Organization Design and Learning in The Remote Era

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ABSTRACT

Remote and hybrid work are now commonplace. Despite their clear benefits, concerns persist about their effects on knowledge transfer, organizational learning, and ultimately performance. We argue that these effects are not inherent to remote work but critically contingent on organizational design. Using a computational model, we examine how *Remote Work Intensity* (RWI) interacts with organizational structure and a firm's task environment to shape learning outcomes. When structure is held constant, higher RWI can impede learning for firms operating in complex and turbulent environments. More importantly, redesigning organizational structure can mitigate these losses, which we show by analyzing canonical structures and then exploring broader design possibilities using evolutionary testbeds. These findings reframe remote work as a design challenge rather than a binary choice of work location.

Keywords: Organization design, organizational learning, computational model, remote work, behavioral strategy

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1. INTRODUCTION

Remote and hybrid work have reshaped the basic conditions under which organizations operate, bringing substantial benefits but also raising questions about how teams learn, collaborate, and adapt without traditional physical contexts (Hansen et al., 2023; Buckman et al., 2025).[5] Management scholars have identified numerous advantages of RW, such as improving workers' wellbeing and productivity, allowing companies to source talent globally, reducing commuting, and enhancing work/life balance (e.g., Sauermann & Cohen, 2010; Bloom et al., 2015; Kryscynski et al., 2021; Choudhury et al., 2020; Choudhury, Foroughi & Larson, 2021). Yet, many prominent firms like Apple, Alphabet, Meta, and Tesla have unequivocally rejected remote work, arguing that it hampers innovation, knowledge transfer, and organizational learning, complex processes widely believed to require face-to-face interaction (Williams, 2021; Brucks & Levav, 2022). A remark by Goldman Sachs' CEO David Solomon encapsulates the concern: "I do think for a business like ours, which is an innovative, collaborative apprenticeship culture, this is not ideal for us, and it is not the new normal" (Kelly, 2021). While debates continue at multiple levels of analysis, the most powerful arguments against remote work emphasize its impact on the transfer of knowledge among employees and ultimately on firm performance.

These concerns are valid and critical, as there is evidence of significant benefits to innovation and knowledge transfer from face-to-face interactions (Boudreau et al., 2017; Ren & Argote, 2011; Catalini, 2018). In the context of remote work, for example, a study of knowledge workers at Microsoft found that remote work "may make it harder for employees to acquire and share new information across the network" (Yang et al., 2022: page 43), similarly Carson et al. (2003) and Lin, Frey, Wu, (2023) found that remote work also complicates the transfer of tacit

[5] For clarity of exposition we use "remote work" and "RW" to denote both fully remote and hybrid work schemas, as both involve at least some remote work component.

knowledge. To the extent this is true, remote work threatens a core function of organizations: transferring and processing information, which is critical for adaptation, innovation, and survival (Simon, 1991; Kogut & Zander, 1992; Bartlett & Ghoshal, 1998; Levinthal, 1997). Not surprisingly, versions of these arguments are used by firms operating in knowledge-intensive industries to draw a line in the sand against remote work (The Economist, 2022, 2023; Kossek et al., 2025).

While critiques of remote work are grounded in well-established theories of knowledge transfer and organizational learning, they often rely on a static conception of how learning occurs and overlook the possibility that redesigning organizational structure might actively reshape these dynamics. Our paper thus shifts the conversation from debating whether remote work is inherently beneficial or harmful for learning, to asking how firms can modify their organizational structures to sustain and enhance it. We start with the premise that remote work is not simply a discretionary managerial decision, instead framing it as an embedded reality shaped by worker expectations, institutional norms, and competitive pressures. In this context, we argue that organizational structure, which is a foundational but often under-examined lever, can mitigate the learning-related downsides of remote work by enabling more tailored forms of coordination and knowledge exchange. Treating structure not merely as a constraint but as a designable system, we position this paper as complementing the traditional research agenda: not how remote work changes organizations, but how organizations can change to benefit more from remote and hybrid work.

