Learning by Connecting: How Rule Networks Evolve through Discovery of Relevance

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ABSTRACT

Learning-by-connecting – the formation of connections between lessons – is a fairly common phenomenon, but how does it evolve? We argue that learning-by-connecting unfolds as the relevance of lessons to other lessons is gradually discovered over time. The process of "relevance discovery" unfolds through a dynamic interplay between lessons and their context which provides opportunities to discover the relevance of lessons to other lessons. We develop a theoretical model in which the availability of these opportunities and their sorting in time drive the formation of connections. We explore and test our model in the context of organizational rules which we conceptualize – following rule-based learning theories – as repositories of lessons learned. Our empirical context is the formation of citation ties between clinical practice guidelines (CPGs) – a type of organizational rules in healthcare – in a Canadian regional healthcare organization. We find that citation tie formation intensifies when opportunities to discover relevance become available. We also find that learning-by-connecting creates rule networks in which the formation of new ties slows down due to the sorting of opportunities in time. Our findings support our assumption that learning-by-connecting is shaped by relevance discovery. Our study extends models of rule-based learning and contributes to discussions on the formation of connections in contexts of dispersed learning and knowledge.

Theories and models of learning have powerfully illuminated our understanding of phenomena of change and evolution in many fields, in particular in organizations and industry (Argote and Ophir 2002, Warglien 2002, Greve 2002, Baum and Ingram 2002, Madsen and Desai 2010, Denrell and Shapira 2008, Rosenkopf and Nerkar 2001, Schilling and Fang 2014, Csaszar and Siggelkow 2010, Carley 1999, Dierkes et al. 2003, Phelps et al. 2007, Knudsen et al. 2014). In many lines of work, learning is conceived as a process that produces lessons[1] (e.g., Starbuck and Farjoun 2009, Juran 1988, Kotnour 2000, Levitt and March 1988, Jugdev 2012, Madsen 2009). What has found less attention is learning that connects the lessons. In organizations, such learning-by-connecting becomes critically important because lessons are dispersed across the organization due to learning processes which are situated and dispersed (Moorman and Miner 1997, Tsoukas 1996, Grant 1996, Hislop 2003, Becker 2001, Brown and Duguid 1991, Lave and Wenger 1991, Lam 2003, Currah and Wrigley 2004, Sole and Edmonson 2002, Wegner et al. 1991, Ren and Argote 2011).

In dispersed learning systems, such as organizations, lessons learned at one time and place can interact with other lessons learned at other times and places (Levinthal and March 1993). The interactions between lessons can have massive implications, both positive (e.g., when knowledge/lessons/solutions of organizational subunits are combined with those of others) and negative (e.g., when different medications or approaches to healthcare, when used together, cause damage). Often these interactions are unclear and participants have no or incomplete awareness of them. Organizations and their dispersed parts have to learn how lessons interact, and to form connections that regulate relationships between lessons. The question is, **how does this learning-by-connecting happen?**

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[1] We understand "lessons" broadly in this paper as insights, conclusions, knowledge, skills, assumptions, etc. learned by an individual or collective actor, such as a manager, a team, or an organization. For the purposes of this paper, we will use "lessons" and "knowledge" interchangeably and not make a systematic distinction between them. We often use the term "lesson" to refer to a specific piece of knowledge.

In this paper, we use the term "learning" to denote processes that change the knowledge[2] of a learner (e.g., an individual, a group, or an organization). We use the term "learning-by-connecting" to refer to the formation of connections between different lessons (or knowledge pieces) of the learner. It is a form of learning that helps the learner to develop intelligent responses which are mindful of the wider context of extant lessons and knowledge. It creates networks of lessons/knowledge that can support complex paths of thinking and acting. It differs from learning that transforms the nodes (e.g., learning of managers, e.g., Lant et al. 1992, or rule-based learning which proceeds through the creation, revision, and suspension of rules, e.g., March et al. 2000). It also differs from learning *from* connections which proceeds through the transfer of knowledge between learners in a social network[3], such as learning from alliances (e.g., Inkpen 2005), or learning by sharing stories in communities of knowledge (Brown and Duguid 1991, 1998). Learning-by-connecting could be seen as a form of organization-level 'thinking' that creates awareness of relationships between different lessons. Like the thinking of individuals, it does not require an external trigger; recognition of relationships can arise from wandering minds, streams of co-incidental and random associations, idle reflections and speculations, fleeting comparisons and analogies, 'Aha! moments', dreams and visions, and so on. As a result, learning-by-connecting is a result of organizational conditions that shape the likelihood of recognizing relevant relationships (and thus we will focus on the likelihood of connection formation).

There is no prior theory of learning-by-connecting, nor is there a well-established literature on this subject. However, related notions exist: (i) In healthcare (the empirical context of this study) a related concept, "Learning by Connecting" was found to contribute to implementation of evidence-based practice and help nurses "to connect new knowledge with existing practice and knowledge, and make connections between actions and outcomes" (Masso et al. 2014, p. 1014). (ii) In dispersed knowledge situations,

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[2] Our definition of learning focuses on knowledge. Other definitions of learning focus on processes that improve performance, e.g., prior learning curve research (e.g., Argote and Epple 1990; Argote 2012). For an overview of learning approaches see Schulz 2002.

[3] Learning-by-connecting and learning from connections differ also in terms of inputs vs outputs of learning (e.g., Levinthal and Rerup 2020). In learning-by-connecting the connections are the output of learning, while in learning from connections, connections are the input of learning.

performance increases if members have 'transactive memory' (Wegner et al. 1991, Ren and Argote 2011), that is, they 'know who knows what' (Liang et al. 1995, O'Leary and Mortensen 2010). (iii) Notions of "meaningful learning" emphasize connections ('subsumption') between new material and previously internalized material in the cognitive structure (Ausubel 1962, Ivie 1998, Anderson et al. 1978). (iv) Connecting dispersed knowledge is a key challenge and a source of strategic advantage for multinational corporations (Lam 2003, Schulz 2003, O'Leary and Mortensen 2010, Buckley and Carter 1999). (v) In the context of innovation, the capacity of organizations to combine knowledge/lessons is essential for knowledge-based approaches (Kogut and Zander 1992, Zander and Kogut 1995, Grant 1996). (vi) Prior work on absorptive capacity highlights the strategic importance of firm capabilities to connect their own knowledge to new, external knowledge (Cohen and Levinthal 1990, Lane and Lubatkin 1998). (vii) Work on connectivism (e.g., Siemens 2005) highlights the performance implications of connections between learners and their environment. It builds on earlier work in brain science that views "the function of the brain as the routing of command signals in an intricate maze of conduits" (Somjen 1972: 204). (viii) Hebbian learning proceeds through the formation of connections between neurons (i.e., "cells that fire together wire together"), and plays a central role in machine learning applications (Hebb 1949, Wimmer and Shohamy 2012, Arbib and Bonaiuto 2016). (ix) Prominent models of organizational learning emphasize knowledge transfer between organizational members mediated by the organizational code (March 1991) and shared through communities of practice (Lave and Wenger 1991, Brown and Duguid 1991, 1998). (x) Research on mental models and conceptual networks has explored relationships between concepts used in natural language conversations in groups (Carley 1997a,1997b; Carley and Hill 2001).

As this (likely incomplete) list shows, connections between lessons play an important role in several applied contexts and lines of prior research. However, the focus of those efforts is on the outcomes (mostly positive) of the connections, while the processes leading to the formation of connections between lessons has not been systematically studied. Although connections are recognized as important, their formation is left in the dark – there has been no research so far on factors that might

facilitate or limit them. We do not know how the organizational context affects the formation of such connections, we do not know if and how characteristics of lessons affect the formation of connections, nor do we know how the formation of connections unfolds over time – whether it escalates (e.g., as lessons become popular), or slows down (e.g., due to system limitations or self-limitation). Research that delves into the complex dynamic of how learning-by-connecting unfolds might contribute to better ways of managing its challenges and to broadening prior theories and models of learning.

We might find answers to our research questions if we shift perspective. Most prior work in the above list takes an economic and management tenor and has focused on the implications of the presence (or absence) of connections and the factors that can contribute to more and stronger connections. The focus on the function of connections in the literature obscures the view on underlying processes from which these connections arise. Connections between lessons are not a production factor that can be increased at will. At any given point in time, it is not clear how lessons will evolve (i.e., be updated as a result of learning) and which interactions they might entail. Opportunities to form useful connections are not given, fixed, readily available, or easily predictable; they emerge as focal lessons and their context evolve. If we want to understand how learning-by-connecting happens, we need to take into account the dynamic ecological context in which it unfolds.

Learning-by-connecting unfolds in an ecological structure of prior knowledge and learning. In such a structure, lessons (as well as their relevance) are not fixed; they evolve through situated learning processes (Sole and Edmonson 2002, Lave and Wenger 1991, Brown and Duguid 1991, March and Sevon 1984). Learners connect new (or revised) knowledge with existing knowledge (e.g., in their minds) and thereby develop meaningful understanding (e.g., Ausubel 1962). It is a dynamic process in which awareness and understanding of underlying relationships emerges.

In this study we explore the idea that learning-by-connecting is a process that unfolds as the relevance of focal lessons is discovered through a dynamic interplay with other lessons in their context.

By "relevance" we mean interactions between lessons that have potential[4] implications for their use. We see "relevance discovery"[5] as a process of identifying and connecting to lessons that have potential implications. We use the term "discovery" to emphasize that this process is mostly not a planned search for connections, but rather a path of unplanned encounters with signals, experiences, or knowledge that illuminate and create awareness[6] about the relevance of lessons to others.

Discovery of relevance is a process through which the relevance of a focal lesson to others is gradually discovered as both the focal lesson and its context evolve. Opportunities to discover relevance fluctuate as the focal lesson is reconsidered and adjusted through encounters with new experiences and knowledge, and as its context evolves through the arrival and elaboration of lessons. The availability of such opportunities will intensify the formation of connections, and their depletion will slow it down. Below, we develop a model in which the availability of opportunities is linked to the characteristics of the focal lesson and its context. The model leads us to hypotheses about the formation of connections between lessons.

The main contribution of this paper is bringing the notion of learning-by-connecting into the foreground of learning theories and research. Learning-by-connecting produces networks of lessons which can assist organizational decision-making. It is a distinct form of learning, which can be facilitated and hindered by organizational factors and mechanisms, the understanding of which becomes increasingly important as knowledge and learning become more dispersed and fragmented in organizations.

