

From Lock-in to Transformation: A Path-centric Theory of Emerging Technology and Organizing

Brian T. Pentland
Michigan State University
632 Bogue St, East Lansing, MI 48824
pentland@broad.msu.edu

Youngjin Yoo,
Case Western University
11119 Bellflower Rd, Cleveland, OH 44106
youngjin@case.edu

Jan Recker
University of Hamburg
Von-Melle-Park 5
20148 Hamburg, Germany
jan.christof.recker@uni-hamburg.de

Inkyu Kim
Michigan State University
632 Bogue St, East Lansing, MI 48824
kiminky1@broad.msu.edu

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Abstract

We offer a path-centric theory of emerging technology and organizing that addresses a basic question: when does emerging technology lead to transformative change? A path-centric perspective on technology focuses on the patterns of actions afforded by technology-in-use. We identify performing and patterning as self-reinforcing mechanisms that shape patterns of action in the domain of emerging technology and organizing. We use a dynamic simulation to show that performing and patterning can lead to a wide range of trajectories, from lock-in to transformation, depending on how emerging technology-in-use influences the pattern of action. When emerging technologies afford new actions that can be flexibly recombined to generate new paths, decisive transformative effects are more likely. By themselves, new affordances are not likely to generate transformation. We illustrate this theory with examples from the practice of pharmaceutical drug discovery. The path-centric perspective offers a new way to think about generativity and the role of affordances in organizing.

Keywords: Patterns of action; dynamic network; performing and patterning; generativity; affordances; routine dynamics; simulation.

Introduction

Some technologies of the recent past, such as social media, smartphones, and tablets have taken off like rockets. Other technologies like artificial intelligence or mRNA-based pharmaceuticals seem likely to take off in the near future. These emerging technologies don't just "go viral" -- they transform the fabric of organizing. By *transform*, we mean they change "how, when, and where work gets done, as well as by whom and for whom" (Bailey et al. 2019). Metaphorically, they change the *form* of organizing: the patterns of action through which work gets done.

However, not all technologies have such a dramatic effect. Many technologies, like Google Glass, just fizzle out on the launchpad or diffuse slowly over decades. Other technologies, like electronic patient record systems, have led to a "lock-in" of existing patterns of action rather than their transformation (Choi et al. 2018). These differences in trajectories of organizing, from lock-in to transformation, point to a gap in our understanding of emerging technology and organizing: under what conditions, and how, does emerging technology transform the trajectory of organizing?

The existence of this gap in understanding may seem puzzling. The role of technology has always been a central theme in organization theory. Early studies conceptualized technology as an exogenous force that determined organizational forms (Woodward 1965, Perrow 1967). Today, there is a growing consensus that technology and organizing are "imbricated" (Leonardi 2011) or "entangled" (Orlikowski and Scott 2008) through recurring and on-going use of technology in practice (Swanson 2019). While current literature provides a deep understanding on how technology and organizing are intertwined, it fails to offer a decisive theoretical account on how and when emerging technology can generate transformative change in organizing and when it does not. This is our goal in this paper.

Emerging technology

By *emerging technology*, we mean any kind of artifact -- material or immaterial -- that affords new possibilities for action. While we have always had emerging technologies, we are seeing a barrage of new tools (e.g., 3D printers), new methods (e.g., CRISPR), new interfaces (e.g., APIs), new platforms

(e.g., blockchains), new protocols (e.g., 5G protocol stack), and new algorithms (e.g., generative adversarial networks), that are qualitatively different from emerging technologies of the past. For organization researchers, these contemporary emerging technologies have been particularly difficult to theorize because they are generally not single devices with defined scope and predetermined roles such as informing, automating, communicating, and coordinating (Fulk and DeSanctis 1995; Malone et al. 1987; Zuboff 1988), whose influence can be neatly isolated. Rather, contemporary emerging technologies are often programmable and recombining, with layered architectures and complex ecologies consisting of other technologies often connected through common standards and global digital infrastructures (Yoo et al. 2010; Tilson et al. 2010). As a result of these characteristics, these technologies are doing much more than just substituting, improving, refining, automating or informing within specific practices. They are transforming and creating new spheres of practice. As we explain below, contemporary emerging technology achieves these effects by not only affording new actions but also new ways of recombining those actions into novel ways of getting things done.

Consider the practice of vaccine development, which has been remarkably stable since the first vaccine for smallpox was developed in 1796 (Gomez and Robinson 2018). It begins with the creation of a “master cell bank” produced from weakened or killed pathogens, or their parts. The master cells are then cultured in a controlled environment to produce large quantities. After the extraction of certain proteins and a purification process, the vaccine is transferred into individual vials for deployment. In organizational terms, this pattern of activity was “locked in” (Sydow et al. 2009).

With the emergence of messenger RNA (mRNA) technology, that century-old process is currently being transformed (Kester et al. 2020). Moderna, one of the leading digital biopharmaceutical firms, notes that “mRNA is the software of life – so the very essence of our medicines is digital.” Synthetic mRNA does not actually carry any physical antigens or proteins. Instead, it carries a set of digital instructions to make our own bodies produce a variant of the target pathogens to produce immune responses (Damiani 2017). The new technology is not just radically shortening the vaccine development process; fundamentally new patterns of activity for drug discovery are emerging (Cui et al. 2020,

Chaudhari et al. 2020, Lin, Li, and Lin 2020, Callaway 2020). “mRNA technology” exemplifies an emerging technology because it is an interdependent collection of tools and techniques that is transforming the established pattern of activity in how vaccine development is organized.

Roadmap of the article

In this article, we offer a dynamic theory of how emerging technology can lead to lock-in or transformation. Table 1 shows three of the central concepts in our theory. We start from the ground up, with situated work practices, such as vaccine development. We describe work practices in terms of *paths*, “time-ordered sequences of actions or events in performing work” (Goh and Pentland 2019, p.1901). Paths are formed through past performances and they guide but do not determine future performances. Within a window of time, paths can be aggregated into *patterns of action*, which can be represented as a network (Pentland and Feldman 2007; Pentland, Recker and Wyner 2017). We can analyze these networks over time to understand the *trajectory* of how these patterns of action change when new technology is introduced.

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

We use computer-based simulation to theorize about the conditions under which emerging technology can generate transformation of patterns of actions and when it does not. We extend an existing simulation model (Pentland, Feldman, Becker and Liu 2012) to model how new technology shapes the trajectory of patterns of action. The simulation is deliberately abstract, so that the results can be interpreted in terms of any kind of emergent technology, be it tool, method, interface, platform, protocol, or algorithm.

We use the simulation to illustrate and generate insights about our theory, not to test it. This is key to our theorizing. There has been a great deal of field research on the transformational impact of technology (e.g., Barley, 1986 1990b; Leonardi and Bailey 2008, Selander and Jarvenpaa 2016, Barrett, Oborn and Orlikowski and Yates 2012, Sergeeva, Faraj and Huysman 2020). With field research, we can document and analyze how a particular technology influences the trajectory of a particular pattern of

action as it changes over time (e.g., the pattern of action in a radiology department after the introduction of computerized tomography, as in Barley, 1986). But with simulation, we can manipulate the theoretical antecedents and analyze the trajectories of thousands of action patterns as influenced by any kind of emerging technology. Simulation is a useful tool for theory generation because it allows us to visualize the interaction of simple mechanisms over a wide range of parameter values (Davis et al. 2007).

The specific contribution of this article resides in our focus on performing and patterning of actions (Feldman 2016, Danner-Schroder and Geiger 2016, Turner and Rindova 2018, Goh and Pentland 2019) to provide a path-centric lens on emerging technology and organizing. While prior research has identified performing and patterning as a mechanism for lock-in and incremental change (Pentland, Feldman, Becker and Liu 2012), our simulation shows that it can explain a much wider range of trajectories in patterns of action, from lock-in to drift to transformative change, when we consider it together with the influence of emerging technology. Emerging technology affords new actions and new ways of recombining actions to form paths to get things done. We show that adding new actions is necessary but not sufficient for transformation of organizing. Transformative change requires the formation of new paths (different ways of getting things done) and the dissolution of old paths, through the emergent, self-reinforcing processes of performing and patterning. Developing this path-centric perspective allows us to demonstrate that generativity is not a feature of technology-as-designed but an emergent property of how technology is used in practice. It also allows us to identify new forays into research on affordances by locating individual possibilities for action as vested in emerging technology within the paths in which work gets done.

We begin by introducing paths and pattern of actions as the foundation of our theory. *Organizing* implies patterns of action that form and take shape over time. We then theorize about how performing and patterning (Feldman, 2016) shapes the form of organizing (i.e., patterns of action) over time and the influence of emerging technology on the trajectory of those patterns. We use examples from the drug discovery pipeline (Ng 2004, Barry 2005, Dougherty and Dunne 2012) to illustrate the basic ideas of the theory. To generalize more broadly, we report results from a computer-based simulation that explores the

conditions under which emerging technology leads to lock-in, drift, or transformation of patterns of action. Finally, we discuss implications for our understanding of technology and organizing, generativity, and affordances.

Theory development

In developing a dynamic theory of emerging technology and organizing, we draw on the concept of morphogenesis to lend structure and coherence to our process-centric theorizing. *Morphogenesis* simply means the “creation of form.” The broad intellectual tradition of morphogenesis spans biology (Bonner 1952), sociology (Archer 1982), and general system theory (Buckley 1967). From cells to cities, morphogenesis explains how new forms emerge, so it provides a useful meta-theory for a theory of emerging technology and organizing. Across these disciplines, the goal is not just to explain how complex patterns *change*, but how they become *more differentiated* and how new forms emerge over time. This differentiation is what Archer (1982) refers to as *structural elaboration*: the creation of a new form. In the following sections, we use the ideas of emergence and structural elaboration from morphogenesis to outline the key elements of a path-centric theory of emerging technology and organizing.