Surprisingly, structural considerations, such as centralization, connectedness and modularity, have largely been absent from academic and managerial discussions on the effects of remote work. This omission is striking given the key role of organizational structure in enabling learning (Tushman & Nadler, 1978; Karim & Kaul, 2015; Piezunka, Aggarwal, & Posen, 2022) as well as evidence that organizational foci (like departments and centers) enable repeated interaction

and multiplex relationships beneficial for knowledge exchange (Dahlander & McFarland, 2013). To address this gap, we use computational modeling, a powerful tool for investigating complex, costly, and hard-to-observe organizational processes (Burton & Obel, 2011). In our model, employees are embedded within organizational structure, learn, and share knowledge about their environment through mutual interactions (March, 1991; Ethiraj & Levinthal, 2004; Fang, Lee, & Schilling, 2010; Csaszar & Siggelkow, 2010). This approach isolates the effects of remote work on learning, removing confounds such as social or political dynamics or employee well-being. In addition to acknowledging the inevitability of remote work, our agenda in this paper is also to explore the implications of remote work being a continuous rather than binary choice (Gajendran & Harrison, 2007; Raghuram et al., 2019; Gajendran et al., 2024). We adopt the construct of *Remote Work Intensity* (RWI), defined as the proportion of time employees spend working remotely, as a more realistic variable that real managers must manage in real-world settings. As we elaborate on later, one of our key findings is that the interaction between RWI and organizational structure is a mechanism that managers can use to make remote work an asset rather than a liability. Importantly, this focus also allows us to address one of the most persistent criticisms against remote work: its potential to undermine knowledge transfer and organizational learning, which we argue stems from a now-outdated view that remote work is an all-or-none organizational choice.

Our computational approach does not attempt to replicate the full complexity of an organization's remote work implementation. As per Knudsen, Levinthal, Puranam (2019, p.1), "a model is inevitably a 'small-world'" representation of a more complex underlying reality." In our modeling, we employ empirically grounded assumptions about learning and knowledge sharing within deliberately simplified organizational structures. This approach allows us to identify the fundamental mechanisms through which structure and remote work intensity jointly shape

organizational learning—mechanisms that might be obscured by the myriad confounding factors present in real organizations (Burton & Obel, 2011). While this generality limits our model's direct application to specific cases, it also provides clarity by isolating structural effects from the post hoc explanations that often dominate discussions of remote work's successes and failures.

For conceptual tractability, we examine four canonical organizational structures that reflect distinct directions towards which managers can steer their organizations: Random networks (Erdős & Rényi, 1959), Scale-free networks (Barabási & Albert, 1999), Connected Caveman (Watts, 1999), and Small-world networks (Watts & Strogatz, 1998). We investigate their performance across varying levels of RWI. We further vary the levels of interdependence and turbulence in the organizational task environment to capture the conditions faced by firms competing in knowledge-intensive contexts (Galbraith, 1974; Tushman & Nadler, 1978).

Our baseline results confirm the managerial concern: absent changes to organizational structure, increasing RWI indeed tends to have a negative impact on knowledge transfer and learning for organizations facing interdependent and turbulent environments—the very type of organizations that we expect to create "'the fundamental impulse that sets and keeps the capitalist engine in motion" (Schumpeter, 1942:83) through innovation, new organizational forms, and entrepreneurial activity. However, we also show that organizational structure *can* be leveraged to mitigate the adverse effects of remote work on learning in these environments, making it a valuable complement to other interventions supporting successful remote work implementation. As RWI increases, organizational structures, on average, benefit from higher connectedness; however, important boundary conditions qualify this relationship. In simple and stable environments, less connected structures perform better, and little to no reorganization is necessary when RWI increases. Conversely, organizations operating in interdependent and turbulent environments may require a much higher degree of connectedness in their structures to accommodate higher RWI,

suggesting advantages for organizational forms like the matrix or networked form. Put simply, it is unlikely that a one-size-fits-all adaptation approach to remote work will be optimal, as our results suggest that lessons gleaned from implementations in a single firm setting may not generalize across industries or even within the same industry if organizational structure and environmental characteristics are not taken into account.