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[4] Note, we use the term "potential" to indicate that the implications might not arise in every case – they might arise only in some cases (e.g., for certain health conditions), and not in others. Even if they are rare, potential implications with big impact tend to be regarded as highly relevant (e.g., rare forms of cancer). Prior research has suggested that information and knowledge about potential implications is collected and shared by organizations even though it might have little immediate decision relevance (Feldman and March 1981; March and Sevon 1984). The idea of potential relevance has also been discussed under the headline of "the relevance of irrelevant knowledge" (Haas and Ham 2015).

[5] With our term "relevance discovery" we do not mean to refer to the discovery of relevance in an absolute or transcendental sense. Rather, it is the discovery of (technical, organizational, etc.) relationships that appear relevant to rule makers (and rule making processes). Also, we consider relevance as a relational concept – the relevance of lessons/nodes to others.

[6] The creation of awareness can take many different forms, and several processes are likely involved (e.g., cognitive processes, but also communication and political processes).

RULE-BASED LEARNING-BY-CONNECTING

We study learning-by-connecting in the context of organizational rules. Organizational rules play an important role – as repositories of organizational knowledge– in rule-based organizational learning (Levitt and March 1988, March et al. 2000, Schulz 2002), and we build on that literature. In that perspective, rules evolve through learning processes that "encode" lessons into rules that guide behavior (Levitt and March 1988, p. 320). In most organizations, rule-based learning processes and the rules they generate are dispersed across organizational subunits, teams, individuals. Organizational rules evolve through dispersed rule adaptation processes located in different parts of the organization.

Prior research on rule-based learning has mostly focused on the change at the level of individual rules, although it has recognized the importance of relationships between rules (e.g., March et al. 2000, Schulz 1998). It has so far not studied the formation of direct connections between rules. Learning-by-connecting of rules proceeds through the formation of rule ties, that is, organizations (decision makers and decision-making processes of the organization) discover relationships between rules and add instructions to rules which reference other rules and regulate their interdependencies. In this sense, learning-by-connecting is an extension of rule-based learning; it connects lessons/knowledge encoded in rules to lessons/knowledge encoded in others.

Our guiding idea is that the formation of rule ties is shaped by relevance discovery, that is, processes that contribute to the discovery of the relevance of rules to other rules. Rule ties are formed as relationships between rules are recognized that are sufficiently relevant to warrant the adding of a formal rule tie. The process is not likely to be a rational, planned one, as the relevance of rules to other rules is often not clear to rule makers and can fluctuate as rules are created and revised. It is more likely a boundedly rational process in which the relevance of rules to other rules is bit by bit discovered, shaped by the prior path of learning.

We derive our model of relevance discovery from an examination of organizational rules and their contexts. Our model is located on the rule level, and it is dynamic. It focuses on the immediate context of rules – the characteristics of the focal rule, of its ego-network (i.e., the group of rules that the

focal rule has been connected to), and of the rule system. In the model, focal rules evolve through repeated revisions, their ego-rule networks evolve as new ties are formed, and the rule system evolves as new rules are created and existing rules are revised. Each focal rule is surrounded by a dynamic context which can shift into states that change the likelihood of rule tie formation events. Our model incorporates theoretical arguments that connect states of the rule context to tie formation events and produces predictions which we test empirically (using discrete-time event history models with fixed effects). Our results offer support for our claim that relevance discovery plays an important role for rule tie formation, and more broadly for learning-by-connecting.

The empirical context of our study is clinical practice guidelines (CPGs). CPGs are "systematically developed statements to assist practitioner and patient decisions about appropriate healthcare for specific clinical circumstances" (Institute of Medicine 1992, p. 27), such as treating a dislocated shoulder or transporting patients from surgery to the outpatient center. CPGs are special kinds of rules that assist decision making in health care organizations. They contain lessons in the form of insights, knowledge, skills, assumptions (etc.) learned (through learning from direct experiences or experiences of others) by the healthcare organization about clinical practice. CPGs are updated and evolve through dispersed rule adaptation processes located in different areas (clinics, institutes) of health care practice. CPGs can be relevant to each other in the sense that they have interactions with potential implications for their use, e.g., when medications for different purposes have negative interactions for patients. CPGs often become connected through citation ties, that is, healthcare organizations add text to CPGs that references other CPGs specialized on related methods, conditions, and practices.

RELEVANCE DISCOVERY AND RULE TIE FORMATION

Dispersed Knowledge and Learning-By-Connecting

We build on theories of organizational learning, in particular, rule-based approaches to learning (e.g., Cyert and March 1963, March et al. 2000, March and Simon 1958). In that perspective, "organizations are seen as learning by encoding inferences from history into routines that guide behavior" (Levitt and March 1988, p. 320). Rules (and similar phenomena) are essentially repositories of knowledge

in that view. "Lessons encoded in rules represent knowledge about solutions to problems found in the past. Rules retain knowledge and allow reuse of solutions to problems" (March et al. 2000, p. 186). The CPGs in our study contain encoded knowledge about appropriate healthcare practice, e.g., how to insert a catheter or perform a knee surgery. The organization 'learns' – in the sense of rule-based learning – as CPGs are created and updated and new knowledge becomes encoded into them. The learning proceeds through separate processes located in different organizational subunits (clinics, practice communities), each concerned with a specialized aspect of healthcare.

Dispersed rule-based learning produces knowledge that is encoded in dispersed rules. The dispersion of knowledge presents challenges for organizations. As scholars have recognized for quite a while; knowledge dispersion presents natural obstacles for efforts to integrate and connect knowledge because the knowledge required for useful combinations consists of "dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess" (Hayek 1945, p. 519). In response to dispersed knowledge, firms need "to develop ways of interrelating and connecting the knowledge each individual has" (Becker 2001, p. 1041; see also Tsoukas, 1996). The challenges of connecting dispersed knowledge becomes especially salient in the context of multinational corporations (Lam 2003, Schulz 2003, O'Leary and Mortensen 2010, Buckley and Carter 1999) where differences between locations can be jarring. But even in regular organizations, communities of practice can be "teased apart" and "division becomes prominent and problematic." (Brown and Duguid 1998, p. 99). In the literature on systems and complexity, connections between parts (sub-systems, sub-assemblies) play a critical role in maintaining the viability of a system (e.g., Simon 1962, 1969). Research on dispersed teams notes that "(S)ituated knowledge is at the same time a valuable resource and a source of communication difficulty for dispersed teams", leading to the question of how "the challenge presented by situated knowledge may be overcome" (Sole and Edmonson 2002, p. 30). Research on absorptive capacity finds that "intense effort is a critical component" which facilitates "learning by connecting the items to be learned and knowledge already in memory" (Park and Ghauri 2011, p. 121).

The challenges of dispersed knowledge and learning can be related to the structural design of the surrounding system. Structuring an organization as a division of labor creates separate subunits that serve specialized functions (Durkheim 1933[1893]; Simon 1957, 1969; March and Simon 1958; Galbraith 1973). The subunits (and subunits within subunits etc.) make decisions (and create and update rules) that support their functions. Their 'subunit orientation' (Lawrence and Lorsch 1967) can produce misalignment with other subunits, dysfunction, and under-utilization of resources. In a context of specialized, dispersed subunits, situated learning processes in a focal subunit create knowledge/lessons and encode them into rules, but they might be imperfectly matched to the functional requirements of other units and this can produce experiences and impulses for the formation of rule ties that regulate their relationships with other subunits.

One way to avoid the challenges of dispersed knowledge/learning is modularization (Simon 1969, Levinthal and Workiewicz 2018). It would mean creating self-contained subunits with rules that minimize reference to others. This can lead to the emergence of separate jurisdictions, e.g., within larger organizations, such as the state. Yet, at the same time, it also tends to produce notorious problems (e.g., law suits between government agencies). Most systems are only "nearly decomposable" (Simon 1962), so interactions between parts are unavoidable. Moreover, the world is not static. Change is everywhere. The decomposability of systems, organizations, problems, tasks, etc. is not fixed. It shifts as subunits adapt, new solutions arise, and tasks get redefined. The fluctuations of decomposability are not easily predictable, and thus organizational efforts to manage them are more like muddling through and discoveries than well planned and executed maneuvers.

In a context of fluctuating decomposability, new interactions can emerge and induce awareness of underlying relationships. Relevance discovery of rules unfolds through processes in which knowledge/lessons encoded in a focal rule become relevant for the use of knowledge encoded in other rules, e.g., when a focal (cited) CPG provides detailed instructions, specifications, and explanations that citing CPGs can refer to and rely on. We assume that relevance discovery is a myopic learning process through which an organization learns the relevance of a focal rule to other rules. This includes

recognizing relevant interdependencies between rules, but also developing understandings about the roles that a focal rule can play for other rules and the alternatives it can provide and the outcomes this can entail. In the healthcare context of this study, relevance discovery includes the processes through which the organization (its decision makers, experts, and healthcare practitioners) finds out that the performance of a CPG has actual or potential implications for the performance of one or several other CPGs. It means discovering the relevance of CPGs to other CPGs in the system.

Learning-by-connecting of rules creates rule networks in which rules play roles for other rules. Individual rules become embedded in a rule network, i.e., each rule develops an ego network of other rules connected by direct ties to the focal rule. The embedding of a rule in a rule network can affect how the rule functions and how it is transformed, and it can affect the further discovery of its relevance and the formation of additional ties. Learning-by-connecting of rules creates rule networks which can shape how learning-by-connecting continues. This can make learning-by-connecting potentially self-limiting or self-enhancing. The model that we develop below can shed some light on the perplexing features of learning-by-connecting and the evolution of rule networks.

Discovery of Relevance

A basic feature of relevance in organizations is that it is ambiguous (March 2010, March and Olsen 1982) and awareness of it can vary dramatically over time and context. If relevance is clear, however, it is a coordinating force of remarkable strength. Clearly recognized relevance is an invitation (or call) for action – to combine the parts relevant to each other and regulate their relationship. Relevance could be considered as the intra-organizational equivalent to prices in markets. In markets, prices serve as signals that coordinate resource combinations (Hayek 1978, Coase 1937). In organizations, prices are usually not effective (Coase 1937, Moran and Ghoshal 1999); instead, perceptions of relevance shape decision making about resource allocations. In markets, prices are not given, they are discovered through "price discovery" (Dow and Gorton 1993, Geltner et al. 2003, Anderson et al. 2007). In organizations, relevance is not clear and is discovered through "relevance discovery".