Paths as the unit of observation

Put simply, a path is a way of getting something done. For any “job to be done” (Christensen et al. 2007), there can be many possible paths. Furthermore, new paths can be formed by random variation (Page 2011) or by mindful deviation (Garud and Karnøe 2001). When technology emerges that affords new ways of getting things get done, it changes the possible paths. Paths are intuitive, concrete and observable, so they can be readily operationalized in empirical research. For example, in a drug discovery pipeline, there are many possible paths. Dougherty and Dunne (2012, p. 1478) quote a scientist who described the development of a successful drug as “a path fraught with all kinds of significant obstacles, each one of which was overcome.”

Pattern of action as the unit of analysis

By *pattern of action*, we mean the aggregation of all paths—both actual and possible—in a given window of time. By analogy, if a path represents one street, then the pattern of action is the map of all the streets. In the language of morphogenesis, the pattern of action is the focal entity that takes shape over time, like a cell or city. We choose patterns of action as the focal entity for three reasons.

First, as Swanson (2019) argues, the “technology-as-device” attitude is inconsistent with current thinking about technology. The last 50 years of research on technology and organizing can be characterized as a shift from a predominantly essentialist/substantialist perspective to a more processual/relational perspective. This movement corresponds to the “relational turn” in sociology in general (Emirbayer 1997, Abbott 2020). We see echoes of the relational turn in Actor Network Theory (ANT) (Law 1992, Latour 2005), affordance theory (Chemero 2003, Volkoff and Strong 2013) and sociomateriality (Orlikowski 2007, Leonardi 2013). Across these theoretical perspectives, a common thread is that technology takes on its meaning in-use or in-practice (Orlikowski 2000), in relation to context, purpose, and other activities. Of course, this relational perspective is also processual. For example, ANT’s classic model of translation (*problematization, interessment, enrollment, mobilisation*) describes the process through which actor-networks form and stabilize as actants (Callon 1984). Entities are stable-for-now, until their constitutive network of relations changes or dissolves. This continually emerging web of relations is axiomatic to the relational perspective (Abbott 2020).

Consider the example of the protein sequenator, “an instrument for the automatic determination of amino acid sequences in proteins and peptides” (Edman and Begg 1967, p.80). From an essentialist perspective, this device automates a particular task that is useful in drug discovery. But the key point about protein sequenators is that they afford *protein sequencing*, which opens up new ways of describing everything from specific molecules to entire genomes. Protein sequencing is not only an improved action, it affords new paths: new ways of getting things done. For example, protein sequencing provides data in a format that AI algorithms can use to search for new drugs (Vamathevan et al. 2019). To understand the

transformative potential of protein sequencing in drug discovery, we cannot just look at the sequencers. We also need to look at related activities, some of which are afforded by other technologies.

Second, the essentialist perspective tends to treat technology in isolation both in level (e.g., an individual user) and context (e.g., a particular task). For example, theories on acceptance (Venkatesh, et al. 2003), adoption (Karahanna et al., 1999), appropriation (DeSanctis & Poole 1994), diffusion (Rogers 1983), or use (Burton-Jones and Straub 2006) largely focus on singular devices, users, and their interactions within single routines and practices. This focus is inconsistent with transformation. By definition, transformative change extends beyond the boundaries of particular activities by particular actors using a particular tool (Bailey et al. 2019). For example, in their field study of drug discovery, Dougherty and Dunne (2012, p. 1469) noted that “digital sciences were injected into discrete steps of the existing innovation process because it was assumed that screening many more proteins and molecules more quickly would result in more drugs. Because the number of new drugs has not increased, this assumption seems incorrect.” When new technology afforded only existing categories of action (e.g., screening molecules), within discrete steps of the discovery process, it did not have much effect.

Third, transformative change will almost always involve more than one technology. Especially in the digital world, no technology emerges in a vacuum. Emerging technology always builds on and connects with technology that is already there. Unfortunately, past research on technology in organizations tends to focus on individual technologies, one at a time, such as ERP (Berente, Lyytinen, Yoo and King 2016) or robotics (Sergeeva, Faraj and Huysman 2020). While studies of individual technologies provide useful insights, the drug discovery pipeline employs dozens of interconnected technologies (e.g., databases, analytical tools, machine learning algorithms, etc.) (Lin et al. 2020, Cui et al. 2020, Chaudhari et al. 2020). Similarly, in practice, “social media” or “online networks” are not single technologies; they are ecologies of layered and interconnected technologies.

To address these issues, we shift away from technology per se and adopt *patterns of action* as our focal unit of analysis. This choice builds on Weick’s (1979) idea that interlocked actions, not actors, are the basic unit of organizing and Czarniawska’s (2004) idea of organizations as action nets. Pentland and

Feldman (2007, p. 781) extended this idea to describe “how technology and organization are intertwined” by including technologically enabled actions (e.g., using a computer to buy an airline ticket).

We formalize *patterns of action* as weighted, directed graphs where the nodes are actions or activities and the edges (or ties or arcs) are sequential relations between actions or activities (Pentland, Recker and Wyner 2017). This class of model provides a particularly useful way to theorize about emerging technology and organizing because it summarizes temporal/processual relations between activities, not relations between actors or devices that are typically represented in other kinds of networks (e.g., communication). Sequential relations define temporal precedence and process.

The importance of sequential relations is easy to see in the context of the drug discovery pipeline. In typical high-level descriptions, the drug discovery pipeline consists of four main stages that are sequentially related: (1) target identification and validation; (2) compound screening and lead discovery; (3) pre-clinical development and (4) clinical development (Dougherty and Dunne 2012; Vamathevan et al. 2019). Within each stage, there are numerous activities that are also sequentially related. For example, a protein must be sequenced before it can be compared to other proteins or matched against a target site. Sequential relations between actions are constitutive of the pattern of action within the pipeline and the pipeline itself.

In addition, because the network describes patterns of action rather than specific technologies, it naturally integrates whatever technologies happen to come into play (Pentland and Feldman 2007). We are not locked into an analysis of the protein sequenator or any other particular artifact. The network provides a way to encompass any and all related technologies through the actions they afford, which is important to building a general theory about *any* emerging technology and organizing.

Performing and patterning

A theory drawing on morphogenesis requires a set of *mechanisms* that generate observable forms. With action patterns as the focal entity, we need to identify the mechanisms that shape them. For this, we adopt Feldman’s (2016) concepts of performing and patterning, which were originally introduced to

explain stability and change in organizational routines. The idea has quickly become very influential in that literature (e.g., Danner-Schröder and Geiger 2016, Turner and Rindova 2018, Goh and Pentland 2019, Feldman et al. in press). Performing refers to the enactment of a path, a particular sequence of actions within the network: a specific way of doing a task, getting something done. Patterning is defined as “the formation of new paths and the dissolution of old paths in the [narrative] network that describes the routine” (Goh and Pentland 2019, p. 1901). Pentland, Mahringer, Dittrich, Feldman, and Ryan Wolf (2020b, p.5) use the metaphor of paths across a grassy meadow to explain performing and patterning:

As people walk across the meadow (i.e. perform the process), paths emerge. Some of these paths may become more beaten than others, because more people follow them. Over time, other paths might vanish as the grass fills in the unused areas. People might be inclined to follow existing paths rather than making new paths. Depending on the situation, however, they could still cross the meadow and not follow a path.

This metaphor can easily be applied to the drug discovery pipeline. Dougherty and Dunne (2012) note that in the organization they studied, there were many well-worn paths (“we’ve always done it this way”). Available digital technologies afforded new paths, but they were “not well integrated into the process” (p. 1469). Now, roughly ten years later, old paths appear to be fading and new paths are forming. As firms such as Moderna, Pfizer, or BioNTech have realized, using mRNA technology for development of COVID-19 vaccines is opening up a new set of possible paths. By performing a successful vaccine development, they have added new possible paths to the pipeline. These new paths make it possible to explore other drug innovations, too (Pardi et al. 2018). All this is leading to heightened expectations that new, even shorter paths to drug developments will become possible, such as future vaccines getting ready in 100 days, or similar paths becoming available in the cure of other diseases (Borenstein 2021).

In our theory, a key distinction we make is between *actual* paths and *possible* paths. Actual paths exist in the past. An actual path traces how something was done (e.g., the path used to create the Pfizer vaccine). Actual paths have been performed (enacted, actualized) at some time in the past, from start to finish. A possible path traces how something *could* be done (e.g., a new mRNA treatment). Possible paths have yet to be performed (enacted, actualized) and may never be. Importantly, the space of possible paths does not exist *a priori*; it is an emergent product of the actual paths combined with new affordances

made possible through emerging technology, as in the example above. Performing and patterning is the processual engine that propels the continual emergence of possible paths.

This distinction between actual and possible paths is important because possible paths are essential to structural elaboration. Possible paths afford new ways of getting things done. Possible paths are formed through the recombination of segments from actual paths together with any new actions that may be afforded by emerging technology becoming available.¹ If we locate our grassy meadow in an urban area, with multiple modes of transport (pedestrian, bicycle, ride-share, taxi, bus, subway...), the idea of recombining actual paths to form a space of possible paths becomes intuitive and obvious. If we add a new technology to the mix (e.g., electric scooters), the possible paths multiply.

The space of possible paths is a direct function of the performing and patterning mechanisms.