In secondary analyses, we use a genetic algorithm approach (Holland, 1975; Goldberg, 1989) to identify specific organizational structures that work best for different combinations of RWI and environment. This model enables us to move beyond the four canonical forms. The genetic algorithm lets communication structures evolve organically, uncovering novel structural adaptations beyond those revealed by traditional approaches. Allowing the algorithm to compare the performance of a vast array of organizational structures, we show how organizational designers might reshape structure in novel ways to implement remote work across a variety of environments.

Overall, our findings illustrate that organizational structure can facilitate remote work, while also revealing the limits of structural adaptations in maintaining organizational learning. They thus provide a foundation for a richer understanding of how organizations might adapt structurally to new forms of work, opening avenues for research at the intersection of organizational design and remote work practices.

2. BACKGROUND AND THEORY

Remote work is no longer an emerging trend, but a defining feature of organizational life. While prior research has explored tradeoffs involved in adopting such arrangements, we shift the focus to a subsequent question: How can organizations maintain effective learning under sustained remote or hybrid conditions? Taking the adoption of remote work as given, we examine ways in which managers can alter organizational structure to aid organizational learning.

2.1. Remote work and knowledge transfer

Despite the clear benefits of remote work that we discussed earlier, researchers and practitioners alike have voiced concerns about broader and longer-term organizational implications of remote work. Importantly, the leaders of many high-profile firms, including Apple, Amazon, JPMorgan Chase and Goldman Sachs, have issued non-negotiable in-office mandates, citing critiques related to diminished collaboration, mentorship, and innovation (Williams, 2021; The Economist, 2022, 2023; Kossek et al., 2025). These concerns are not capricious. They are backed by emerging empirical findings that remote work can alter communication patterns in ways that reduce cross-team connections, reinforce silos, constrain the flow of valuable knowledge, and can hinder idea generation (Gibbs et al., 2023; Leonardi, 2020; Brucks & Levav, 2022; Yang et al., 2022). We do not claim that knowledge transfer or socialization are the only, or even the primary, channels through which remote work impacts organizations. However, we argue that they are existential factors for organizations in knowledge-intensive and innovation-driven industries (Kogut & Zander, 1992, 1996). This fear is reflected in frequent concerns expressed by executives hostile towards remote work (Williams, 2021; The Economist, 2022). We believe that focusing clinically on organizational learning and addressing head-on how this challenge might be mitigated is essential to easing adoption and unlocking remote work's potential not only for individuals but also for the long-term adaptability and competitiveness of organizations.

2.2. How remote work reduces the rate of information flow

We explore an essential feature of remote work that should affect both individual and organizational outcomes in knowledge-based and innovative contexts: the shift from face-to-face to remote interactions should tend to reduce the quality of information exchange among individuals, thereby slowing their rate of learning. This is broadly the concern expressed by the

various industry leaders demanding a face-to-face workforce. Indeed, research from various disciplines has shown that the rate of information transfer between individuals drops in organizations where face-to-face interactions are reduced or where individuals become spatially separated. Physical proximity generally promotes more frequent and spontaneous interactions (Allen, 1977; Kiesler & Cummings, 2002), an important factor influencing the design of working spaces for knowledge transfer (Oldham & Brass, 1979; Catalini, 2018). More importantly, face-to-face interactions facilitate more efficient (higher bandwidth) communication and learning, especially in the case of tacit knowledge (Carson et al., 2003; Lewis, 2004; Lin et al., 2023). Face-to-face interactions also reduce misunderstandings and conflict, both of which impede information sharing between individuals (e.g., Cramton, 2001; O'Leary & Mortensen, 2010; see also the excellent review of the literature by Ren, 2020). Interestingly, while remote work itself is a relatively new phenomenon, Herbert Simon intuited a similar insight about telecommunication as far back as 1947 in his seminal book Administrative Behavior:

> *Physical propinquity may be a very real factor in determining the frequency of oral communication, and hence, the layout of offices is one of the important formal determinants of the communication system. Even the advent of the telephone has not very much diminished the importance of this factor, since a telephone conversation is by no means equivalent to a face-to-face contact.* (Simon, 1947:158)

In sum, the literature suggests that as RWI increases, the conditions for effective learning deteriorate: interactions become less frequent, the learning environment becomes less supportive, and communication quality declines, making it harder to extract and absorb useful knowledge from others. We do not claim that these effects always occur, as there can be meaningful differences between different types of knowledge such as explicit vs. tacit, tasks, hierarchical levels, or the personalities of the individuals involved. However, a robust pattern identified by the literature is

that face-to-face interactions improve, rather than attenuate, knowledge transfer among individuals (Ren, 2020). We operationalize this with a knowledge transfer parameter p. Such reduced-form representation of learning is standard in computational models of organizational learning and has been used to represent limits arising from tacitness, low interaction frequency, communication noise, constrained bandwidth, and existence of organizational boundaries (March, 1991; Miller et al., 2006; Kane & Alavi, 2007; Hanaki & Owan, 2013; Martignoni & Miller, 2016). An extensive body of literature shows that face-to-face collaboration mitigates these frictions by enabling richer cues, more spontaneous interactions, and more effective transfer of tacit and hard-to-codify knowledge (Winter, 1987; Nonaka, 1994; Hansen, 1999; Allen & Henn, 2007). Accordingly, we model the impact of remote work interactions through a reduction in the effective rate of information flow between individuals (Simon, 1947; Galbraith, 1990; Ren, 2020).

2.3. The role of organizational structure

While remote work reduces the quality of individual interactions, its broader organizational consequences depend crucially on how those interactions are structured. Indeed, organizational learning depends on individual cognition and learning processes, but it becomes *organizational* through the structural context that connects those individuals (Simon, 1947; March, 1991; Puranam & Maciejovsky, 2017). Foundational work in organization theory has emphasized that organizational structure fundamentally shapes an organization's ability to process information, manage interdependence, and adapt to uncertainty in its environments (Simon, 1962; Thompson, 1967; Galbraith, 1974; Tushman & Nadler, 1978). Structural design entails a range of linking and grouping choices within the organization, including who is assigned to the same unit, who reports to whom, how units are connected, how communication flows, and how decision rights are allocated (Galbraith, 1974; Mintzberg, 1979). These structural choices define the architecture

through which learning occurs, and are especially consequential when informal interaction channels (e.g., hallway chats, spontaneous meetings) become less available in remote work settings, tilting the balance further towards the impact of formal structure. In other words, formal design may be even more consequential in shaping informal structure in remote work settings because of increased control over the configuration of communication and collaboration networks.

Subsequent research has examined how specific structural dimensions such as centralization, clustering, and connectivity address distinct organizational learning challenges. For example, centralization, often modeled as hub-and-spoke structures, can facilitate coordinated responses and stability in the face of environmental turbulence, but can limit variation and exploration (March, 1991; Schilling & Fang, 2014). Clustering, defined by dense intra-group ties and sparse cross-group links, has been shown to preserve diversity and support parallel search, but may impede the spread of superior solutions (Miller, Zhao & Calantone, 2006; Fang et al., 2010). A consistent result across both modeling and empirical studies is that a moderate level of clustering ("optimal clustering") can strike a balance between the cultivation of knowledge diversity and the propagation of its diffusion (Uzzi & Spiro, 2005; Schilling & Phelps, 2007; Yayavaram & Ahuja, 2008). In addition, connectivity, or network density, influences how quickly and broadly information flows: dense networks may improve coordination in the short term, but can lead to premature convergence on suboptimal practices over time (Lazer & Friedman, 2007). Together, these studies highlight how structural configurations help organizations manage the core tension in organizational learning: balancing exploration and exploitation (March, 1991), especially salient in environments characterized by high interdependence and high turbulence (Siggelkow & Rivkin, 2005).