The relevance of rules to other rules – that is, the degree to which encoded knowledge of a rule has potential implications for the use of knowledge in another rule – is not "given," nor is it immediately apparent to organizational decision makers. It emerges over time as rules are used in practice, as the rule system evolves, as new uses of rules are found, and as new perceptions and typifications arise. Due to the bounded rationality of organizational actors and myopia of learning processes, the awareness of the relevance of a focal rule to others arises gradually and can stimulate changes of other rules that incorporate references to the focal rule. Over time, the focal rule becomes connected to other rules for which it is regarded as relevant. Relevance discovery is essentially a learning process that encodes 'directory knowledge' (Wegner et al. 1991, Ren and Argote 2011) into rules which reference relevant lessons/knowledge in other rules. The process reflects the complex and dynamic part-to-whole relationships between the focal rule and the rule system which it is part of. As the focal rule and the surrounding rule system evolve, its relevance to others can be 'discovered', and this can produce characteristic patterns of citation tie arrival.

Relevance discovery unfolds in a dynamic and unpredictable context in which relevance is neither fixed nor clear. Organizational mechanisms operating in this dynamic context can accelerate and decelerate relevance discovery processes and thereby shape patterns of tie arrivals. We focus on two sets of mechanisms that make the focal rule's knowledge appear relevant to other rules. The first set of mechanisms is related to the availability of opportunities to discover relevance and the second set is related to the dynamic sorting of these opportunities. The two types of mechanisms reflect the concern with abundance/paucity and heterogeneity of experiences in the learning literature (e.g., Levitt and March 1988, Lampel et al. 2009, Haunschild and Sullivan 2002, Rodan and Galunic 2004). We essentially assume that relevance discovery is a learning process which is affected by abundance and heterogeneity of learning opportunities. Abundance affects the intensity of learning-by-connecting and heterogeneity shapes the path (sorting order) of learning-by-connecting.

Availability of Opportunities to Discover Relevance

Rules are surrounded by an ecological context of other rules from which opportunities to discover relevance arise. The discovery of relevance can intensify (i.e., speed up) when more opportunities become available to connect the focal rule to other rules. The intensity of discovery of the relevance of a focal rule to other rules in a rule system is (among others) a positive function of the rules available to connect with in the rule system. The latter increases with rule density (i.e., the count of rules in the rule system). The argument is similar to "volume" arguments of relevance (Schulz 2003), that is, a larger rule system presents more opportunities for discovering the relevance of the focal rule for other rules in the system, and this should elevate tie arrival rates. It is important to note that this relevance-based mechanism is different from a competition-based mechanism. In population ecology models, density-dependent competition creates negative effects for survival rates (e.g., Lomi 2000, Carroll and Hannan 2004). However, in the context of rule inbound tie formation, rules do not compete for citation with other rules because each can be cited by the same citing rule.

It is important to note that the positive effect of rule density is not an automatic result of larger system size. Rule systems can be structured in many ways, and they can form subsystems, modules, or clusters that are rather irrelevant for other rules in the system. New technologies or practices diffusing into the system can make some (older) parts of the rule system less relevant and depress their tie arrival rate. This means that rule density could potentially produce positive, negative, or zero effects on tie formation. We believe however, that positive effects will prevail because opportunities to find relevance increase with rule density. In many innovating fields, including the healthcare field, alternative ways to apply rules (or parts of rules) emerge (e.g., a new method of pain treatment), and these often evolve into specialized rules which can become relevant to other rules because they can substitute or complement them (in part or whole). In rule systems that evolve in that fashion, the availability of opportunities to find relevant connections will increase with rule density. We thus expect that the arrival rate of new inbound citation ties for focal CPGs is positively related to rule density.

Hypothesis 1a. *The arrival rate of new citation ties increases with rule density.*

Discovery of relevance can be stimulated by rule-related activities in the system. Making and revising of rules in the system present opportunities/occasions for discovering relevance. Making and revising of rules involves problem-solving activities and "search aimed at discovering alternatives" (March and Simon 1958, p. 140) that can identify relevant interdependencies between rules which warrant formation of a tie. As organizational attention to rule making and rule changing activities intensifies, it can stimulate efforts to analyze and adjust the relationships between rules. An elevated level of rule making and revising activities in the system can stimulate the discovery of relevance of rules to other rules and thereby can intensify the formation of new ties. When rates of rule birth and revision in the system increase, discovery of relevance (of the focal rule to other rules) will intensify and the likelihood of tie formation will increase. A similar relationship has been explored in the field of bibliometrics where studies have found that the likelihood of articles being cited depends on the rate of change in information quantity produced per year (e.g., Vinkler 1996). It is important to note that our argument is relevance based and the underlying mechanism is not a tautology. A higher intensity of rule making and revising in the system does not automatically produce a positive effect on the arrival of new ties of the focal rule. The rule making and revising activities in the system could potentially make rules more self-contained and thereby depress the rate of tie arrival. However, we think this is not too likely because as rules grow more specialized, they usually also grow more interdependent (March and Simon 1958) and thereby can offer more opportunities for discovering the relevance of rules to others and stimulate the formation of ties. Furthermore, knowledge intensive contexts (such as health care) are characterized by increasing specialization and interdependence (Feldman et al. 2016) and can provide ample occasions for discovering relevance of rules to other rules and can stimulate the formation of ties between them that handle their relationship. We thus expect a positive effect of the rule change activity (birth rate and the revision rate) in the system on the arrival rate of citation ties at the focal rule.

Hypothesis 1b. *The arrival rate of new citation ties increases with the rule change activity in the system.*

In the preceding two hypotheses, opportunities for relevance discovery arise from other (existing and new) rules, that is, from the potential sources of ties to the focal rule. For relevance discovery, the knowledge volume of both the source and the target are likely to be important (Schulz 2003). Opportunities for relevance discovery also arise at the target of the ties, i.e., the knowledge encoded in the focal rule. A rule that encodes a large volume of knowledge provides more opportunities to discover relevance. A rule rich in encoded knowledge presents a more salient and attractive target for citing. The argument is also supported by research in information retrieval (for a review see Saracevic 1975, 2007a, 2007b) which found that the length of documents has a positive effect on finding relevant hits; e.g., the likelihood of a document being judged relevant by a user increases with the document length (Losada and Azzopardi 2008, Robertson and Walker 1994, Singhal et al. 1996). This would imply a positive[7] effect of encoded knowledge volume on the discovery of the relevance of the focal rule to others.

Hypothesis 2. *The arrival rate of new citation ties increases with the volume of knowledge encoded in the focal rule.*

Sources and targets can interact and moderate the salience of relevance. That is, the effect of encoded knowledge on tie formation might depend on rule density and rule change activities in the rule population at that time. A focal rule with a large amount of encoded knowledge will be more salient and stand out more in a smaller rule population. Due to its high level of encoded knowledge, it is more likely to appear among the most relevant in a smaller population. As a result, it may enjoy a high rate of inbound tie arrivals. As the rule population grows, the population will include more rules with a level of encoded knowledge that is as high or higher (than that of the focal rule), and the focal rule will not stand out as much anymore. As a result, it will be less likely to appear among the most relevant rules in the population and suffer a lower rate of inbound tie arrivals. This salience-moderation mechanism entails negative interactions of encoded knowledge volume with both rule density and rule change activities.

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[7] Our argument about a positive effect is not tautological because encoded knowledge volume could potentially also have negative effects, e.g., there might be a higher coordination effort involved in connecting knowledge-intensive rules which then might discourage tie formation.

Larger rule populations are more likely to include more members that have high (or higher) levels of encoded knowledge. Likewise, rule populations that grow and change fast are more likely to create rules that have high (or higher) levels of encoded knowledge. As a result, the encoded knowledge of the focal rule appears relatively less relevant in the larger population and when the population undergoes fast change. Rule density and rule change activities should thus negatively moderate the positive effect of encoded knowledge volume.

Hypothesis 3. *Rule density and rule change activities weaken the positive effect of encoded knowledge volume on the arrival rate of new citation ties.*

Sorting by Relevance

A focal rule can be more or less relevant to other rules in the system. Usually, a focal rule is highly relevant to a few others, moderately relevant to some, and not relevant to the majority of other rules. The degree of relevance of a focal rule to the other rules in the system is specific to the focal rule. For example, a healthcare guideline on appropriate wound treatment is highly relevant only to other guidelines involving wounds; it is moderately relevant to other guidelines on lifting and transporting patients, and it is pretty irrelevant for most of other guidelines in the system, such as those on continuous bladder irrigation, dialysis, and care of chemically dependent patents.

Relevance discovery unfolds on a time path that is shaped by a dynamic sorting of opportunities. Rules for which the focal rule is highly relevant are likely to add a citation tie to the focal rule sooner than other rules in the system for which the focal rule is less relevant. Relevance discovery proceeds from most relevant (e.g., most salient/obvious/important) to less relevant to a point where the focal rule is too irrelevant for remaining rules to cite[8]. On average, at each stage in this sorting process, the focal rule's

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[8] The probability that rule makers (or rule making processes) discover relevance normally increases with the underlying level of relevance. The relationship is usually not linear and often characterized by a relatively sharp transition between what is seen as "irrelevant" and "relevant".

relevance to remaining rules (not yet connected to the focal rule) declines. As a result, the rate of tie arrival of the focal rule should decrease with the number of ties already present in its ego network[9].

Hypothesis 4. *The arrival rate of new citation ties decreases with the size of the inbound network of the focal rule.*

The sorting mechanism underlying H4 operates on rule level (the inbound network of the focal rule). A similar sorting mechanism can unfold on rule version level. A new version of a rule incorporates new knowledge. This (re-)starts a sorting process of its own related to that new knowledge. New knowledge with high relevance will be discovered sooner. Rule makers of other rules for which the new knowledge of the focal rule is highly relevant will discover this relevance earlier and reference the focal rule version sooner than rule makers of other rules for which the new knowledge is less relevant. As time passes, there are fewer remaining rules for which the new knowledge encoded in the focal rule version is potentially relevant, and the focal rule is decreasingly relevant for them. As a result, relevance discovery will slow down as the focal rule version ages. After each revision, the rate will return to its initial (higher) level (as the version age clock is reset). We expect that inbound tie arrivals will reflect this pattern.