Figure 1 shows how the mechanisms of performing and patterning in organizing shape the space of possible paths through actual performances. It shows that performing implies enacting an actual path from a space of possible paths. Actual performances influence but do not determine future performances through patterning. Patterning, in turn, can expand or contract the space of possible paths.

Metaphorically, following an old path makes the ruts in the road deeper and more likely to be followed in the future. Venturing off the beaten tracks creates new paths and expands the possibilities for new paths.

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

Through this dynamic process, performing and patterning alters the trajectory of patterns of action. If the space of possible paths is shrinking, it indicates that the trajectory is moving towards lock-in

¹ The concept of *possible paths* does not refer to all mathematical combinations of actions in a fully connected network, where any action can potentially follow any other action. Rather, it refers to the set of paths that can be plausibly constructed based on the performances that have already occurred together with any new actions that may be afforded from time to time. Some combinations of actions are plausible — legally, materially, and culturally — while others are not. So, the set of possible paths is always greater than actualized paths, but smaller than all mathematically possible paths. Also, new actions or new combinations of actions do not stem *only* from emerging technologies. A range of circumstances, such as changes in legislation or even changes in social norms, can enable new actions or combinations of actions.

(Sydow et al. 2009). If the space of possible paths is growing, it may be moving towards transformation (Pentland et al, 2020a). Currently, the drug discovery pipeline seems to be undergoing rapid growth in the number of possible pathways, as new technologies like mRNA and AI are affording new actions and new ways for getting things done (Vamathevan et al. 2019, Senior et al. 2020).

Performing and patterning can be interpreted as a kind of learning process (Rerup and Spencer, 2021). Following existing paths is like exploiting, while performing new paths is like exploring (March 1991). This general mechanism is extremely well established. In our theory, patterning and performing are the basic mechanism that describe how patterns of action move along trajectories toward structural elaboration.

Emergent trajectories in patterns of action

Morphogenesis implies a *trajectory*, typically a progression towards a more complex, differentiated pattern (Archer, 1982). We define *trajectory* as the set of changes in patterns of action (i.e., form of organizing) over time. It entails the evolutionary progression of performances, actualized paths, and the space of possible paths. A trajectory can be described by a series of networks over time (Moody, McFarland, Bender-deMoll 2005; Rossetti and Cazabet 2018), each of which provides a snapshot of an aggregate set of actual performances and possible paths—a pattern of actions.

In the theory we offer here, Figure 1 can be located on a continuum from lock-in to drift to transformation, as shown in Figure 2. Each point along the continuum represents a trajectory where the space of possible paths is (or is not) changing over time. At one extreme, we see a fully locked-in trajectory (e.g., Sydow, Schreyögg and Koch 2009). In terms of the grassy meadow, it is as if the paths are paved and there are signs that say “keep off the grass.” This kind of material restrictiveness is quite common within particular technologies. For example, in ERP systems, highly restrictive menus, forms, and processes encourage lock-in (Sia and Soh 2007).

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

It is also possible to see trajectories that embody a modest level of endogenous change, as shown in the middle of Figure 2. This “drift” (Ciborra et al. 2000) is typical in technology-enabled organizational routines (Pentland et al. 2020a). The immediate effect is incremental, but if a trajectory drifts over a long enough period of time, the cumulative effect can be substantial.

At the other extreme, we have transformation. Transformation entails a major change in the space of possible paths and a major change in actual performances, and thus the trajectory of morphogenesis. As mentioned above, we see many examples of transformation around us and we expect more to come (Bailey et al. 2019). While we understand lock-in (Sydow et al. 2009) and drift (Ciborra et al. 2000; Feldman et al. 2016), rapid and decisive transformations have been hard to explain.

The idea of trajectory itself is not new. It simply implies a longitudinal or diachronic analysis, which is a common feature in research on technological change (Barley 1990a; Garud, Kumaraswamy and Karnøe 2010; Van de Ven and Poole 1990). Prior research on technology and innovation already refers to changes in patterns of action as indicative of a trajectory. For example, Barley (1986, 1990b) showed how interaction patterns shifted in two radiology departments after the introduction of new imaging technology. Based on data collected through participant observation, Barley argued “technologies change organizational and occupational structures by transforming patterns of action and interaction” (1990b, p. 61). More recently, Leonardi (2013) showed that use of computerized simulation technology led to changes in advice networks in engineering teams in a large automotive manufacturer. Both of these studies emphasize the role of human agency in enacting these new patterns.

We extend on these views by considering the space of possible paths and structural elaboration. A new form of organizing does not simply entail a new actualized pattern of action. It also entails changes in the space of possible paths. As we will show in our simulation, the space of possible paths can grow dramatically when new technology is introduced. This growth in the space of possible paths is a necessary condition for transformation and structural elaboration. Without it, new technologies are more likely to fizzle out without influencing the old ways of doing things. By extending the concept of trajectory to

include the space of possible paths, we provide the necessary vocabulary to explain on how emerging technologies can lead to transformation.

How emerging technology influences trajectories in patterns of action

Finally, we need to ask how emerging technologies influence the space of possible paths. The grassy meadow provides a good metaphor, but it envisions a process that is incremental. Paths slowly form and dissolve over time. Further, to the extent that paths are followed, there is an inherent tendency towards lock-in. This does not align well with the transformative phenomena we are seeking to explain.

Archer (1982) argued that significant change is most likely when *degrees of freedom* are high and *stringency of constraints* are low. The intuition behind these two factors is simple. At one extreme, when there are no degrees of freedom and stringent constraints, lock-in is the only plausible trajectory. At the other extreme, when the space of possible paths is larger and more readily accessible, we are more likely to observe more structural elaboration.

Archer (1982) defined degrees of freedom as the choices available for actors to do something new or different. In a theory of emerging technology and organizing, degrees of freedom can be interpreted as the number of new actions afforded by a new technology. Archer (1982) also framed stringency of constraints as a cost or a barrier to exploiting new degrees of freedom. In our theory, stringency could be interpreted as technology restrictiveness (Silver 1988). For example, modern enterprise systems are designed to be very restrictive in order to enforce policies and controls (Berente et al, 2016). In contrast, smartphones and social media apps with open APIs are much more flexible.

Conceptually, stringency can be framed positively (as enabling action) or negatively (as constraining action) without changing the theoretical implications (Zammuto et al. 2007). When talking about emerging technology, the term flexibility seems more natural than stringency (Leonardi 2011). Also, flexibility, or lack thereof, may not necessarily come from the technology itself. It can be influenced by non-technical factors such as institutional norms, regulations, routines, installed technology base, and market expectations.

These two dimensions have a clear, intuitive interpretation when applied to contemporary emerging technology. When the protein sequenator technology was introduced in the late 1960s, it afforded a new action: identifying the sequence of amino acids in a protein. This technology afforded a new action, not just a faster/better/cheaper version of an existing action. The recent development of nanopore sequencing technology affords the same basic action, but it also increases the speed and physical portability of protein sequencing (Kono and Arakawa 2019). As a result, it can be more flexibly combined with other actions where sequencing might not have been practical (e.g., diagnosing diseases). The new action comes with fewer constraints for use, or put differently, it can be more flexibly incorporated into different paths, simply because protein sequencing is no longer a time or physical bottleneck for time-critical applications.

Based on this analysis, we would expect that the space of possible paths would be maximized by emerging technology that creates a large number of new actions that can be flexibly recombined into new paths. Some technology affords lots of actions, but very few *new* actions (e.g., electronic health record systems). Other technology affords new actions, but lacks flexibility in how they can be recombined (e.g., ERP systems). We expect that both dimensions are needed for transformation.

Tracing the trajectories

In our simulation, we model how patterns of action change over time in response to new emerging technology. We characterize change over time in terms of three dimensions, as described in Table 2. These dimensions vary interdependently throughout the course of each trajectory.

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

Magnitude of change. Because we use a network model to describe emerging technology and organizing, we can measure the magnitude of change of actualized paths as the Euclidian distance between networks in a time series, as in Pentland et al (2012). This metric summarizes changes in

frequency across the entire set of edges in the network. If actualized paths change, it is reflected in the Euclidean distance. The distance between networks is a fundamental concept for classifying networks, detecting temporal changes in network structures and their tracing their temporal evolution (Borgatti et al. 2009). Magnitude of change also provides an intuitive indicator of lock-in versus transformation. For example, prior to the introduction of mRNA technology, the magnitude of change in vaccine development from year to year was relatively low; the process in 2010 was very similar to the process in 2000. If mRNA affects the current trajectory as much as expected, the vaccine development process in 2030 will be very different.

Space of possible paths. A second key characteristic of change is the size of the space of possible paths. To the extent that new technology affords new actions that can be flexibly recombined, it should generate new ways of getting things done and thereby increase the space of possible paths. In our simulation, we estimate the number of possible paths based on the number of nodes and edges in the network, as described by Goh and Pentland (2019). Because the effect is exponential, we report the logarithm (base 10) of the number of possible paths in our simulation. For example, nanopore protein sequencing (Kono and Arakawa 2019) opens up possible paths for pharmaceutical research and development. When actualized, these new paths will further increase the space of possible paths.

Structural elaboration. Morphogenesis implies more than just change; it implies the creation of new forms. In a network, new forms occur through clustering, which indicates a set of paths that reoccur frequently. We measure the extent of structural elaboration by measuring changes in the network's global clustering (Watts and Strogatz 1998), which provides a measure of the tendency of a network to form clusters. With a network time series, one can also examine the tendency of specific clusters to form and dissolve of time (Rossetti and Cazabet 2018). For example, drug discovery has been on a trajectory from “in vivo/in vitro” to “in silico” (Pina et al. 2010, Rao and Srinivas 2011). As Dougherty and Dunne (2012) report, the boundaries between the traditional methods (in vivo/in vitro) and the computational methods (in silico) are not clear cut. If we represent the drug discovery pipeline as a network, closely

related activities would be clustered together (e.g., in vivo vs. in silico). Over time, the structure of the network would change as the practice of drug discovery changes.