Of course, while realized social interactions often diverge from formal structure (McEvily, Soda, & Tortoriello, 2014), the formal design of an organization provides the scaffolding that

shapes access, channels communication flows, and determines the patterns of interaction (Clement & Puranam, 2018). Subsequently, the classic M-form divisional structure induces the 'connected caveman' network, with tightly knit subunits and limited intergroup links. Centralized organizations, like a U-form—particularly those in R&D-intensive contexts—align naturally with scale-free structures, characterized by a few central hubs coordinating dispersed units. While random and small-world networks are more abstract, they serve as useful benchmarks for less structured, flat, or project-oriented coordination modes.

Shaping the underlying network of information exchange through organization design becomes even more critical in remote work contexts, where informal and spontaneous interactions are diminished and learning impediments increase due to systemic reductions in knowledge flows, as discussed earlier. If structure has historically facilitated learning in the face of organizational challenges (Ethiraj & Levinthal, 2004), then overlooking it in the context of remote work risks ignoring one of the most powerful design levers available to managers. And so in this paper, we bring organizational structure to the remote work discussion and focus on its role in shaping knowledge exchange as a central mechanism for facilitating learning in the remote work era.

2.4. Computational approach

An exploration of how organizational structure matters for firms dealing both with remote work and complex internal and external interactions is challenging, as it must capture a) the impact on individuals, b) the impact on organizations, and c) the interaction between these two levels, under different learning contexts shaped by interdependencies and turbulence (Thompson, 1967; Lawrence & Lorsch, 1967; Galbraith, 1974; Csaszar & Siggelkow, 2010). Performing detailed, long-run studies on a representative sample of firms and across the spectrum of industries would be ideal, but is practically unfeasible (Greenwood & Miller, 2010). Within the study of

organizations, an alternative to granular firm-level studies has traditionally been the large-scale, longitudinal statistical analysis of data. However, such econometric approaches, which tend to isolate univariate relationships, are often unable to unpack complex interdependent mechanisms such as those behind within-firm employee dynamics. Such trade-offs between depth and breadth, while unavoidable given the strengths and limitations of different methodologies, hamper our understanding of the impact of remote work on organizations. Thus, in order to make progress on this front, we turn to computational modeling, an approach that for decades has generated valuable insights in settings where the actions of individuals aggregate in a non-simple way (e.g., Levinthal, 1997; Rivkin, 2000; Rivkin & Siggelkow, 2007; Burton & Obel, 2011).[6]

Our approach incorporates dynamics between agents (e.g., workers), the organization, and the environment. The latter is characterized by varying levels of interdependence and turbulence—two key characteristics driving information processing needs in organizations (Tushman & Nadler, 1978; Puranam, Raveendran & Knudsen, 2012; Levinthal & Workiewicz, 2018)—to examine the mechanisms and interactions that arise from remote work in knowledge-based settings. We model organizational structure as the pattern of communication between organizational members, while muting the confounding impact from social or informal networks that might arise organically in a real-world setting. Consistent with prior work, organizational structure within our model is operationalized from the grouping and linking of decisions made by an organizational designer (say the manager), while allowing resulting patterns of communication to emerge naturally (Nadler & Tushman, 1997; Smith-Doerr & Powell, 2010; Fang, Lee & Schilling, 2010; Clement & Puranam, 2018; Puranam, 2018, Kocak, Levinthal & Puranam, 2023). We are thus able to simulate the impact of a number of archetypal structures (e.g., centralized, decentralized, semi-isolated

[6] See Puranam et al., 2015, for an overview of key computational approaches to study organizational phenomena.

teams, etc.) on organizations with varying levels of RWI. To complete our analysis, we use a genetic algorithm (Holland, 1975) that lets the most optimal structures emerge organically when remote work is imposed under various combinations of interdependencies and turbulence in the task environment. This approach allows us to identify subtler features and mechanisms that may benefit organizations implementing remote work and frees us from the constraints of conforming solely to canonical structural archetypes.