Hypothesis 5. *The arrival rate of new citation ties decreases with the version age of the focal rule version.*

RULES AND RULE NETWORKS IN HEALTHCARE

We explore our hypotheses drawing on the archives of CPGs of a large Canadian regional healthcare organization. The organization provides comprehensive healthcare services to the residents of a large metropolitan area and tertiary care for the surrounding province. It operates through a number of facilities (hospitals and health units). It uses a large set of CPGs to guide the work of its healthcare practitioners in its acute-care facilities. CPGs are supposed to offer scientifically valid recommendations

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[9] Given the dynamic nature of our model, it is easy to misunderstand the sorting mechanism and attribute it to limitations of system size. However, the negative effect of sorting is *not* an automatic result of the limited number of rules in the system. The sorting order of the process is a theoretical assumption (the process could in principle follow any sorting order or none). If anything, sorting will be stronger (and have more drastic outcomes) in a larger system because it offers a wider range of potentially relevant connections for a focal rule (and larger differences in relevance between connections).

in clinical practice (Grimshaw and Russell 1994, p. 45). The CPGs at the organization are managed and archived by the Professional Practice department. Impulses for CPG changes can arise from anywhere in the system – practitioners can make suggestions, health administrators can notice legal and technical problems, new therapies and approaches become available. The Professional Practice department responds to such input, and creates committees of experts who develop CPGs and review and revise them.

We consider CPGs as a form of organizational rules that operate in healthcare organizations. As guidelines, they do not always determine the behaviour of healthcare practitioners, but they assist decision making in recurrent clinical practice situations. Indeed, the main purpose of CPGs is to guide health practitioners' behaviours and standardize their decision making so that appropriate healthcare is delivered. Moreover, like other rules, CPGs function as important repositories of organizational knowledge. They contain knowledge accumulated over time through revisions that incorporate lessons drawn from organizational experiences (e.g., with costs and risks associated with a given CPG), or from external sources such as published healthcare research. The knowledge encoded in CPGs is naturally multifaceted and can vary along many dimensions. For example, CPGs can include more or less knowledge about specific healthcare problems, complications, prevention, treatment, short and long-term health implications, cost implications, legal risks, capabilities of diagnostic tools, and training levels of nurse practitioners. The relationships between different dimensions of encoded knowledge are highly complex, and this can produce unexpected interdependencies and tensions between CPGs (and within them, but that is less important for this study). The awareness of interdependencies between CPGs arises gradually over time, and we model this as a relevance discovery process that can shape the formation of citation ties between CPGs, that is, text in citing CPGs that references other CPGs specialized on related conditions and practices. Citation ties direct the attention of practitioners from one CPG to relevant others and thereby facilitate the delivery of appropriate and consistent healthcare in practice.

Citation ties between CPGs play a vital role in patient treatment and professional training in healthcare. Ties between CPGs are important for the management of multimorbidities. Individual CPGs are usually developed to deal with one single disease or condition. However, many patients, particularly

seniors, have multiple diseases with complex medical conditions. Treating patients with such multimorbidities requires combining knowledge of different CPGs. It poses enormous challenges because there is insufficient research on the care of these types of patients and unexpected outcomes can occur. As experiences accumulate with patients that have certain combinations of diseases, linkages between relevant guidelines are articulated and become encoded into them in the form of explicit references. The connected CPGs then comprise a CPG network that can handle increasingly complex types of patients.

CPG networks can also facilitate the professional training for healthcare providers. Studying CPGs and learning how to search and use relevant CPGs in various clinical situations constitutes an important part in the training of healthcare professionals. The citation ties between CPGs serve to direct the attention of a trainee from one CPG to a cited one, which might be related and relevant in certain clinical situations. These explicit connections between CPGs can also help trainees to form a mental map of the CPG collection and facilitate the development of transactive memory (Liang et al. 1995, Ren et al. 2006, Rulke and Rau 2000, Wegner 1995).

METHODS

Data

We built our longitudinal dataset of dynamic rule networks from the archives of CPGs that were in use between 1989 and 2010[10] in the healthcare organization. The archives of CPG collection consist of two parts – a paper-based collection and an electronic collection. The paper-based archives include the CPG versions that were in force until August 2002, when the organization converted all the paper-based guidelines electronically. Our data include both collections of CPGs, which to a large extent facilitated us to trace the entire history of CPG revisions and networks.

We drew relevant information from the document of each guideline version and coded it into a spreadsheet, in which each row represents a version of a guideline. For each version of a guideline, we recorded its characteristics such as CPG code, title, effective date, number of words, and number of

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[10] Our observation period ends on January 1st, 2011.

healthcare references. We connected the versions of the same guideline and reconstructed their revision histories to extract dynamic, guideline-level covariates. We also recorded the outbound network of each guideline version, that is, the list of all CPGs that it cites. We used this outbound network information to reconstruct the inbound networks of guideline versions and extract the event history of inbound network changes. We developed special-purpose FORTRAN programs that track the changes of guidelines and ties, and compute dynamic covariates about guidelines, versions, and their networks. This permits us to combine event history analysis with dynamic network analysis.

We observed totally 802 CPGs that have been in force in the healthcare organization. The CPG collection started with 13 guidelines in 1989 and grew to 677 at the end of 2010. The number of ties among CPGs grew from 0 in 1989 to 913 in 2010.

Models

We model the rate of inbound tie arrival with discrete-time event history models (Allison 1982, 2005). To prepare the dataset, we split each guideline version into sub-episodes of 1/5 year[11]. This procedure yielded a dataset that contains 37,966 sub-episodes. All our covariates are time-varying and are updated at the beginning of each sub-episode.

We adopted fixed-effect logit models (Allison 2005, Beck et al. 2008) to test our hypotheses. Our models allow us to analyze within-guideline effects (i.e., compare before and after a change of characteristics occurs), rather than between-guideline effects. The basic form of the fixed-effect logit model is:

$$P(Y_{it} = 1) = \frac{\exp(\beta' X_{it} + v_i + \varepsilon_{it})}{1 + \exp(\beta' X_{it} + v_i + \varepsilon_{it})},$$

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[11] We experimented with varying length of the sub-episode from 2 months to 1 year, and the differences in the parameter estimates were negligible. We did not explore settings with the length of sub-episode below 2 months as some of our guideline versions (early versions) had revision dates that were only accurate to the month. We present results of analyses that use a relatively short sub-episode (1/5 of a year, i.e., 2.4 month) to track the time path of dynamic covariates as exactly as possible without running into accuracy problems. Using larger time periods makes the covariates grainier and can entail larger standard errors (and weaker tests).

where $P(Y_{it} = 1)$ represents the probability that an inbound tie arrival event of guideline i occurs during sub-episode t. X_{it} represents the vector of time-varying covariates at the beginning of sub-episode t, β' indicates the vector of estimated coefficients. $v_i + \varepsilon_{it}$ denotes the error term, with v_i indicating the guideline-specific time-constant error term and ε_{it} the time-varying term. The separate error terms allow us to control for the unobservable guideline-specific characteristics that might correlate with the propensity of inbound tie arrival. The fixed-effect model automatically excludes those guidelines that have not experienced any tie arrival event[12]. As a consequence, the reduced dataset for estimating the rate of inbound tie arrival contains 230 guidelines and 11,929 observations (i.e. sub-episodes).

Variables

Dependent variables. Our dependent variable is the probability of receiving an inbound tie during a sub-episode. We coded it as 1 when we observe a tie arrival event and 0 otherwise.

Independent variables. All the covariates (including control variables) in our statistical analyses are time-varying and updated at the start of each sub-episode. We have five independent variables. First, we measured rule density with the number of guidelines in the CPG collection in a given year. Second, we constructed a measure of rule change activities by adding the counts of the number of rule birth events and rule revision events in a given year. Third, we constructed the measure of encoded knowledge volume in a guideline version using the information on the research publications cited by CPGs. As an important instrument of evidence-based medicine approach, many of the CPGs include cited references to published healthcare research, which is updated along with the content of the guidelines as they undergo repeated revisions. We measured this variable with the number of healthcare publications a guideline version cites. Fourth, we captured inbound network size with the number of CPGs that are citing the focal guideline when the current sub-episode begins. Finally, we measured version age with the number of years between

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[12] Non-changers do not contribute to the likelihood of the model and are not needed for estimating the parameters of the model (Beck et al. 2008).

the effective date of a guideline version and the beginning of the current sub-episode. To reduce the potential biases caused by outliers, we used the square root transformations of the variables encoded knowledge volume, inbound network size and version age in the analyses (Cohen et al. 2003, p. 245). We did not use square roots for rule density and rule change activities as these are system-level variables that have no outliers. Instead, we rescaled these two variables by dividing them by 100 in order to obtain coefficients that display more digits.

Control variables. We included several control variables to exclude other plausible alternative explanations of inbound tie arrival. First, we included rule size measured by the number of words of a guideline version, because longer guidelines might have higher visibility, thus can attract more attention that increases the probability of being cited. Second, we controlled for number of prior revisions that a guideline has gone through. Rules adapt to experiences through successive revisions. Prior revisions represent a path of rule adaptation (Beck et al. 2008, March et al. 2000) that can shape how a rule becomes relevant to other rules, and this can have important implications for the rate of inbound tie arrival for the focal rule. Third, we included outbound network size measured as number of CPGs a focal guideline version cites. Including this variable makes our parameter estimates independent of the presence and characteristics of an outbound network. To avoid the impact of outliers on our estimates, we transformed the above three variables – rule size, number of prior revisions, and outbound network size – into square roots before including them into the models. Fourth, we included inbound network density, because dense guideline networks resemble cliques that can prevent further addition of citing CPGs. We calculated this variable as the ratio of the number of ties among the guidelines that cite the focal guideline version to the maximum number of potential ties among them. Finally, we included historical time periods to control for the effects of historical and institutional shifts. We distinguished three time periods that reflect the differences in conditions surrounding the guideline collection. The first (January 1, 1989 - July 31, 2002) captures the time period when the guideline collection was still paper based. It serves as the reference category in our model (and its dummy variable is thus excluded). The second time period (August 1, 2002 - December 31, 2005) starts when the healthcare organization shifted its guideline

collection to digital format. The third time period (Jan 1, 2006 – December 31, 2010) begins when the healthcare organization began with the process of "regionalizing" guidelines, that is, gradually integrating selected guidelines with those of other healthcare organizations in the wider region into a more encompassing system[13], and it ends at the end of our observation time period. The descriptive statistics of all variables in our study and the correlation matrix are presented in Table 1.