Simulating the dynamics of emerging technology and organizing

Design and parameters

While there is a great deal to be learned from field studies of particular cases, like drug development, our ambition is to theorize about emerging technology and organizing in general. We propose that in organizing, the same mechanism -- performing and patterning -- can lead to a range of trajectories, from lock-in to transformation. Emerging technology alters the conditions under which these mechanisms lead to different trajectories, depending on degrees of freedom and stringency of constraints emerging technology offers to organizing. We can characterize these different trajectories through our measures of magnitude of change, space of possible paths, and structural elaboration.

We use simulation to demonstrate this process. Details are presented in Appendix A. Since it is not feasible to simulate the situated details of technology-in-practice that can be observed in field research, we build on a simulation model introduced by Pentland, Feldman, Becker and Liu (2012) that captures the basic idea of performing and patterning in an abstract way. The original model showed that two parameters used to model performing and patterning, variation (V) and retention (R), are necessary and sufficient to explain lock-in and drift. For example, zero variation (V) means that performances will never venture beyond existing paths. This situation will result in lock-in, with zero change in the space of possible paths. As variation (V) increases, the routine begins to drift. When retention (R) is high, the drift is slow.

Variation (V) and retention (R) can explain lock-in and drift, but they are not sufficient to explain transformation through emerging technology. We therefore extend the basic model of performing and patterning by Pentland, Feldman, Becker and Liu (2012) with two new parameters that model the idea that structural elaboration is more likely in situations with high degrees of freedom, expressed as number of new actions afforded (A), and low stringency of constraints, expressed as high flexibility (F).

To help build intuition about the nature of our simulated trajectories where we vary A and F under different levels of V and R, Figure 3 shows three extreme examples. The upper row shows six snapshots from a trajectory where no new technology is introduced ($A=0$). The middle row shows a trajectory where new technology is introduced after $t=300$, with up to 10 new actions ($A=10$), but with minimum flexibility ($F=0$). The new actions are diamonds instead of circles. The bottom row shows six snapshots from a trajectory with same number of new actions ($A=10$), but with maximum flexibility ($F=1$). In all three of these trajectories, $V=0.01$ and $R=50$. To make the images simpler and easier to see, the edge weights do not vary and we show only 6 snapshots. In the full analysis, edge weights vary and we use 25 snapshots.

******* Insert Figure 3 here *******

Figure 3 shows the central idea of our path-centric theory about structural elaboration in patterns of action: each “point” along the trajectory is a network and that network is changing over time. In the top row of Figure 3, we can see how V and R produce an on-going background level of drift in the patterns of action. The effects of V and R are intuitive, gradual, and monotonic. More variation increases change; more retention reduces change.

When new actions enter the simulation with minimal flexibility ($F=0$), as in the middle row, they are not integrated into the overall pattern of action. This echoes Dougherty and Dunne’s (2012) observation about digital technologies in drug development, at least initially. By the sixth time slice, more paths in/out of this island of new actions have formed, but they are still quite isolated.

When new actions enter the simulation with maximum flexibility ($F=1$), as in the bottom row, they can be integrated throughout the overall pattern of action. For this reason, the same number of new actions can generate a much higher number of possible paths. This increase in possible paths creates the necessary condition for transformation, as we demonstrate in the simulation.

Simulation results

We present the main body of our simulation results in Figures 4-6, each of which shows a different perspective on the same set of 10,000 simulated trajectories. Each trajectory consists of a set of 25 snapshots like the ones in Figure 3, with a different set of randomly chosen parameters (V, R, A and F) for each trajectory.

Effects of (A) and (F)

Figure 4 shows the main effects of emerging technology on morphogenesis. It shows changes in magnitude of change, the number of possible paths, and the cluster coefficient, in relation to the simulated levels of new actions (A) and flexibility (F). For each parameter, Figure 4 shows averages over all values of the other parameters, so that the independent contribution of each parameter can be easily seen. Thus, the lines in Figure 4 can be interpreted as average trajectories from thousands of emerging technologies. Across all three measures, an increased number of new actions (A) results in large changes. Likewise, increased flexibility (F) results in large changes.

******* Insert Figure 4 here *******

Figure 4 illustrates four key points. First, where there are no new actions ($A = 0$), there is no transformation, only drift. This smooth, base level progression is the bottom line in each of the graphs. It reflects the average of all values of V and R, including the trajectories with the highest and lowest levels of drift.

Second, Figure 4 shows what appears to be a ceiling effect when structural change is measured by Euclidean distance. Above a certain level, increasing A and F does not appear to have much effect. Distance measures are intuitively appealing, but the magnitude of change in the actualized paths does not tell the whole story. This is one reason why the other indicators are theoretically important.

Third, when new actions are introduced, the number of possible paths can increase by *many* orders of magnitude. By itself, across all values of V, R and F, the number of new actions (A) has a large effect on the number of possible paths. Similarly, flexibility (F) has a large effect on the possible of new paths.

Finally, new actions (A) and flexibility (F) also have a large effect on the cluster coefficient. In particular, F leads to substantial increase in clustering. The more flexibly actions can be recombined, the greater the tendency towards structural elaboration.

Interpretation. On the whole, the simulation results are aligned with the theory: new actions (A) and flexibility (F) affect all three indicators that a trajectory is moving towards transformation. However, while the simple distance measure of actualized paths is intuitively appealing, it seems to be the weakest indicator of potential transformation. Changes in A and F have a rather ambiguous effect on this measure.

In contrast, our simulation suggests that small changes in A and F can have an extremely large effect on the number of possible paths and on the tendency for structural elaboration. Thus, when new technologies emerge in the drug discovery pipeline, we can ask how many new actions they afford and how flexibly those actions can be recombined with existing actions. As these numbers grow, we can expect the potential for transformation to grow. This result is particularly interesting because emerging *digital* technologies can potentially be high on both dimensions. Thus, it is interesting to see how these dimensions interact.

Interaction of A and F

The graphs in Figure 5 show how the interaction of A and F influences our three dependent variables. Flexibility increases from left to right, from 0 to 1, in increments of 0.2. For each increment,

the range of values for A are shown (from 0 to 20, in increments of 5). This allows us to see the effect of the interaction of A and F on our outcome indicators.

***** Insert Figure 5 here *****

First, we can see that new actions (A) provide a necessary condition for transformation, but it is not sufficient. When F is low, the effect of A is minimized, as we saw in the examples in Figure 4. In a way, F acts like a “volume control” for the effect of new actions. On the left, when flexibility is low (F=0), the effect of A is smallest. On the right, when flexibility is high (F=1), the effect of A is highest. The difference is dramatic. When emerging technology affords twenty new actions (A=20) but imposes stringent constraints (F=0), Figure 5 shows that $10^{2.5}$ new paths are possible. With perfect flexibility (F=1), more than 10^{20} new paths are possible.

In terms of structural elaboration, the interaction of A and F is more complicated, but also very strong. The right graph in Figure 5 shows that when emerging technology offers no flexibility (F=0), it even reverses the effect of A: new actions tends to reduce the global clustering coefficient. Conversely, when flexibility is high, increases in A lead to substantial increases in the clustering coefficient. Finally, we note that for the Euclidean distance, the interaction effect between A and F is muted by the ceiling effect we observed in Figure 4. No matter how extreme these parameters become, there is a limit to how different the pattern of action can be when measured this way.

Interpretation. The strong amplifying interaction of A and F is a key insight from our simulation. A technology that affords new actions with low flexibility is less likely to be transformative than one that affords the same number of actions with high flexibility. As we discussed above, this combination of parameters – high A and high F – is more common with emerging digital technologies. For example, the fact that modern protein sequencing technology produces digital data that can be readily used by other digital technologies for other purposes increases its flexibility, which increases its transformative potential. This interaction of new actions and flexibility has been particularly powerful in the case of

smartphones, which readily integrate other apps that afford new actions that can be easily recombined-in-use (Henfridsson et al. 2018).

Distribution of outcomes

Finally, Figure 6 shows the distribution of dependent variables across all 10,000 simulated trajectories at the end of 2500 iterations. While this is an arbitrary end point, the trajectories have generally stabilized by then. In interpreting these histograms, it is important to remember that the cases are generated by a random combination of all four parameters (V, R, A, F), sampled from a uniform distribution over the range of values described in Table A-1.

***** Insert Figure 6 here *****

Under this assumed distribution of inputs, the most common trajectory ends with a very small number of possible paths, no clustering and minimal change. In other words, the most common trajectory is lock-in, as shown in the tallest bars in Figure 6. In our simulation, lock-in with zero changes to possible paths, across all values of the four parameters (V, R, A, F), occurred in more than 2,500 of the 10,000 trajectories. Likewise, in more than 2,300 trajectories, the change in clustering was zero.

After lock-in, the next most common trajectory evident in the distribution all three indicators could be characterized as drift. It would be difficult to put specific bounds on this region, but in this simulation, as in real life, drift occurs over a wide range of conditions (Ciborra et al. 2000; Berente et al. 2016).

The most interesting part of each distribution is the long tail, where the trajectories lead to changes of enormous magnitude. About 500 times in the simulation, the trajectory ended with a space of possible paths of the magnitude of 10^{27} and beyond. About one tenth (1,000) of the runs led to a change in clustering ≥ 0.45 . These kinds of transformations occur rarely but their effects are dramatic.