The purpose of this modeling exercise is not to replicate the full complexity of real-world remote work implementations, which are shaped by organizational culture, incentives, management practices, industry dynamics, and countless other contextual factors. Rather, our goal is to identify parsimonious and plausible behavioral mechanisms that could theoretically generate observed patterns of organizational learning under remote work. This abstraction enables us to investigate the relationship between micro-level interactions and macro-level learning outcomes with a theoretical precision that is often impossible in empirical settings where structural reorganization is too costly and disruptive to observe systematically (Gulati & Puranam, 2009; Knudsen et al., 2019). Importantly, computational models are designed to rule in potential explanatory mechanisms rather than rule out alternatives, i.e., they demonstrate what could explain a phenomenon, not what must explain it.

3. MODEL

We incorporate remote work in the manipulated and controlled experimental setting of an agent-based computational simulation, which allows us to examine the effects of organizational structure and environment on employee learning and how they aggregate into firm-level outcomes. Following widely accepted methods from the literature, we conceptualize the organization as a collection of individual agents who interact with their environment by learning from performance

feedback (March, 1991; Levinthal, 1997; Siggelkow & Rivkin, 2006). Our model is consistent with the approach that sees learning in organizations as a dynamic process of information flow among distributed members who are embedded in an organizational structure, and who learn about their external environment and exchange knowledge from other individuals with whom they interact (Fang, Lee, & Schilling, 2010; Argote & Miron-Spektor, 2011). We specify (i) organizational members (agents) embedded in a communication structure, (ii) a task environment that exhibits varying degrees of interdependence and turbulence, and (iii) a learning process through which employees act based on their beliefs (representations) of the task environment, receive environmental feedback, and update those beliefs via interactions with connected colleagues (March & Olsen, 1976; Puranam et al., 2014).

The organization. Our organization consists of m employees embedded in an organizational structure, represented by network communication links. In our model, connected employees interact through these links and update their beliefs by learning from others within their network (defined below). The dynamics of learning are thus determined by the pattern of communications among the individuals – the structure. This structure determines the degree of centralization and isolation of individual employees (Fang, Lee, & Schilling, 2010).

The task environment. We use a standard approach (e.g., March, 1991; Levinthal, 1997) to represent the task environment as consisting of N binary choices $f = \{d_1, d_2, \ldots, d_N\}$, each taking a value of either -1 or 1, representing two discrete decision alternatives for each choice. The task environment represents a reality independent of employees' beliefs. We focus specifically on two features of the task environment which have been theorized as the key drivers of information processing requirements, namely interdependence and turbulence (Galbraith, 1974; Tushman & Nadler, 1978). First, choices facing employees may be independent (simple environment) or interdependent (complex environment). Consider an academic setting. For example, the decision

to shift to case-based teaching requires more than just altering instructional materials. It necessitates changes in class size, classroom layout, the number of whiteboards or display surfaces, seating configurations, and the sequencing of sessions. Each of these choices interacts. Thus, smaller classes may enhance discussion but demand more instructional resources, while flexible seating can support engagement but may require different classroom infrastructures. Such interdependence is captured by parameter *K,* which describes the average number of other choices with which a focal one interacts. Thus, when parameter $K = 0$, all choices are independent of each other, and as K increases ($K > 0$), the contribution of a given decision depends on the other K decisions, as in the above academic example. Formally, the overall fitness (performance) of a given combination of decisions is defined as:

$$V(f) = \frac{1}{N}\sum_{i=1}^{N} V(d_i, d_{-i}), where\ i \neq -i \quad (1)$$

where d_{-i} are the K other decisions with which the focal one d_i is interdependent. This operationalization creates a task environment that is rugged, i.e., has multiple local optima (Levinthal, 1997).