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RESULTS

Table 2 shows the parameter estimates of the fixed-effect logit models for the effects of covariates on the rate of inbound tie arrival. We first include rule density and rule change activity in Model 2 to test Hypotheses 1a and 1b. Both parameters are positive. The effect of rule change activity is statistically significant ($p < 0.01$) and consistent across subsequent models[14]. The effect of rule density is not significant in this model, but it has highly significant effects in Models 5 and 6, probably because it is confounded with inbound network size and version age which are positively correlated with rule density (r=0.33 and r=0.29, respectively) and which have negative effects on tie arrivals. These estimates provide support for our H1a and H1b. When number of guidelines in use increases, and when the guideline change activity intensifies in the system, more opportunities for discovering relevance are generated and this elevates the rate of inbound tie arrival for individual guidelines.

--------------------------------- Please insert Table 2 about here. -----------------------------

In Model 3, we add encoded knowledge volume to test hypothesis 2. As predicted, its effect is positive and significant ($p < .05$), and consistent across all the subsequent models. The parameter

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[13] We observed a total of 36 regionalization events and treated guidelines after their regionalization as censored observations.

[14] We estimated separate effects of system births and revisions (the estimates are available from the authors) and found that the effects had the same direction, but the effect of revisions was smaller, indicating that the effect of each revision in the system is smaller than the effect of each birth. However, revisions are much more common than births (83.7 revisions per year versus 21.6 rule births per year in the average), and thus the aggregate (per year) effect of revisions is likely as strong as that of births.

indicates that the likelihood of a guideline being cited by other CPGs increases with its number of references to external healthcare publications.

In Model 4, we add the interaction terms between sources (i.e., rule density, and rule change activity) and targets of citation ties (i.e., encoded knowledge volume) to test the salience moderation hypothesis 3. Both interaction effects are negative and significant. Their negative effects are consistent across Models 4, 5 and 6, (although their level of significance varies somewhat). The findings thus provide support for our salience moderation hypothesis. The results suggest that the relevance of a guideline (in terms of encoded knowledge volume) is less salient when the number of guidelines in use increases and when the guideline change activity intensifies. Relevance is context dependent.

In Model 5, we add inbound network size to test H4. The parameter is negative and significant (p < .01), same as in Model 6. It suggests the probability of adding additional inbound ties declines as a guideline's inbound network expands. This result provides strong support for the sorting H4.

Finally, in Model 6, we add rules' version age to test H5. The negative and significant (p < .05) effect is consistent with our prediction. It implies that as a guideline version ages, the probability of it receiving additional inbound ties decreases. H5 is therefore supported[15]. The negative effect means that rule versions undergo their own sorting process. Each time a rule is revised, version age is reset to zero and its rate of tie arrival shifts back to the baseline level (see Figure 1). The result is a saw-tooth pattern of tie arrival. Rates of tie formation decrease with decreasing decrements as versions age. The sorting effects are more drastic at early version age than at old age.

------------------------------- Please insert Figure 1 about here. -------------------------------

We further probed our models in separate analyses. First, we explored counts of tie arrivals (instead of logits in Table 2). A small number of guidelines in our data experienced multiple tie arrivals in a given sub-episode (actually only 0.13 percent). To account for these cases, we estimated fixed-effect

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[15] In separate analyses, we explored the possibility that version-level sorting is confounded by obsolescence of encoded knowledge of rule versions. Our findings did not support confounding effects. It appears that knowledge obsolescence does not play a significant role for tie arrivals, nor for the sorting effect.

negative binomial models using the same set of covariates. The parameter estimates (available from the authors upon request) are highly consistent with those in Table 2. Second, we probed our square-root specification for encoded knowledge volume, inbound network size and version age with a more flexible functional form that adds linear terms (the results are available from the authors). We found that it improves fit only marginally (though the larger model is less parsimonious) and that the underlying functional form is very close to our square root specification (e.g., for version age depicted in Figure 1). Third, we explored the role of time lags for rule density and rule change. We estimated models that use a one-year lag for the independent variables for H1 to H3. The parameter estimates were very similar to the ones we report in Table 2. This suggests that overall levels of rule density and rule change drive rule ties, and that our parameter estimates are robust. Fourth, we also explored interactions between availability and sorting variables. We found significant interactions between inbound network size and availability variables (i.e., rule density and encoded knowledge volume). The estimated parameters indicate that availability moderates the effect of sorting; the negative effect of inbound network size gets stronger (more negative) when more opportunities for discovering relevance are available. This means that sorting gets stronger the more opportunities are available. It also means that the negative effect of inbound network size is not likely to be a product of limited system size.

We also found some noteworthy effects of the control variables. Number of prior revisions has a positive effect (though the effect is not very consistent across model specifications). It could indicate that adaptation of guidelines could make them more refined and thereby more attractive for others to cite. Inbound network density has negative effects that are significant in all models, indicating that guidelines embedded in sparse networks (i.e., they are connected to unconnected others) might become more attractive targets of citations. Lastly, both time period dummy variables have a negative effect. They indicate that guideline tie formation proceeded faster before August 2002 in the healthcare organization (i.e., there is no indication of a positive time trend). Overall, the effects of the control variables suggest that discovery of relevance mechanisms are accompanied by a number of other mechanisms that shape tie formation. They point to intriguing directions for future research.

DISCUSSION

How does learning-by-connecting happen? Our study explores this question in the context of organizational rules (a form of organizational knowledge repositories). We propose that it happens through an unfolding process in which the relevance of rules to other rules is discovered and ties are formed. In our model of relevance discovery, connections between rules arise from mechanisms which drive the availability of opportunities to discover relevance and their sorting in time. The mechanisms affect the speed of relevance discovery, and they lead to testable hypotheses about the likelihood of formation of inbound citation ties.

The first set of mechanisms relates to the availability of opportunities for discovering relevance. We analyze features of individual rules and the rule system that affect the availability of opportunities for discovering relevance and find that they have strong positive effects (H1a, H1b, and H2 are supported). This supports our assumption that the relevance of rules to other rules induces the formation of rule ties. Taking into account that rule ties transport knowledge between rules, our findings also lend support to prior research on knowledge, which found a link between relevance and knowledge flows (e.g., Asmussen et al. 2013; Augier et al. 2001; Haas and Cummings 2015; Haas and Ham 2015; McGuinness et al. 2013; Miao et al. 2011; Monteiro et al. 2008; Nag and Gioia 2012; Schulz 2001, 2003; Yang et al. 2008), between relatedness and knowledge flows (e.g., Hansen 2002), and between patent citations and knowledge flows (e.g., Alcácer and Gittelman 2006, Jaffe et al. 1993).

We examine salience moderation with interaction effects and find that rule density and rule change activities (births and rule changes in the system) have negative interactions with encoded knowledge volume, consistent with the salience moderation hypothesis H3. The finding suggests that the relevance of a focal rule is relative to alternatives. In a smaller or closed system, a rule with a larger amount of encoded knowledge might appear to be among the most relevant, and attract more ties. In a larger or fast changing system, the same rule is less likely to be among the most relevant and thus attract less ties. The findings illustrate how relevance can be affected by contextual factors (e.g., a small system versus a large system) that moderate its salience.

The second set of mechanisms involves sorting of opportunities by relevance. Sorting entails that citation ties arrive in declining order of relevance to the focal rule. It leads to hypotheses about the effect of inbound network size and rule version age on tie arrival (H4 and H5) which are supported. These findings suggest that relevance discovery is shaped by sorting processes which proceed from high to intermediate to low relevance. Relevance discovery slows down as the network of a rule expands and its version age increases.

Together, our results suggest that the formation of rule ties is shaped by relevance discovery. Other organizational factors might also play a role, but they are not likely to cause significant biases in our estimates because we control fixed effects of individual rules. Other organization theories could offer alternative predictions about rule tie formation; however, the findings of our study do not fit well with them. While institutional models would predict a positive effect of ego network size because a larger ego network would make the focal rule appear more legitimate and thereby attract further citations, we predict and find a negative effect. While institutional models predict a positive effect of version age because an older rule version would be more institutionalized and appear legitimate and thus should attract increasing numbers of inbound ties, we predict and find a negative effect. Predictions of institutional theory might be aligned with our prediction of a positive main effect of encoded knowledge on the rate of tie arrival, but it is less clear how it would explain the salience moderation (H3) effects. Furthermore, while models of power would likely predict a positive effect of ego network size because a rule with a large network would presumably have more power (as more other rules depend on it) and would presumably be in a position to expand its power base by forcing other rules into its network, we predict and find a negative effect of ego network size. Taking our findings together, it seems our relevance discovery model provides a better fitting and more parsimonious explanation than alternative theoretical models. Still, our study is a first one, and more research will be needed to study relevance discovery and rule tie formation further.

Theoretical Implications

Learning-by-connecting denotes the formation of connections between lessons (encoded in rules). Even though its core principle is simple, it unfolds in somewhat surprising and complex ways. We

find that the formation of new ties in the inbound network of a focal rule slows down as the network expands and the focal rule version ages. It means that learning-by-connecting is self-limiting, a feature shared by other learning processes (e.g., vividly expressed in learning curves, Argote and Epple 1990; Argote 2012).

Learning-by-connecting differs from other forms of learning common in the literature. The notion that we develop in this study is *not* a planned or induced form of learning, such as learning by students in educational institutions (e.g., Barber 2014, Golnaraghi et al. 2014). Learning-by-connecting emerges in a topology of dispersed knowledge and learning, and evolves through relevance discovery. Learning-by-connecting describes a process of learning that leads to knowledge change; it does not focus on performance improvement (while it does not exclude it). It is a form of learning that can shape the evolution of structures in society, organizations, groups, and minds.

Learning-by-connecting broadens the scope of organizational learning theory from changes of single knowledge nodes (i.e., content of knowledge bases) to including the emergence and transformation of connections among them (i.e., structure of knowledge bases). While the bulk of learning theories has focused on improvements of performance and knowledge of single entities, learning-by-connecting highlights the relationships between dispersed learning processes. While most prior work has focused on learning through (the use of) existing connections, learning-by-connecting focuses on the making of connections as a form of learning. Learning-by-connecting highlights that organizational learning involves more than just learning by all the different parts of an organization; it also involves connecting/integrating the lessons learned by the different parts in an intelligent fashion. Lessons learned in different parts can have implications for each other. Learning how lessons are related to each other and how their relationships can be managed is important for organizational adaptation in practice and deserves more consideration in theories of organizational learning.

