ≤ Locations ≤ 26
ORTHO A	28.05	Joint disorders Leg/lower knee injury Elbow/forearm injury		27 ≤ Actions ≤ 116 3 ≤ Clinicians ≤ 26 3 ≤ Locations ≤ 32
ORTHO B	14.50	Arthritis Joint disorders Soft tissue disorders		45 ≤ Actions ≤ 111 3 ≤ Clinicians ≤ 29 5 ≤ Locations ≤ 30
PED ONC	9.45	Leukemia Carcinoma Sickle-cell disorders		7 ≤ Actions ≤ 98 1 ≤ Clinicians ≤ 15 2 ≤ Locations ≤ 23

[1] Each row shows the temporally ordered sequence of actions for one patient visit. The colors (visible in the on-line version) indicate different actions by specific actors, in specific locations, so they provide a visualization of the diversity of the action sequences. Colors are assigned separately for each clinic because each clinic is different.

Table 3. Network characteristics and changes

	Before Disruption					After Disruption					Network dynamics		
Clinic	**Nodes**	**Edges**	**Density**	**% Actor Coherent**	**% Location Coherent**	**Nodes**	**Edges**	**Density**	**% Actor Coherent**	**% Location Coherent**	**% Edges Forming**	**% Edges Persisting**	**% Edges Dissolving**
User Interface Level													
DERM A	2,579	12,855	0.0019	72.3%	69.5%	2,328	10,736	0.0020	66.7%	64.3%	60.1%	23.4%	76.6%
DERM B	9,253	38,512	0.0004	84.3%	77.8%	7,755	32,821	0.0005	79.9%	74.9%	64.4%	20.8%	79.2%
ORTHO A	8,354	36,182	0.0005	77.4%	75.4%	7,472	32,411	0.0006	74.5%	72.0%	66.1%	23.4%	76.6%
ORTHO B	5,041	18,879	0.0007	72.9%	70.5%	6,006	22,325	0.0006	70.9%	68.7%	97.7%	20.5%	79.5%
PED ONC	5,349	19,912	0.0007	84.3%	81.7%	4,199	15,047	0.0009	84.2%	81.5%	59.4%	16.2%	83.8%
Workflow Level													
DERM A	153	989	0.0425	15.0%	2.3%	153	991	0.0426	11.4%	0.6%	63.8%	36.4%	63.6%
DERM B	478	4,103	0.0180	28.2%	3.4%	429	3,818	0.0208	19.6%	3.3%	71.4%	21.6%	78.4%
ORTHO A	527	3,575	0.0129	8.4%	5.6%	502	3,522	0.0140	7.3%	3.9%	73.0%	25.5%	74.5%
ORTHO B	368	2,047	0.0152	11.2%	2.1%	449	2,674	0.0133	8.9%	4.5%	105.6%	25.0%	75.0%
PED ONC	264	1,786	0.0257	20.5%	4.7%	205	1,412	0.0338	21.0%	4.7%	63.5%	15.6%	84.4%

Table 4-1. User Interface level edge persistence

	DERM A	DERM B	ORTHO A	ORTHO B	PED ONC	Meta Results
Repetition	0.326*** (0.022)	0.422*** (0.020)	0.474*** (0.026)	0.406*** (0.024)	0.398*** (0.028)	0.404*** (0.069)
Duration	0..320*** (0.025)	0.043*** (0.016)	0.279*** (0.018)	0.297*** (0.022)	0.045 (0.024)	0.189** (0.064)
Actor coherence	1.952*** (0.128)	3.462*** (0.080)	2.731*** (0.089)	2.418*** (0.139)	3.004*** (0.198)	2.731*** (0.254)
Location coherence	2.386*** (0.169)	1.406*** (0.129)	2.254*** (0.129)	2.294*** (0.204)	1.938*** (0.196)	2.025*** (0.178)
Constant	-5.710*** (0.225)	-5.992*** (0.227)	-6.050*** (0.243)	-6.032*** (0.289)	-6.461*** (0.304)	-6.026*** (0.225)
# persisting edges	3,014	8,024	8,479	3,875	3,221	26,613
# nodes (Before)	2,579	9,253	8,354	5,041	5,349	30,576
# edges (Before)	12,855	38,512	36,182	18,879	19,912	126,340