Interpretation. The important point to glean from Figure 6 is that the basic mechanism of performing and patterning is capable of generating a wide range of trajectories. While we cannot claim

that a random distribution of inputs is realistic, the distribution of outputs shown in Figure 6 does correspond to intuition, experience, and theory. The vast majority of the time, we experience stability or drift. Lock-in is particularly common. But occasionally, we experience transformative change, and the simulations let us understand under which conditions transformation occurs.

Over the last 10-15 years, social media has provided a vivid example of such transformative change. It seems possible that drug discovery may provide another example over the next 10-15 years. The morphogenetic perspective suggests that, all else being equal, transformative change is most likely when emerging technology affords new actions that can be easily recombined. This is exactly what emerging technologies – especially digital ones – can sometimes offer.

Discussion

The value of an abstract theory is that it can be applied to a wide variety of specific cases. Consider two extreme examples: Electronic Health Record (EHR) technology and Twitter. In the case of EHR, the technology affords hundreds of actions to its users (Strong et al, 2014). After decades of investment and widespread, mandatory use, EHR technology has had very little impact on the way medicine is practiced (Choi et al. 2018). Twitter, on the other hand, affords only a handful of actions (tweet, retweet, reply, follow, unfollow...). Use is optional but also flexible. We all came to see how using twitter has transformed politics, advertising, and journalism (Aral 2020, Oh et al. 2015).

Our theory explains the difference quite easily. Both dimensions – new actions and flexible recombination – are necessary for transformation. EHR systems have not transformed healthcare because they did not add many *new* actions. As pointed out by Choi et al (2018), EHR technology merely replaced the paper in the same clinical documentation processes that have been in place since Mayo Clinic invented a centralized patient record keeping system. The few new actions it did afford clinicians (e.g., automatically checking for drug interactions) could not be flexibly recombined. In contrast, Twitter afforded new kinds of actions (Leonardi and Vaast 2017; Vaast et al. 2017), but they could also be flexibly recombined with other actions (e.g., capturing an image or a video, making a purchase or

donation, reading a news article, visiting a web site, etc.). In combination with other digital technologies (e.g., APIs, smartphones, web browsers, wireless networks, etc.), users of Twitter generated a large number of new paths, forming entirely new patterns of action over time (e.g. in political processes).

As these cases demonstrate, technology may enter the world by design, but it changes the world through dynamic patterns of technology-in-use (Orlikowski 2000; Swanson 2019). The path-centric lens we propose here thus offers a new way of looking at technology, organizing, generativity and affordances, as we discuss in the following sections.

Technology as space of possible paths

From a path-centric perspective, technology should not be understood as a discrete object packed with features. As Swanson (2019) argues, technology affords “routine capabilities” that are deeply integrated with practice. Technology affords ways of getting things done. Following this line of thinking, is it more useful to understand technology as a space of possible paths. This theoretical move puts the relations between actions in the foreground. The key insight is that devices do not transform organizing. Devices and their features only create conditions for new possible paths. In fact, in our simulation model, devices do not appear at all and neither do actors. A device-centric view of technology is like the actor-centric view of action: it draws attention away from the relations between actions (the paths) that are constitutive of whatever, if anything, is happening.

This perspective marks a point of convergence between streams of literature that have stood isolated so far. Path creation, path following, and path dependence are all well-established ideas in research on organizations and innovation (Garud and Karnøe 2001; Sydow et al. 2009). Recombination is a well-established idea in technological innovation (Arthur, 2009; Henfridson et al. 2018), but generally from a device-centric perspective. For example, the iPhone is a phone *and* a camera. The missing piece to the theoretical puzzle that explains the transformative effect of some technologies and not others is the idea of *recombining paths*. Put it more bluntly, it takes recombination of tasks, not features, to transform patterns of organizing.

Our view of technology as the space of possible paths departs fundamentally from essentialist views of technology that focus on devices, artifacts or objects and their properties. For example, economic theories of technological disruption (e.g., Anderson and Tushman 1990, Christensen, Raynor and McDonald 2015) focus on the competitive effects of changes in unit cost or price/performance. Without question, innovations that offer large reductions in unit cost can disrupt incumbents in a market. But device-centric thinking cannot explain why Twitter is transformational, while EHR technology is not.

The path-centric view is also different from the traditional actor-centric agential view of technology. Scholars in this tradition argue that the outcome of technology is not determined by technology alone, but by the agential choices made by the actors (Orlikowski and Scott 2014, Orlikowski 1992, Leonardi 2011), the perceptions of the actors (Venkatesh, Morris, Davis and Davis 2003), or the social interactions of the actors (Leonardi and Barley 2010). The move away from actor-centric thinking aligns with other recent efforts to theorize technological change (e.g., Baygi et al, 2021).

The picture that emerges from a path-centric perspective is both simpler and more nuanced than a device- or actor-centric view. It is simpler because it brackets off the inscrutable interactions of technological devices and human agency: *regardless of why paths form*, path formation drives morphogenesis. Paths embody a dialectic between the past and the future; they reflect what has happened and predict what might happen. Furthermore, actualized paths are readily observable. In a grassy meadow or a drug discovery pipeline, we can watch paths form and dissolve through use and disuse.

The picture is also more nuanced because path formation is neither determined by the features of devices alone nor completely in the hands of the agentic choice by the actor. Through intensive field study, it may be feasible to explain why particular actions are taken or not taken, by particular actors, using particular devices, at particular times and places. But the emergence of an overall trajectory entails countless actions along a large, tangled set of paths—some actualized and some possible—, which is why it is better understood as a space of possible paths, conditioned by history. As in our simulation, the trajectory is *probabilistic*, as emerging technologies change the probability of which paths are actualized, and the actualized paths shape the space of possible paths, recursively over time.

Because it is focused on actions rather than technologies, the path-centric view is also well suited to the fact that technologies are rarely, if ever, used alone. Today, almost all paths - all jobs to be done - involve multiple technologies. This is a step forward from past discussions on technology, where the focus almost always has been on a singular technology -- an algorithm, an enterprise planning system, a platform, or a smartphone. Yet, no task, not to mention path, in contemporary organizing can be accomplished with a single device. While we have all been desperately seeking "IT artifacts" (Orlikowski and Iacono 2001), the world has been transformed by new paths.

A new model for generativity

The path-centric lens also provides a useful perspective on the concept of generativity. Zittrain (2006) argued that generativity "denotes a technology's overall capacity to produce unprompted change driven by large, varied, and uncoordinated audiences" (p. 1980) based on the technology's capacity for leverage, adaptability, ease of mastery, and accessibility. This definition locates generative capacity in technology but implies that it is driven by subsequent action and use. In a recent review of 93 articles on generativity, Thomas and Tee (2021) emphasize that combinatorial innovation is just one part of a larger set of processes that foster generativity. Technology is only one part of the story; legal, economic, social, and institutional factors affect generativity, as well.

A path-centric perspective provides a unified view of generativity based on the space of possible paths. In this view, the key to generativity is path formation. Unless a new technology has some influence on the paths – the sequential steps through which work is accomplished – then there is no generativity. The space of possible paths creates a common denominator with which different sources of generativity can be visualized and compared. For example, when new actions are isolated (as in the top row of Figure 4), generativity is low. When the new actions are enmeshed into the network of other actions (as in the bottom row of Figure 4), generativity is high.

Two distinct mechanisms can amplify the effect of new actions and flexibility on generativity. First, network path formation can be an exponential process (Bax 1994). If you add one new sequential

relation between two actions in a network, it can add a very large number of new paths. The non-linear nature of the network is what accounts for the difference between technologies that fizzle on the launch pad and technologies that take off. Second, by definition, path formation adds relations in the network, as upstream and downstream actions are connected through a common path. When the number of new paths starts to grow, it creates a self-reinforcing process that generates more new paths. When technology provides refinement to existing actions (faster, better, cheaper), it tends to reinforce existing paths and limit generativity. In that case, the self-reinforcing mechanism of performing/patterning leads to lock-in. When technology affords new actions that can be flexibly recombined, then the same basic mechanism can generate transformative structural elaboration.

The exponential proliferation of new relations provides a powerful engine for transformative change. This engine is powered by path formation. The enacted paths are performative. These new paths are not determined at “design-time”; they are not properties of tools, features, methods, interfaces, platforms, protocols or algorithms. Rather, new paths exist as possibilities until they are enacted at “run-time”, through on-going technology-in-use (Orlikowski 2000, Swanson 2019).

A path-centric view on emerging technology and organizing also offers insight into why emerging digital technologies are particularly powerful sources for generativity and transformation. First, digital technologies are re-combinable (Arthur 2010, Leonardi 2010, Yoo et al. 2010) because they consist of bitstrings (Faulkner and Runde 2019). Digital technologies can be easily combined and recombined with other digital objects, dramatically increasing the number of paths available. For example, nanopore protein sequencing technology produces digital bitstrings that can be readily accessed by other algorithms and flexibly recombined with other digital data.

Second, digital technology is inherently more flexible than traditional non-digital technology because its non-material components can be more easily reprogrammed (Yoo et al. 2010) to make them fit for other purposes (Henfridsson et al. 2018). For example, the mRNA technology used for COVID-19 can be used to treat a wide range of diseases (Damiani 2017) because the synthetic mRNA that carries the

instruction to produce certain proteins in the human body is digital and can be changed based on the target disease, which can instigate a series of therapeutic paths that were not possible in the past.