Learning-by-connecting opens a new perspective of learning in which lessons and their relevance for other lessons interact and co-evolve. It is a view that takes organizations as places in which learning and knowledge are dispersed; successful adaptation requires the formation of knowledge networks that

bring relevant knowledge together, because it can leverage diverse knowledge resources to facilitate intelligent action in complex contexts.

Learning-by-connecting is related to theories of **transactive memory systems** (TMS) (Wegner et al. 1991, Ren and Argote 2011). It creates transactive memory in rules; it adds "directory knowledge" to rules about knowledge located in other rules. In the context of CPGs, learning-by-connecting produces citation links between CPGs. The citation links direct the attention of healthcare practitioners to other CPGs so they can learn and use that knowledge in their local practice. Our study essentially expands TMS into the domain of rules and examines the development of TMS in a rule system. Clearly this is just the beginning. Future studies could build on prior TMS-related work and study the performance implications of having a (or having an inaccurate or outdated) TMS of rules.

Learning-by-connecting of rules is an extension of **rule-based learning** that leads into new directions. While prior notions of rule-based learning (March et al. 2000) emphasize the change of rules, we focus on the formation of connections between organizational rules. Our study suggests that rules are not independent of other rules; rather, their connections transport knowledge and instructions between rules, the functioning of citing rules becomes dependent on cited rules, and rule ties formalize and recognize the relevance of other rules. Rule-based learning processes, operating on a focal rule, thus are often connected to those of others. This means that the lessons encoded into a focal rule can be shaped by (including complement) the lessons encoded in connected rules. This can have implications for learning-by-encoding, e.g., it is conceivable that rule ties expose rules to other rules and thereby can affect learning processes and rule change processes of cited rules (e.g., Zhu and Schulz 2019). In this sense, rule-based learning proceeds through interlacement of learning-by-connecting and learning-by-encoding. We hope future research will continue into that direction.

Rule networks come to the forefront in our study. Learning-by-connecting creates rule networks. We have focused on the first-degree inbound ego citation networks. They expand as citation ties arrive at a focal rule. Our parameters suggest that the evolution of these rule networks is shaped by characteristics of the rule ecology – the characteristics of the focal rule, of its ego-network, and of the rule system. The

parameters suggest that the expansion of rule ego-networks intensifies when the rule ecology provides more opportunities to discover relevance; that is, when the rule system expands, when more rules were created or revised, and when the focal rule is rich in encoded knowledge. The expansion of rule networks decelerates with features that reflect the dynamic sorting of those opportunities, that is, with network size and the age of the focal rule version. A remarkable aspect of this dynamic is that a revision of the focal rule can make it relevant to new or different rules in the system (see Figure 1), spawn new relevance discovery processes, and stimulate new tie formation. It means that as individual rules evolve, their networks evolve. Another remarkable aspect of the dynamic of rule networks is that network growth slows down with the number of existing inbound ties in the ego network of a focal rule. 'Popular' rules thus do not attract more cites, but rather less. Our interpretation of this slow-down is sorting by relevance. At the heart of this sorting mechanism is a self-selection process in which rules for which the focal rule is highly relevant form ties earlier than others for which the focal rule is less relevant. It is important to be aware that sorting by relevance is not an intended or planned phenomenon. It emerges from the organizational rule ecology and the bounded rationality of actors who discover the relevance of rules to other rules.

Discovery of relevance plays a central role in this study. We take it as a form of unplanned search that can produce awareness of relevance of rules to other rules. The relevance discovered through this search is neither predetermined nor absolute. It is *context dependent* – the rule context (the surrounding rule system) offers opportunities to discover relevance and can alter the salience of relevance and moderate its effect on tie formation. At the same time, we also need to recognize that discovery of relevance is also intensely *path-dependent* – knowledge encoded in a focal rule at one point in time can become relevant to knowledge encoded in other (new or existing) rules at a later point in time. Rules evolve, and so do the roles that they play for others.

Discovery also plays an important role in organizational change (e.g., Miner and Robinson 1994), innovation (Spector 2017; Locke et al. 2004), and in work on reorienting of habits in planned organizational change (Golden-Biddle 2020). In recent work, discovery is seen as driven by reasoning

styles of actors, e.g., through "abductive reasoning" – a form of reasoning that focuses on finding a plausible explanation for a given observation or problem (e.g., Golden-Biddle 2020, Spector 2017, Behfar and Okhuysen 2018). In the context of this study, the discovery of relevance between organizational rules could potentially be affected by reasoning styles, such as "abductive reasoning", e.g., when medical personnel involved in CPG revisions develop a 'diagnosis' of a problem. It might be worthwhile in future studies to explore whether the ability of participants to use abductive reasoning varies over time independently of the other variables in the model and varies so strongly that tie formation can be intensified or throttled.

The theoretical model of our paper builds on the concept of **knowledge relevance**. The concept has been used in prior work on knowledge flows in multinational corporations (e.g., Schulz 2001, 2003; Yang et al. 2008), a setting that seems relatively distant from our current study. However, in both settings, relevance regulates how knowledge comes to be connected with other knowledge. Knowledge relevance shapes knowledge flows between subunits of multinationals, and in our study, it shapes the formation of connections between organizational rules (which can facilitate knowledge flows from the application context of one rule to that of another). The notion of knowledge relevance plays a key role in different streams of research, and it is conceivable that it might play a more central role than previously assumed for the evolution of knowledge structures in other contexts. Knowledge relevance essentially functions as a binding force. One could compare the effect of knowledge relevance to that of 'valence' in Chemistry, where it regulates the formation of molecules (e.g., two hydrogen atoms can bind to one oxygen atom to form a water molecule). Knowledge relevance could be seen as a characteristic of knowledge 'atoms' (e.g., lessons) that permit each atom to bind to others, forming knowledge 'molecules' (combinations of lessons/rules) that can accomplish unusual feats. In this speculative perspective, organizational knowledge processing and production could be seen as the unfolding of some kind of 'chemical' reaction in which thoughts/assumptions/lessons bind with others of matching valence (relevance). The analogy is inspiring, but also reveals instructive differences. One difference is that in Chemistry, atoms are fixed, while in organizations (and learners in general), lessons evolve as new experiences are made and new

inferences are drawn. Knowledge relevance is not a fixed characteristic of lessons, but rather evolves as the lessons change and their context changes. A second difference is that relevance discovery is not just a mindless combining of knowledge atoms with matching valence, but rather it is an organizational interpretation process that sorts out how lessons are related to each other and that retains these interpretations in network structures (connected repositories of knowledge), which reflect/represent the multifaceted meaning of the lessons. Lessons thereby attain their meaning through the network of other lessons in which they become embedded. A third difference is that knowledge relevance (the 'valence' of each lesson) is inherently multi-dimensional, and efforts (in theory or practice) to reduce it to one dimension are likely to incur significant biases. The relevance of a focal lesson emerges from the context of other lessons which consider and reference it. Each referencing lesson can contribute its own dimensions of relevance to the focal (referenced) lesson. A focal lesson can be relevant to others for different reasons, and new ways of being relevant can be discovered as the focal lesson and others around it evolve.

Sorting by relevance is a key mechanism in our model. It is similar to other **sorting mechanisms** that have been discussed in the literature. One is social sorting (March and March 1978), and another is sorting by problem recurrence (Schulz 1998). Sorting also plays a very important role in tournaments (e.g., Lazear and Rosen 1981), and it can shape entry into entrepreneurship (Sørensen and Sharkey 2014). One common characteristic of sorting processes is an absorption of high-risk units from the risk set, altering its composition such that lower risk units remain, producing a lower rate of event occurrences (for a mathematical treatment, see Schulz 1992). In organizational rule populations, sorting by problem recurrence can produce negative density dependence of rule birth rates (March, et al. 2000, Schulz 1998). In this study, the dynamic sorting of opportunities produces rates of tie arrival that decline with inbound network size and version age. A second common characteristic of these sorting processes is that replenishment of high-risk units in the risk set can reset the sorting process, similar to resetting a liability-of-newness clock (e.g., Amburgey et al. 1993). In rule populations, this weakens the effects of rule density in rule populations that face turbulent environments (March et al. 2000, Schulz 1998). In this

study, opportunities for discovering relevance are replenished when the focal rule is revised and updated knowledge is encoded (see Figure 1). These commonalities suggest that sorting mechanisms might play an important role in diverse contexts and should find more attention in future research on the emergence and transformation of social and organizational order.

Inserting sorting mechanisms into learning theory might seem like a radical move, but it offers predictions about what is learned and when it is learned. It broadens the frame of learning theory from a focus on learning outcomes (in terms of performance or knowledge accumulated) to the shape of trajectories of organizational learning processes. In the presence of sorting, learning processes unfold in a particular way – one that reflects the underlying sorting order, and this can affect the speed and direction of learning processes. Inserting the sorting mechanism into learning means essentially that lessons/knowledge vary in their propensity of being learned, and those with greater propensity are learned faster and sooner than others which have a lower propensity and are learned later (or not at all). Thus, sorting can offer a general explanation for the slowing down of learning processes. We hope future research will deepen and sharpen the connections between learning and sorting.

Our project might appear to be close to recent work on the "**dynamics of routines**" (e.g., Feldman et al. 2016). Research in that line has recently begun to explore clusters of routines (Kremser 2016, Kremser and Schreyögg 2016) in which "complementarities between routines" are managed through "programming of interfaces" (Kremser and Schreyögg 2016, p. 698) between the routines. That research clearly shows the importance of connections between routines and the need to understand their formation. But their notion of routine (dynamic patterns of interdependent action of actors) is quite different from our notion of rules (repositories of lessons that guide action), and that limits comparisons between the two. Also, research on routine clusters sees connections as result of the "binding forces of complementarities" (Kremser and Schreyögg 2016, p. 716), but does not analyze the underlying processes that lead to the emergence and recognition of complementarities. Our study can potentially add on to that research because we identify mechanisms that can shape the discovery of complementarities (which could be seen as a form of relevance) and other relationships between rules. Our study thus might potentially

inspire research on the dynamics of the formation of connections between routines and the evolution of routine clusters.