Table 4-2. User Interface level edge formation

	DERM A	DERM B	ORTHO A	ORTHO B	PED ONC	Meta Results
Actor coherence	3.618*** (0.096)	4.341*** (0.037)	3.252*** (0.039)	3.541*** (0.051)	3.934*** (0.064)	3.743*** (0.185)
Location coherence	0.357*** (0.098)	0.587*** (0.049)	1.393*** (0.044)	1.365*** (0.057)	1.063*** (0.064)	0.975*** (0.207)
Constant	-3.945*** (0.023)	-4.482*** (0.051)	-4.362*** (0.035)	-4.270*** (0.028)	-4.352*** (0.039)	-4,243*** (0.088)
# formed edges	7,722	24,797	23,932	18,450	11,826	86,727
# nodes (After)	2,328	7,755	7,472	6,006	4,199	27,760
# edges (After)	10,736	32,821	32,411	22,325	15,047	113,340

Table 5-1. Workflow level edge persistence

	DERM A	DERM B	ORTHO A	ORTHO B	PED ONC	Meta Results
Repetition	0.417*** (0.081)	0.38*** (0.036)	0.133** (0.042)	0.38*** (0.059)	0.187** (0.07)	0.294** (0.103)
Duration	-0.168* (0.077)	0.156*** (0.043)	0.005 (0.041)	0.028 (0.061)	0.065 (0.065)	0.033 (0.104)
Actor coherence	1.987*** (0.188)	3.305*** (0.098)	3.190*** (0.168)	2.946*** (0.192)	3.085*** (0.166)	2.939*** (0.234)
Location coherence	1.139 (0.635)	2.137*** (0.178)	2.625*** (0.154)	2.603*** (0.365)	2.284*** (0.273)	2.293*** (0.246)
Constant	-4.877*** (0.294)	-5.036*** (0.164)	-6.104*** (0.244)	-6.422*** (0.3)	-5.814*** (0.23)	-5.624*** (0.298)
# persisting edges	360	888	912	512	278	2,950
# nodes (Before)	153	478	527	368	264	1,790
# edges (Before)	989	4,103	3,575	2,047	1,786	12,500

Table 5-2. Workflow level edge formation

	DERM A	DERM B	ORTHO A	ORTHO B	PED ONC	Meta Results
Actor coherence	1.811*** (0.150)	2.435*** (0.062)	2.229*** (0.098)	2.652*** (0.100)	3.044*** (0.109)	2.453*** (0.204)
Location coherence	3.808*** (0.676)	3.036*** (0.134)	2.678*** (0.134)	4.463*** (0.252)	2.318*** (0.181)	3.171*** (0.378)
Constant	-2.506*** (0.082)	-2.894*** (0.056)	-2.919*** (0.047)	-2.835*** (0.044)	-2.709*** (0.090)	-2.805*** (0.108)
# formed edges	631	2,930	2,610	2,162	1,134	9,467
# nodes (After)	153	429	502	449	205	1,738
# edges (After)	991	3,818	3,522	2,674	1,412	12,417

Table 6. Sensitivity Analysis Results (Case Replacement Percentage)

	Persistence		Formation	
Mechanism	**UI**	**Workflow**	**UI**	**Workflow**
Repetition	10.7%	3.97%	N/A	N/A
Duration	2.86%	n.s.	N/A	N/A
Actor Coherence	38.3%	40.3%	44.9%	38.1%
Location Coherence	35.3%	35.3%	17.6%	38.2%

Table 7. Interpretation of results as change in odds

	Meta Coefficient	Unit change	Change in odds
User Interface Persistence			
Repetition	0.404***	1 std. dev. (0.66 repetitions)	50%
Duration	0.189**	1 std. dev. (2.41 seconds)	21%
Actor coherence	2.731***	Same/Different	1435%
Location coherence	2.025***	Same/Different	658%
User Interface Formation			
Actor coherence	3.743***	Same/Different	4122%
Location coherence	0.975***	Same/Different	165%
Workflow Persistence			
Repetition	0.294**	1 std. dev. (0.65 repetitions)	34%
Duration	0.033	1 std. dev. (2.66 seconds)	3%
Actor coherence	2.939***	Same/Different	1790%
Location coherence	2.293***	Same/Different	890%
Workflow Formation			
Actor coherence	2.453***	Same/Different	1062%
Location coherence	3.171***	Same/Different	2283%