Third, digital technology makes it easier to connect different sets of paths that were previously unrelated as they belong in different realms of activities. For example, by connecting online search, crowd-based product reviews from e-commerce, hotel business, and restaurant industries, platforms like Yelp and Travelocity have transformed the travel and hospitality industry (Orlikowski and Scott 2014). The flexibility of smartphones that allows people to share a photo right after they take it can change how collective action can take place (Oh, Eom and Rao 2015). Ordinary activities such as walking and sightseeing can be connected with distant activities such as scientific data collection through citizen science (Bonney et al. 2009). In these examples, digital technology affords new actions (new nodes) that connect previously separate networks, thereby filling structural holes (Burt 1992). Just as filling structural holes in knowledge networks can facilitate innovation (Hansen 1999), filling structural holes in patterns of action can facilitate transformation.

Extending the view on affordances

The path-centric lens also provides a new perspective on the familiar concept of *affordances* (Zammuto et al. 2007, Leonardi 2011, Volkoff and Strong 2013). Affordances describe “the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relationship between an object (e.g., an IT artifact) and a goal-oriented actor or actors” (Volkoff and Strong 2013, p. 823). In understanding how emerging technology influences organizing, scholars have argued that an affordance is fundamentally relational and is constituted in relationship between an actor and a technological artifact (Volkoff and Strong 2013).

Consistent with the roots of this concept in ecological psychology (Gibson 1977), the emphasis has been to zoom in on a particular artifact and a users’ intent or purpose for which this artifact is used. While useful in overcoming the essentialist approach to technology, the focus is usually on a singular technology and the possible actions that actors can take with it. While relational, the concept has been

used predominantly in a device-centric way, as when scholars try to identify new affordances that technologies bring to certain practices such as collaborating (Malhotra, Majchrzak and Lyytinen 2021). Furthermore, the focus has been a narrowly defined action possibilities that the artifact affords. By analogy, it is as if the study of language was limited to particular words, without considering sentences, talk, and narrative. These larger structures are like paths (or lines, as Ingold 2012 would say). Just as we rarely use a single, isolated word, we rarely use a single, isolated affordance.

The path-centric perspective zooms out to offer a broader view. What actors do is always part of a path. Paths usually involve multiple devices, multiple actions and maybe multiple actors. By focusing on the narrow set of possible discrete actions that a particular technology affords, a narrow affordance lens misses what has happened before and what might happen next along the path. We would miss the potential for recombination-in-use (Henfridsson et al. 2018). In order to understand transformation in organizing, individual affordances are just the first step. To understand the significance of an action, we need to locate it on a path. To understand the significance of a path, we need to locate it in a network. When we make this move, it provides a way to connect the very micro-level notion of affordance with the large-scale phenomena we are now experiencing. By zooming out, we see how individual affordances generate entire spaces of possible paths, which in turn, if enacted, can lead to transformative changes in the way work gets done. Affordances alone fail to explain these changes.

Conclusion

Our path-centric dynamic view offers new insights on technological emergence and organizing that go beyond the dominant actor- and device-centric ideas that originated from economics, psychology and their derivatives (e.g., technology acceptance, marketing, etc.). By focusing on performing and patterning we begin to see how emerging technology can lead to lock-in or transformation depending on many actions it affords and how flexibly these can be incorporated into the ways in which work gets done.

The path-centric view also helps us understand key consequences of technology emergence. A critical insight is that adding more features to a device is not intrinsically generative. Generativity is not a property of devices. The transformational effect of new technology, when it happens, is not just a result of more features, but of adding new paths and removing old paths. It changes the space of possible paths. A focus on performing and patterning calls for a radical turn away from noun (*what it is*) to verb (*what it does*), as a focal point of research. Furthermore, because of the need to constantly reinforce existing paths and forge new ones, it calls attention to on-going dynamics. In short, by building on an action-centric view of organizing and emergence, performing and patterning provide insights that are not available through actor- and device-centric perspectives.

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APPENDIX A: Simulation Model

We model emerging technology as the effect of new technology entering into an on-going, dynamic network of actions. We simulate *trajectories* consisting of 2500 performances of an action pattern. Each performance consists of many discrete actions drawn from a lexicon (L) of possible actions. When new technology becomes available for use, it affords a new set of actions that become available and may (or may not) influence the trajectory of the action pattern.

Figure A-1 shows our simulation model which features the dynamic relationship between the network that represents the space of possible paths (on the left) and the actualized performances (on the right). The network summarizes the current state of the action pattern; it describes the sequential relations between each of the possible actions. Darker squares represent more frequent sequential relations in the overall pattern. To simulate performing, the network is used to generate specific sequences, which may include random variation (depending on V). To simulate patterning, recent performances get folded back into the network (depending on R). This recursive relationship between performing and patterning is the core principle of the model.

***** Insert Figure A-1 here *****

This simulation framework has been used in prior research (Table A-2). We extend the model to consider how the space of possible paths changes when emerging technology affords new actions.

***** Insert Table A-1 here *****

Model parameters used in this paper

Lexicon of Actions (L). The simulation creates patterns of action using a lexicon of L actions. Pentland et al. (2012) simulated one value (L=10). Here, we start with (L=20) and add A new actions $\{0 \leq A \leq 20\}$ to simulate the introduction of new technology.

Variations (V). The parameter V represents the effect of sequential variation in a path through sources such as workarounds, improvisation, errors, or mindful deviations (Page 2011). It governs the

amount of novelty in each performance. When $V=0$, the routine will follow and therefore reinforce an existing path in the network. When $V=0.001$, there is a one-in-a-thousand chance that a variation will arise at each step. We simulate variations in the range of $\{0 \leq V \leq 0.01\}$ in increments of 0.001.

Retention (R). The parameter R refers to how many past iterations influence the current performance. In a sense, R sets a limit on the effect of history; it determines how quickly the ruts in the road are filled in and forgotten. R is implemented as a “moving window” of previous performances. When the most recent iteration is added to the pattern, the oldest iteration in the window is dropped. We simulate variations in the range of $\{0 \leq R \leq 250\}$ in increments of 25.²

Number of new actions (A). To simulate the emergence of technology we introduce A new actions $\{0 \leq A \leq 20\}$ to the lexicon L. We explored much larger values of L and A and the qualitative results were the same. So, A is how we model degrees of freedom offered through emerging technology. As an upper bound, at the maximum value ($A=20$), we model the situation where a new technology doubles the number of possible actions. We include $A=0$ in order to have a baseline (control group) where no new actions are introduced. It is important to note that A models the number of new actions afforded by emerging technology that are actualized in practice.

Flexibility (F). Flexibility controls how easily new actions can be sequentially related to other actions, hence F models stringency of constraints. When flexibility is low, fewer relations between actions can form, so fewer paths are possible. When flexibility is high, more ways of integrating actions into paths are possible. We model the full range from highly constrained ($F=0$) to perfectly flexible ($F=1$). These extremes are important to capture because digital technologies can operate at either end of this spectrum. For example, an ERP system provides a very large number of actions (A is high), but many of them must be performed in a particular sequence, from one algorithmically determined transaction screen to the next (F is low). When flexibility is high, new actions can easily be recombined in any sequence. For example, application program interfaces (APIs) can be used in a variety of different ways and

² We tested different values of V and R and the qualitative results were the same.

bundled with a host of heterogeneous devices (Yoo et al. 2010). Flexibility allows recombination, a key source of innovation in modern digital technologies (Henfridsson et al. 2018).

Magnitude of change. We measure the magnitude of change of actualized paths as the Euclidian distance between networks in a time series, as in Pentland et al (2012). This metric summarizes changes in frequency across the entire set of edges in the network. If actualized paths change, it is reflected in the Euclidean distance.

Space of possible paths. We estimate the number of possible paths using the method described by Goh and Pentland (2019). Because the effect is exponential, we report the logarithm (base 10) of the number of possible paths.

Structural elaboration. We measure the extent of structural elaboration by measuring changes in the network’s global clustering (Watts and Strogatz 1998), which provides a measure of the tendency of a network to form clusters.

Model Operation

We analyze 10,000 trajectories, each of which simulates the introduction of a new technology into an on-going pattern of action. For each of these trajectories, we choose random values for each of the model parameters (V, R, A and F) and run the model for 2500 performances. We stopped the trajectories after 2500 performances because larger values did not add any insight. The time scale of the model is arbitrary. Performances and trajectories could correspond to hours, days, or years. To visualize the results, we store a snapshot every 100 performances, resulting in a sequence of 25 snapshots for each trajectory.³

Initial conditions: an on-going pattern of action

We introduce new technology into an on-going pattern of action. We started from a fixed sequence (1, 2, 3, 4, 5...) and let it drift for 100 iterations so that the initial conditions of each trajectory

³ The simulation is not very resource intensive; 10,000 trajectories can be computed in less than an hour on an 8-core MacBook Pro running MatLab 2020b.

are slightly different. In the analysis below, it will be apparent that this drift is on-going when the new technology is introduced.

Performing and patterning

The current state of the pattern of action is described by a weighted, directed graph. Each cell (i,j) in the matrix represents the probability p_{ij} that action i will be followed by action j . In Figure A-1, the shading of each cell in the history matrix reflects p_{ij} for one pair (i,j) of actions. This matrix can be interpreted as a first order Markov transition matrix (Anderson and Goodman 1957). It represents a nexus of past and future; it is based on actual paths (the past) and it is used to generate possible paths (the future).

Performances of the action pattern are generated based on the probabilities in the history matrix. Each performance of a path unfolds, one step at a time, starting from the same initial action. The path continues until it reaches a predetermined end state. This way, the algorithm reproduces the intuition of the grassy meadow described in the main paper: the most frequent paths in the past are the most likely paths in the future. Following an existing path will tend to reinforce it, making it more likely to occur in the future. If a path is not reinforced through use, it eventually disappears. If the probability of choosing a particular action next is zero, it can only be reached by random variation.