Implications for future research arise when we shift from **low to high intellect** mechanisms of relevance discovery. In our model of relevance discovery, rule ties and rule networks evolve from relatively "low intellect" (March 2010) mechanisms related to the availability and sorting of opportunities for discovering relevance. Higher intellect mechanisms are likely to play a significant role too, e.g., the interpretations of decision makers, their discourse and consensus formation, processes of organizational innovation and communication, and the availability and utilization of new resources and funding opportunities. Higher-intellect relevance discovery mechanisms are more complex and likely produce more complex patterns of rule network evolution. They are harder to observe (especially in archives) because they are so much more unique (and usually don't leave a clear paper trail). In that light, our study captures only the tip of the iceberg of the evolution of rule networks. We hope future research will explore high-intellect mechanisms of relevance discovery and their impact on the dynamics of rule networks.

Clearly, rule ties and rule networks evoke images of **Weber's iron cage** (Weber 1988). Rule networks could be seen as a mesh (ribs and bars) of an iron cage that imprisons the human spirit and determines the lives of all the individuals who are born into it "with irresistible force" (Weber 1988, p. 181). Rule networks could turn into "total institutions" (Goffman 1961) that control minute segments of a person's conduct (Armaline 2005, Holmes 2005, Malmedal 2014, Series 2013, Stark 1994). However, regarding the underlying reasons for the elaboration of the iron cage, we differ from Weber. While Weber saw a historical process of rationalization, fueled by a Puritan compulsion to rationalize and organize social and economic relationships, we see myopic relevance discovery processes weaving the mesh of the iron cage. We think that our paper might be able to bring new questions into Weberian (and neo-Weberian, and related) discourses, e.g., about the alignment (or mis-alignment) of relevance and rationalization in the process of bureaucratization and corporate expansion (e.g., Johnson and Kaplan 1987, Johnson 1992, Seal 2006).

Implications for Practice

It is possible that our findings reflect general patterns that play out in the healthcare field overall. The rule networks in our study might reflect **field-level rule networks** (e.g., best practices), and our findings might reflect tie formation processes that originate at the field-level. Relevance discovery is a rather general process, and it is conceivable that it also plays out at the field-level. From the perspective of this study, we would expect that relevance discovery shapes the evolution of field-level rule networks. Furthermore, in multi-level settings, connections between levels are important. How strong is the connection between organizational and field-level rule networks? Is it characterized by strong institutional isomorphism whereby the evolution of organizational rule networks tightly tracks the evolution of field-level networks? Our study suggests that relevance discovery processes are inherently path dependent. A consequence of path dependence is that small differences between rule systems become amplified over time. Rule networks (and knowledge networks) will tend to evolve into idiosyncratic structures, and thus it seems likely that discovery of relevance processes unfolding on different levels become decoupled. Of course, the degree to which this happens is an empirical question. We hope that future research will explore this further.

Rules contain encoded knowledge and thus, rule networks are also **knowledge networks**. They are networks in which the nodes – in the form of rules as repositories of knowledge – are connected by citation ties. The ties direct attention of users from one node to relevant knowledge residing in other nodes. Activation of a node (in terms of using it, or paying attention to it, or thinking or talking about it, or tacitly taking it into account) spreads to connected other nodes. Actors that operate in these knowledge networks (i.e., nurses in a healthcare organization that uses clinical practice guidelines) combine relevant knowledge and apply it to the focal situation. Action can proceed on appropriate paths shaped by the knowledge encoded in the tie structure of the rule network.

The dynamics of knowledge networks can pose challenges for organizational knowledge managers and **knowledge management** (Argote and Miron-Spektor 2011, Argote et al. 2003, Bingham et al. 2015, Hislop et al. 2018) efforts. Knowledge nodes (e.g., in the form of routines, skills, interpretations,

job descriptions, or policies) become connected to other nodes, forming networks that handle the interdependencies between different parts of the system. They form a system of evolving nodes and ties. The relevance of each part (an individual node or a group of nodes) depends on the other parts present in the system at that time, and the discovery of its relevance can slow down or speed up depending on how other parts evolve. The contribution of each part is a complex interaction with the contributions of other parts. As a relatively sparse network, organizational knowledge has features of a moderately rugged fitness landscape with an intermediate level of interdependence, facilitating evolution processes (Fleming and Sorenson 2001, Kauffman 1993). Management of organizational knowledge needs to take into account its delicate and evolving nature. It requires focusing attention on and carefully examining the unique contributions that arise from combining a set of specialized organizational knowledge nodes. It requires some level of awareness of how relevance discovery naturally shapes the evolution of the system.

The implementation of organizational learning in practice depends on learning capabilities (Stata 1989, Goh and Richards 1997, Jerez-Gomez et al. 2005, Prieto and Revilla 2006, Svetlik et al. 2007, Goh et al. 2012). Likewise, the implementation of learning-by-connecting can be shaped by capabilities of discovering relevance. **Relevance discovery capabilities** can potentially vary greatly between organizations or learning contexts. Organizations can fail at relevance discovery or succeed more or less. Reliably discovering relevance is challenging for organizations as relevance is in many ways subjective – it is perceived by participants and processes – and there can be massive biases. Nevertheless, is it possible to assess and compare the relevance discovery capabilities of organizations? Perhaps yes. Imagine an organization (most likely a fairly chaotic one) that defies relevance and connects rules that are irrelevant to each other and does not connect rules that are relevant to each other. In that organization, the conditions that shape the likelihood that relevant relationships are discovered (rule system density, births/revisions of other rules, rule knowledge volume) should not matter. The conditions that give rise to sorting (network size and rule version age) should not matter either. Using our statistical model in that organization would produce non-significant results. On the other hand, the more the formation of ties between rules (or knowledge nodes) of an organization is shaped by relevance, the more will parameter

estimates of our models in that organization show significant effects. In that view, one could consider the improvement of fit due to our model variables as a measure of the relevance discovery capability of an organization. One could potentially compare the relevance discovery capabilities of different organizations (or organizational rule systems) by comparing the degree to which our model variables contribute to explaining their rule tie formation rates. Research going into that direction could study performance implications of relevance discovery capabilities. It could also lead to insights about boundary conditions of our model.

Our discovery of relevance perspective can help to create awareness of possible pitfalls in the management of organizational knowledge networks. Biases are likely to arise in applied contexts where **cumulated citation counts** are used as performance metrics of the cited nodes. In our study, we do not model cumulated tie counts of rules, but rather model individual rule tie formation. Our approach can illuminate the problems of cumulating tie counts. Our results indicate that ties are non-homogenous in terms of relevance. Each tie is unique in terms of its impact. Cumulating citations is not a semantically valid operation as the impact of each tie varies. One tie can have immense impact (in terms of benefits it creates or losses that it prevents), while another tie (or a whole group of ties) can have marginal (or even negative) impact. In that view, it seems that cumulated tie counts are too coarse to really reflect usefulness or performance of a node in a knowledge network. Research that takes cumulated citation counts of a knowledge node (e.g., patent, rule, lesson, publication) as an indicator of usefulness (or relevance in some absolute sense) is potentially incurring massive biases.

Our study explored rule networks in a system of CPGs. The rule networks in that system play an important role for the consistent delivery of appropriate healthcare. More research on the evolution of rule networks in the healthcare sector could produce potentially rather impactful outcomes (e.g., monitoring and avoiding unintended interactions between rules) with implications for the management of rule systems. Moreover, rule networks play an important role in many **adjacent domains**, and it is conceivable that they might also be shaped by discovery of relevance mechanisms and that it might be possible to predict their evolution. This can potentially produce fresh impulses for a rather wide range of

related research because rule networks can come in a rather broad range of manifestations, e.g., as grammars they determine the formation of proper statements and actions (e.g., Chomsky 1967, Pentland and Rueter 1994, Woods 1970), as scripts they structure restaurant transactions (Schank and Abelson, 1977), as networks of routines they produce unique capabilities of teams and firms (e.g., Cohen and Bacdayan 1994, Grant 1991, Nelson and Winter 1982), as cross-references that list citing statutes they structure action in the fields of accounting and law[16], as networks of commuting practices they shape the lives of individuals and societies (e.g., Heisserer 2014), as a "metier" of posing they shaped the relationship between artists and models in the Paris art scene in the nineteenth century (Waller 2007). We don't know at this point whether these diverse instances of rule networks evolve through relevance discovery mechanisms, but we hope future research will explore this possibility – and its implications – further.

Limitations and Future Research

The empirical analysis of this study is based on archival data of a regional healthcare organization in Canada. At this point, we do not know if rule ties form in the same way in other organizations in other contexts. It is possible that cultural and organizational differences shape the development of rule ties and rule networks and might moderate the effects of relevance discovery. Given the increasing availability of organizational databases and archives, future researchers will have more powerful data at hand to study the dynamics of rule ties and rule networks in greater detail, and we hope our study will encourage their efforts.

In this study, we assume that the relevance of rules to other rules is not 'given' but is gradually discovered by organizational decision makers and decision-making processes. To strengthen the relevance

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[16] E.g., sections of the US tax code cite related sections, case law evolves through court cases that reference prior cases (e.g., Ponzetto and Fernandez 2008), and government regulations are characterized by "heavy referencing between provisions" that make them hard to use without specialized relatedness analysis tools (Lau et al. 2006). In the German legal code, rule networks of legal statutes are prominently displayed in the form of cross-references ("Querverweise") that list citing statutes (an example is publicly available at https://dejure.org/gesetze/StGB/68.html).

discovery model, future research could test this assumption in more detail, using direct measures of relevance and relevance discovery (e.g., through surveys, etc.).

We also need to be aware of limitations of interpretation arising from our findings. Our findings are based on observations of written healthcare guidelines. The encoded knowledge of healthcare guidelines does not capture the entire richness and depth of knowledge that exists in a healthcare environment. Practitioners develop their own knowledge, and build their own routines into the gaps and loopholes of CPGs (e.g., Crozier 1964, Reynaud 2005). At this point it is not clear if relevance discovery also shapes the formation of ties between user-level routines. We hope future research will explore this possibility.

The main drivers in our relevance discovery model are organizational mechanisms that operate in the rule ecology. Our focus on mechanisms does not mean that agency is absent from our model. In fact, our model leaves considerable space for its influence. Activists wishing to influence the development of rule ties or knowledge networks can organize initiatives that affect stakeholders' perceptions of relevance. Relevance is easily biased, thereby providing ample space for manoeuvres of activists, career-minded executives, determined policy makers, publicity-craving experts, and narcissistic leaders. But even though these players can shape relevance, they are themselves subject to bounded rationality and their own perceptions of relevance are likely to be shaped by some kind of relevance discovery processes (of which they have limited understanding and awareness). We hope future research will explore these ideas further.