Second, turbulence determines the degree of dynamism in the environment. We model this using *t*, which specifies the number of periods the organization has to learn and disseminate information among its employees before the task environment changes. Lower values of *t* increase the environmental turbulence by shortening the window available for learning, while high values of *t* signify more stable environments (Siggelkow & Rivkin, 2005). Organizational performance is measured as the average performance across all employees at the end of those *t* periods.

The learning process. Employees hold beliefs about external reality. The belief vector of an employee *i* consists of beliefs regarding the N choices of the task environment $B_i = \{b_{i1}, b_{i2}, \ldots, b_{iN}\}$. A belief can be -1, 0, or 1, where -1 or 1 means that the employee has a preference for the

decision and considers their belief the correct one. A belief of 0 means that the employee is uncertain regarding which decision will lead to a better outcome.

At each round, individuals execute their actions (each action $\in \{-1, 1\}$) based on their beliefs. If they are uncertain about a particular decision (i.e., belief = 0), they randomly choose either −1 or 1 for their action. Individual actions are then compared with reality (the task environment) and each individual receives a corresponding performance score, as defined in Equation (1). Learning then starts based on these actions and their associated performance: each employee observes the actions of all of their connected, better-performing colleagues and, with probability *p*, updates their beliefs. If their belief currently conflicts with the majority of better performing peers (e.g., believing 1 while the majority chose -1), they shift to a neutral belief (0) with probability *p*. If their belief is already neutral, they adopt the majority action (e.g., revising belief from 0 to -1). If there is a tie among superior colleagues, the employee's belief remains unchanged.[7] As discussed in section 2.1, the parameter *p* captures the learning rate, that is, the likelihood that an employee updates their beliefs after interacting with a better-performing peer, and can vary depending on the communication channels available (e.g., virtual vs face-to-face), as detailed in the next section.

4. RESULTS

In the subsequent analysis, we ask: *how does organizational structure moderate learning for different levels of RWI, and conversely, which structure presents the best choice for a given combination of RWI and environmental characteristics?* This allows us to isolate the role of a structure in channeling knowledge while muting social interactions. As George Box famously

[7] With respect to individual beliefs, our model builds on the seminal paper by March (1991). In his original model, March used organizational code and associated learning rate to model how both organizations and individuals learn from each other. Because organizational structure is one of our variables of interest, we follow Fang, Lee, and Schilling (2010), who themselves adapted March's model to study the role of organizational structure. Consequently, in our model, individuals learn from their local organizational code, which is represented by their better-performing direct contacts.

stated, “All models are wrong, but some are useful” (Box, 1979, page 202). In that spirit, our model does not aim to capture all possible factors influencing individual- and organizational-level performance; rather, it seeks to examine whether RWI hampers knowledge transfer in organizations and whether structure can mitigate that effect. As noted, we do not claim that knowledge and learning are the only relevant factors impacted by remote work; however, they remain critical to the functioning of knowledge-based organizations. We conduct a series of computational experiments to investigate the interaction among environmental characteristics, organizational structure, and RWI.

4.1. Relative comparison of the four organizational structures

In the first set of analyses, we compare the organizational learning performance of different remote and hybrid work schemes across various task environments, examining how these patterns shift under a range of organizational structures. RWI is operationalized as the number of days employees work remotely. Consistent with general norms, RWI is at maximum when employees work remotely five out of five weekdays (5/5). The lowest level of RWI occurs when employees work on-site for all five days (0/5). Intermediate values (RWI = 4/5, 3/5, 2/5, and 1/5) represent hybrid remote work arrangements. We operationalize remote work by reducing the information flow in a communication link when it shifts away from in-person interaction. Specifically, we set the learning rate p=0.3 for remote interactions, and p=0.7 for on-site ones (the results are robust to other parameter pairs, for example {0.2, 0.8} or {0.4, 0.6}).