Patterning is simulated by updating the history matrix after every performance. The algorithm simply counts each pair of actions in the most recent R performances. The frequency of each pair of actions is used to compute the probabilities in the history matrix. Variations (V) create precedents that can be followed immediately, on every subsequent iteration of the action pattern.

Introducing new technology

We introduce new technology after the first 500 performances (five time slices). When new technology enters the simulation, it opens up A new actions in increments of five $\{0 \leq A \leq L\}$ that expand the size of the history matrix from L to $L+A$. At the time the new actions are introduced, they are

randomly assigned a level of flexibility, in increments of 0.2 $\{0 \leq F \leq 1\}$. In choosing this range of values, we have attempted to stake out the extremes of each parameter.

Limitations of the simulation

Abstract simulations provide questions, not answers, and include a number of important assumptions and limitations. First, in order to keep it simple (Neumann and Secchi 2016), we have excluded a range of complementary explanations that are known to influence technology adoption and use. A more descriptive approach (Edmonds and Moss 2004) could include economic, social and technical factors that are not included here. Second, while we talk about technology-in-practice, we are not simulating practice. Practice is situated in time, place, and community, but our abstract simulation includes none of that. Third, in our simulation, performances occur one at a time. In real life, they are occurring simultaneously, competing for resources and mutually influencing each other. Finally, we simulate the formation of paths, but the simulation does not model the *significance* of those paths. For example, the rapid development of a COVID-19 vaccine stands out as a particularly significant achievement. The role of mRNA technology in actualizing this path may influence whether and how it gets used in other paths.

Author Biographies

Brian T. Pentland (“From Lock-in to Transformation: A Path-Centric Theory of Emerging Technology and Organizing”) is Main Street Capital Partners Intellectual Capital Endowed Professor in the Broad College of Business at Michigan State University. He received his PhD in Management from the Massachusetts Institute of Technology. His research is focused on routine dynamics. **Address:** Broad College of Business, N270, 632 Bogue St, East Lansing, MI 48824; email: pentland@broad.msu.edu.

Youngjin Yoo (“From Lock-in to Transformation: A Path-Centric Theory of Emerging Technology and Organizing”) is Elizabeth M. and William C. Treuhaft Professor of Entrepreneurship and professor of information systems in the Department of Design & Innovation at the Weatherhead School of Management, Case Western Reserve University. He is WBS Distinguished Professor of Research Environment at Warwick Business School, UK. He received his PhD in information systems from the University of Maryland. His research is focused on design and innovation, especially in digital technology. **Address:** 11119 Bellflower Rd, Cleveland, OH 44106; email: _youngjin@case.edu.

Jan Recker (“From Lock-in to Transformation: A Path-Centric Theory of Emerging Technology and Organizing”) is Nucleus Professor for Information Systems and Digital Innovation at the University of Hamburg. He received his PhD in Information Systems from Queensland University of Technology. His research is focused on digital innovation, transformation, and entrepreneurship. **Address:** University of Hamburg, Von-Melle-Park 5, 20146 Hamburg, Germany; email: jan.christof.recker@uni-hamburg.de.

Inkyu Kim (“From Lock-in to Transformation: A Path-Centric Theory of Emerging Technology and Organizing”) is a doctoral candidate in Business Information Systems at Michigan State University. His research interests include process management, healthcare information systems, sequential network analysis, big data analytics, and economics of information systems.

Address: Broad College of Business, N270, 632 Bogue St, East Lansing, MI 48824; email: kiminky1@broad.msu.edu.

Figure 1: Performing/patterning shape the space of possible paths
 (from Pentland et al., 2020b)

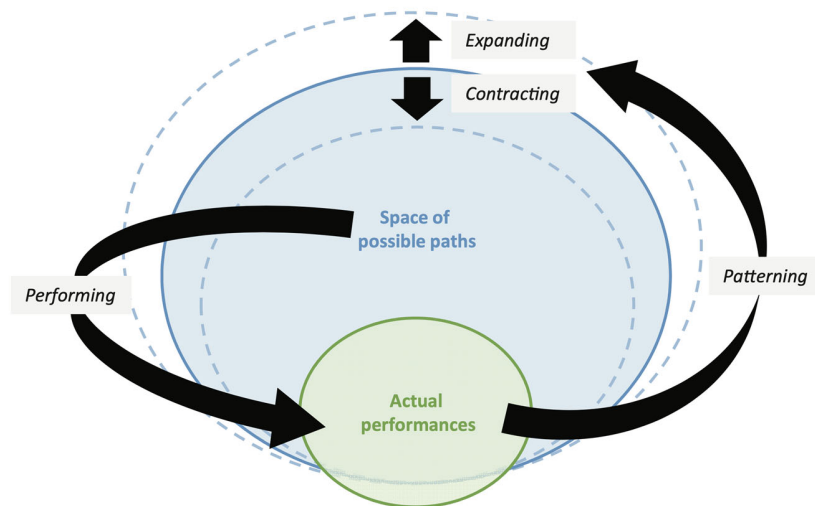


Figure 2: Performing/patterning can generate a continuum of outcomes

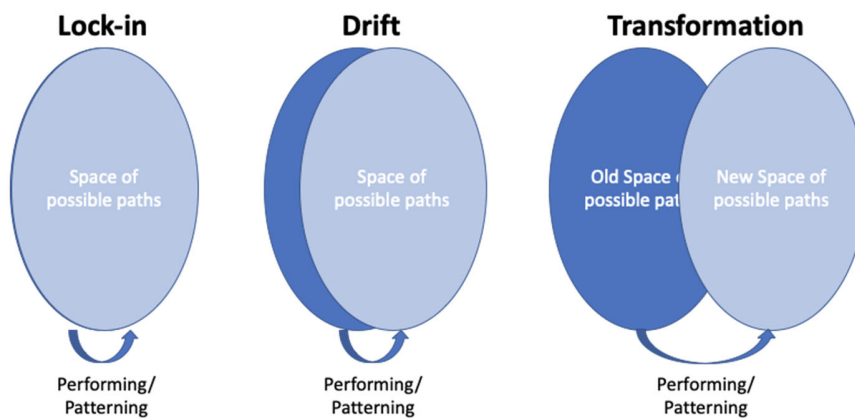
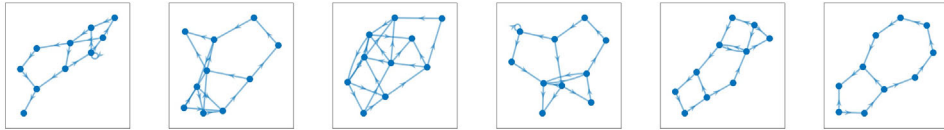
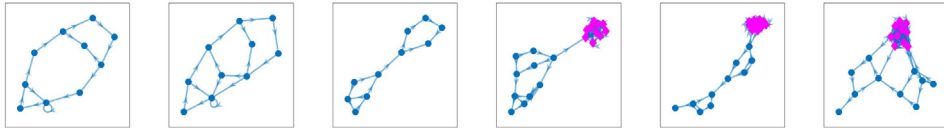


Figure 3: Example trajectories

Trajectory without new actions



Trajectory with new actions, low flexibility



Trajectory with new actions, high flexibility

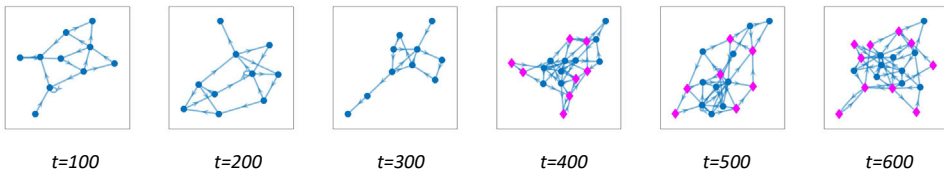


Figure 4: Effects of New Actions (A) and Flexibility (F)