We focus on inbound ego-networks of focal rules in this study. Of course, other network approaches can be considered too. For example, whole network approaches could be used to study how the network structure of the entire system evolves. Outbound networks, tie dissolution, and second and third-order networks could be studied as well.

CONCLUSION

Learning-by-connecting denotes the formation of connections between different lessons in a dispersed knowledge environment. It is a form of learning that plays an important role in many contexts, but there is virtually no prior research on the conditions that make it happen. This study explores how it

unfolds in a system of organizational rules (organizational knowledge repositories in the form of clinical practice guidelines). Our guiding idea is that connections between rules arise from the discovery of relevance of rules to other rules, and hence we focus on conditions that shape the likelihood that rules are found to be relevant to others. We develop a model of relevance discovery in which relevance emerges from a dynamic interplay between focal rules and other rules in the rule system. That interplay is the causal engine of relevance discovery. It provides opportunities for discovering relevance and thereby can shape the formation of connections between rules.

The broader picture arising from our study is that learning-by-connecting is a multi-faceted phenomenon with striking features. We find that most rules in our sample become connected, but the rate of rule tie formation varies quite significantly. One source of variation are conditions that affect the availability of opportunities to discover relevance (e.g., through changes of the focal rule, as well as births and revisions of other rules in the system). A second source of variations of the rate of tie formation are temporal sorting mechanisms which add ties of higher relevance earlier than ties of lower relevance, and thereby create declining tie formation rates (with network size and version age). The first shapes the speed of learning-by-connecting, and the second its path.

Another remarkable feature of learning-by-connecting is that it has a rather manifest outcome: it creates knowledge networks which orchestrate the use of nodes (lessons, rules). Knowledge networks can integrate dispersed knowledge, produce powerful knowledge combinations, and facilitate mindful decision making. Knowledge networks are powerful structures that can direct attention and shape decisions, actions, and experiences. As a result, they can shape how and when knowledge nodes are updated (e.g., Zhu and Schulz 2019) and thereby affect how learning continues, making learning-by-connecting path dependent. This means that the evolution of knowledge networks can proceed on rather complex paths – a terrain for exciting future research.

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Figure 1: Predicted Tie Arrival Rates for Four Simulated Guideline Versions
(Based on parameter estimates of Model 6, Table 2)

Assumed revision history of one guideline:
Version 1: T = 0.0 - 1.0
Version 2: T = 1.0 - 3.8
Version 3: T = 3.8 - 5.2
Version 4: T = 5.2 - 6.9
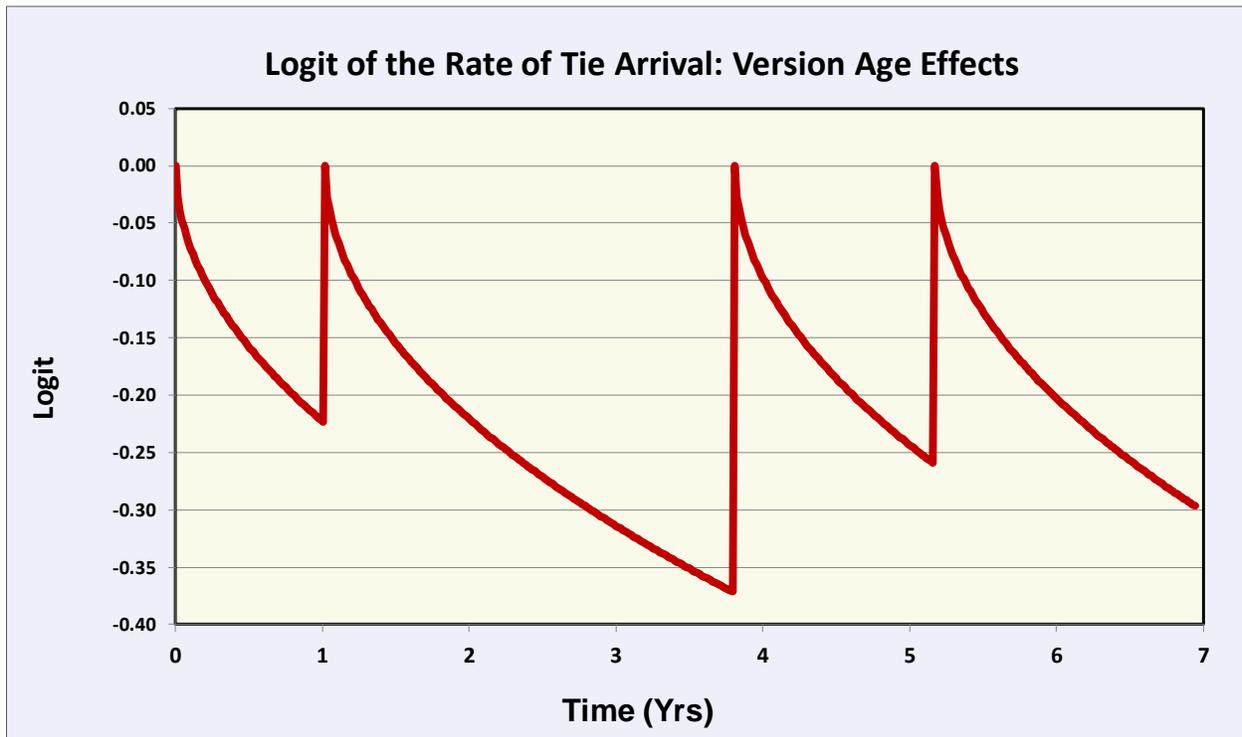As each version ages, the rate declines, but is reset at the next revision.

Logit of the Rate of Tie Arrival: Version Age Effects

Table 1: Descriptive Statistics and Correlation Matrix [a]

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1	Inbound Tie Arrival	0.036	0.187	0	1												
2	Rule size [b]	28.511	11.868	8.246	83.108	0.018											
3	Number of prior revisions [b]	0.964	0.795	0	3.606	0.000	0.299										
4	Outbound network size [b]	0.698	0.872	0	5	0.017	0.131	0.102									
5	Inbound network density	0.095	0.213	0	1	-0.017	-0.084	0.184	0.133								
6	Time period 1	0.282	0.450	0	1	0.014	-0.105	-0.222	-0.111	-0.130							
7	Time period 2	0.278	0.448	0	1	-0.005	-0.044	-0.006	-0.042	-0.028	-0.389						
8	Time period 3	0.440	0.496	0	1	-0.009	0.134	0.207	0.138	0.143	-0.556	-0.550					
9	Rule density	622.091	93.360	310	706	0.006	0.116	0.268	0.119	0.156	-0.830	0.092	0.669				
10	Rule change activity	105.701	51.211	35	207	0.051	-0.043	-0.049	-0.054	-0.035	-0.091	0.467	-0.338	0.021			
11	Encoded knowledge volume [b]	1.449	1.189	0	5.568	0.010	0.545	0.288	0.095	-0.099	-0.067	-0.023	0.081	0.087	-0.037		
12	Inbound network size [b]	1.182	0.848	0	4.359	0.001	0.132	0.297	0.175	0.259	-0.296	-0.016	0.283	0.331	-0.074	0.086	
13	Version age [b]	1.676	0.870	0	3.950	-0.051	-0.168	-0.326	-0.101	-0.042	-0.244	0.006	0.215	0.291	-0.111	-0.145	0.118

a. The table includes only the observations that are included in the fixed-effect logit models.
b. Square root
n=11929

Table 2: Fixed-Effect Logit Models of Inbound Tie Arrival Rate

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent Variable:			Inbound Tie Arrival Rate			
Rule size [a]	0.024	0.030+	0.008	0.012	0.003	-0.002
	(0.017)	(0.017)	(0.021)	(0.021)	(0.022)	(0.022)
Number of prior revisions [a]	0.461*	0.522*	0.473*	0.460*	0.662**	0.403
	(0.205)	(0.209)	(0.209)	(0.209)	(0.215)	(0.247)
Outbound network size [a]	-0.037	-0.038	-0.052	-0.064	-0.137	-0.171
	(0.198)	(0.202)	(0.203)	(0.204)	(0.210)	(0.206)
Inbound network density	-1.426**	-1.475**	-1.513**	-1.618**	-0.913*	-0.926*
	(0.452)	(0.448)	(0.451)	(0.453)	(0.437)	(0.436)
Time period 2 [b]	-0.397**	-1.014**	-1.002**	-1.003**	-0.584**	-0.528*
	(0.143)	(0.201)	(0.201)	(0.202)	(0.214)	(0.214)
Time period 3 [c]	-0.646**	-0.920**	-0.899**	-0.896**	-0.328	-0.232
	(0.165)	(0.242)	(0.243)	(0.244)	(0.262)	(0.265)
Availability of Opportunities						
Rule density [d]		**0.188**	0.184	**0.316***	**0.668****	**0.806****
		(0.114)	(0.114)	**(0.142)**	**(0.158)**	**(0.172)**
Rule change activity [d]		**0.718****	**0.728****	**1.014****	**0.870****	**0.783****
		(0.114)	**(0.114)**	**(0.159)**	**(0.163)**	**(0.168)**
Encoded knowledge volume [a]			**0.414***	**1.223****	**1.712****	**1.717****
			(0.208)	**(0.432)**	**(0.451)**	**(0.450)**
Rule density [d] **x** Encoded knowledge volume [a]				**-0.094+**	**-0.150***	**-0.158****
				(0.056)	**(0.059)**	**(0.059)**
Rule change activity [d] **x** Encoded knowledge volume [a]				**-0.197****	**-0.191***	**-0.188***
				(0.075)	**(0.077)**	**(0.077)**
Sorting of Opportunities						
Inbound network size [a]					**-1.217****	**-1.171****
					(0.124)	**(0.125)**
Version age [a]						**-0.223***
						(0.111)
Log-likelihood	-1477.12	-1452.84	-1450.82	-1445.55	-1391.73	-1389.76
$\Delta\chi^2$		48.56**	4.03*	10.55**	107.62**	3.95*
Δdf		2	1	2	1	1
Observations	11929	11929	11929	11929	11929	11929
Number of guidelines	230	230	230	230	230	230

Standard errors in parentheses
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
[a.] Square root
[b.] Period 2: Aug 1, 2002 – Dec 31, 2005 (Note, the reference category is Period 1: Before Jul 31, 2002)
[c.] Period 3: After Jan 1, 2006 (Note, the reference category is Period 1: Before Jul 31, 2002)
[d.] Rescaled, divided by 100