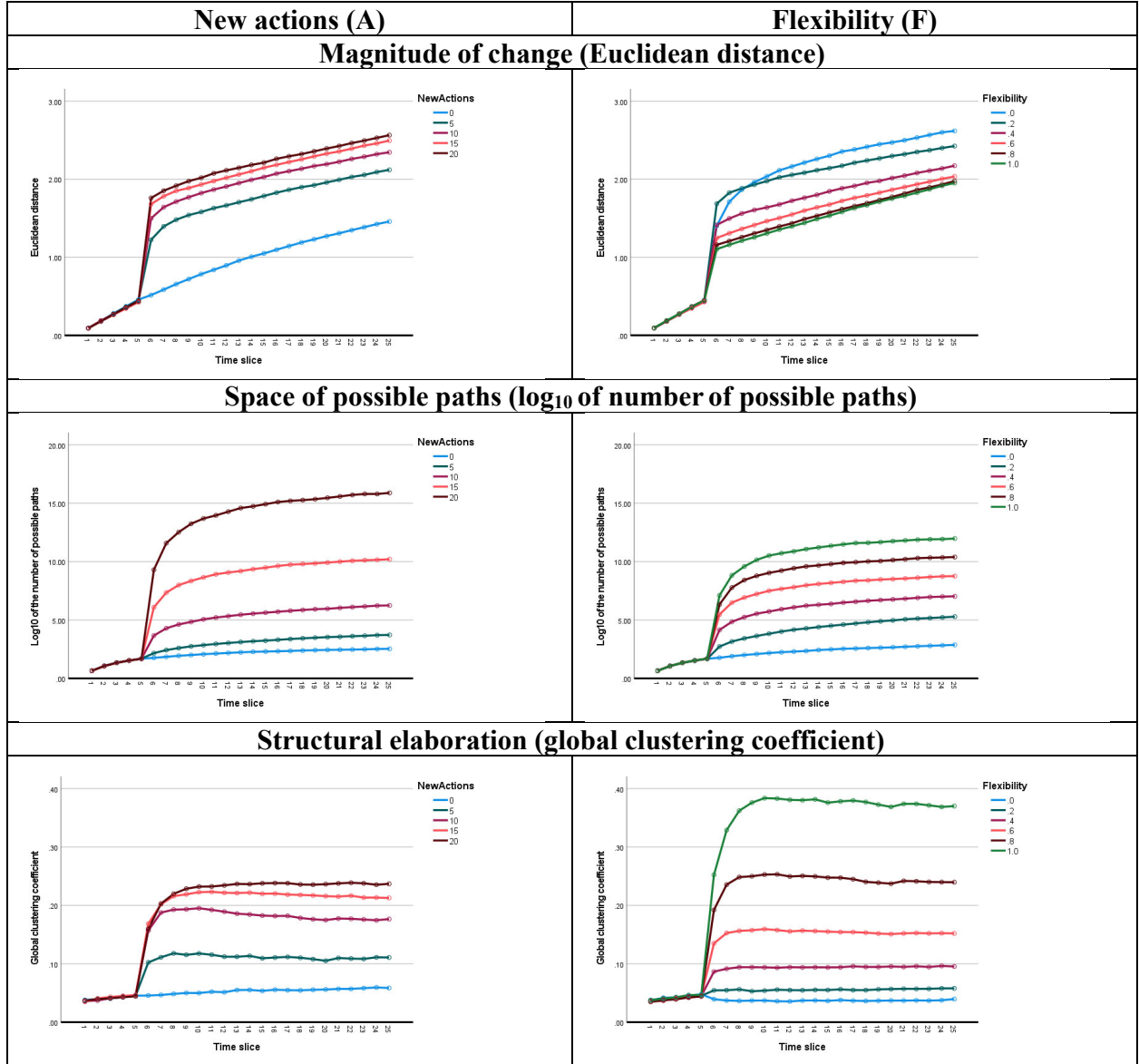


Figure 5: Interaction of New Actions and Flexibility

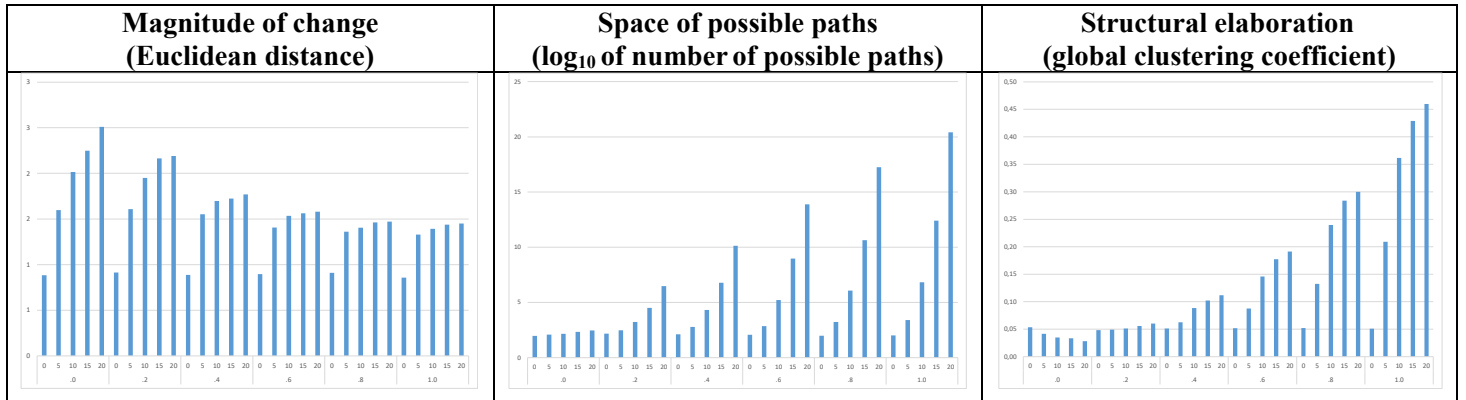


Figure 6: Distribution of trajectories

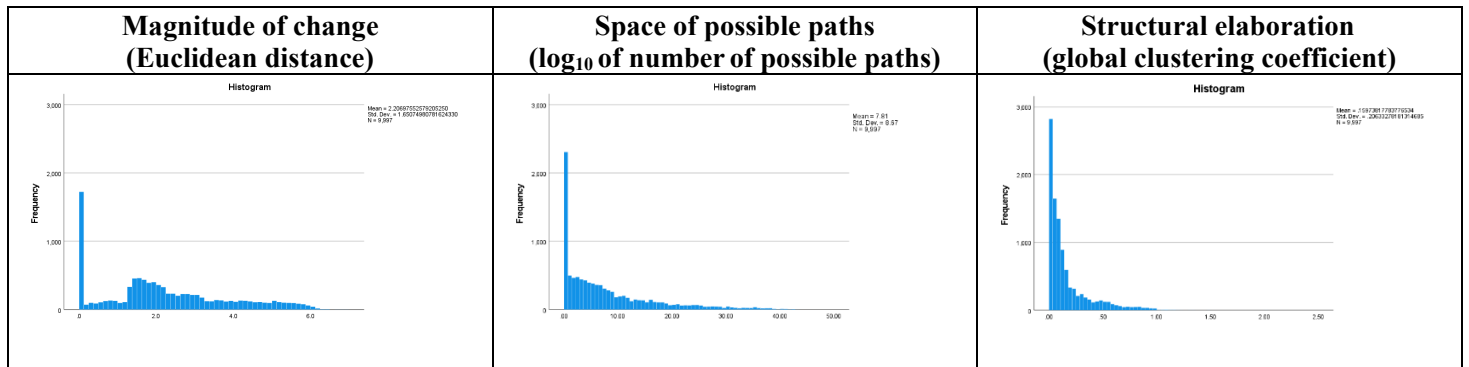


Table 1: Definitions and examples of central concepts (need to renumber others)

	Path	Pattern of Action	Trajectory
Definition	Time-ordered sequences of actions or events in performing work	An aggregation of paths at a particular time	Changes in pattern of action over time
Example	How a particular drug or vaccine was developed	Ways of developing drugs or vaccines	Changes in how drugs or vaccines are developed

Table 2: Three dimensions of morphogenetic trajectory

Dimension	Towards Lock-in	Towards Transformation	Indicator used in simulation
Magnitude of Change	Decreasing towards zero	Large	Euclidean Distance from initial pattern
Space of possible paths	Constant or decreasing	Growing	Estimated number of possible paths
Structural Elaboration	Constant or decreasing	Growing	Global clustering coefficient

Figure A-1: Adding new technology to an on-going trajectory

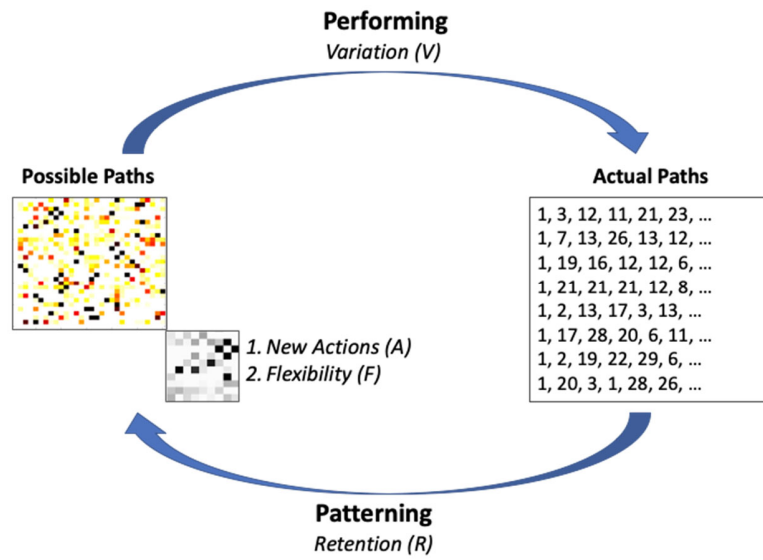


Table A-1: Characteristics of the simulation model

	Pentland, Feldman, Becker & Liu (2012)	Pentland, Liu, Kremser & Haerem (2020)	This paper
Main findings	Variation, retention and selection can account for essential characteristics of routines: formation, stability, endogenous change and learning in routines	Incremental variations can lead to irreversible “phase changes” in routines over a wide range of conditions; after such a change, routines are likely to remain stable	Transformative change is more likely when new technology affords a large set of new actions and flexibility is high
Model Parameters			
Lexicon Size (L)	10	$\{100 \leq L \leq 400\}$	$20 + A$
Variation (V)	$\{0 \leq V \leq 0.10\}$	$\{0.001 \leq V \leq 0.01\}$	$\{0 \leq V \leq 0.01\}$
Retention (R)	$\{1 \leq R \leq 100\}$	$\{0 \leq R \leq 200\}$	$\{0 \leq R \leq 250\}$
Selection (S)	$\{0, 1\}$	n.a.	n.a.
Modularity (M)	n.a.	$\{1 \leq M \leq 20\}$	n.a.
New Actions (A)	n.a.	n.a.	$\{0 \leq A \leq 20\}$
Flexibility (F)	n.a.	n.a.	$\{0 \leq F \leq 1\}$
Model Operations			
Initial condition	Clean slate or Formed routine	Happy Path $\{1,2,3...10\}$	Formed Routine
Performances per trajectory	1000	5000	2500