We further distinguish between two types of hybrid remote work conditions: synchronous and asynchronous. In the synchronous hybrid condition, all employees are on-site on the same designated days each week and work remotely on the remaining days. In the asynchronous condition, each employee is expected to be on-site a certain *number* of days per week, but their

schedules do not necessarily overlap. Consequently, employees may be in the office on different days, resulting in scenarios where some are present while others work remotely on the same day. We operationalize this by randomly assigning each employee to work remotely on certain "days". Knowledge transfer between two connected employees occurs at a rate of p=0.7 only if both of them are "in the office" on the same day.

We set the number of choices to $N = 12$ and the number of employees to $m = 20$. We then varied the *degree of interdependence* and *turbulence* of the organizational task environment as key drivers of information processing demands in organizations (Galbraith, 1977; Tushman & Nadler, 1978; Siggelkow & Rivkin, 2005; Joseph & Gaba, 2020). The degree of interdependence was examined at four levels: negligible ($K = 0$), low ($K = 3$), medium ($K = 6$), and high ($K = 11$). For each level of K, we considered four levels of environmental turbulence: negligible ($t = 400$), low ($t = 100$), medium ($t = 50$), and high ($t = 25$).

These values were chosen to align with the dynamics of the model. In an environment with medium interdependence, a random graph with an average degree of 4 typically requires approximately 94 periods on average to fully converge under fully remote work condition (RWI=5/5), and about 45.5 periods on average in fully on-site condition (RWI=0/5). Setting these values allows us to examine performance in periods much longer and much shorter than these convergence benchmarks.

To facilitate comparisons and ensure that raw connection count would not drive results, we configured the structure-generating algorithms so that all resulting graphs had the same average degree of 4 (i.e., the same average number of connections per employee), thereby isolating the effect of structural form. Our aim was not to conduct an exhaustive review of all possible organizational configurations, but rather to assess whether the impact of RWI differs across a few representative canonical structures that vary in their degree of centralization and extent of subunit

isolation (i.e., modularity). Identifying such differences would support the call for further research into how organizational structure moderates the effect of remote work.

To ensure the statistical validity of our results, we ran 10,000 simulations (100 organizations x 100 NK landscapes) for each combination of parameters and organizational structure, reporting average values. All results are statistically significant at a minimum of the 99% confidence level. We first investigate what level of RWI yields the best learning outcomes across four canonical organizational structures under different environmental conditions, with the key characteristics of each structure summarized in Table 1.

[Insert Table 1 Here]

Our objective is to examine whether an organization would benefit from adjusting its level of RWI depending on its structure and environment. To address this, we identify the optimal RWI level for each combination of organizational structure, interdependence, and turbulence. Results are presented in Figure 1.

[Insert Figure 1 Here]

Three important observations emerge from this analysis. First, *the environment matters*. The results show that organizations operating in task environments characterized by low interdependence and low turbulence will, on average, benefit from high RWI. This is because under such conditions, it is relatively easy to achieve high performance. These baseline results are consistent with prior studies showing that remote work is particularly well-suited for environments with low interdependencies, such as call centers and patent offices (Choudhury et al., 2020; Bloom et al., 2015). However, an increase in either environmental interdependence or turbulence makes lower values of RWI more advantageous from the organizational learning perspective, with the lowest level of RWI present in more interdependent and turbulent environments.

Second, *organizational structure matters*. Even among organizations operating in identical task environments, a given level of RWI may produce different learning outcomes depending on the organizational structure. In the cases examined here, high RWI benefits organizations in simpler and more stable environments. However, structures characterized by higher centralization (e.g., scale-free networks) benefit from higher RWI across a broader range of environmental conditions. In contrast, organizations with structures exhibiting greater modularity (e.g., connected caveman networks) benefit from high RWI only when operating in the simplest and least turbulent environments.

We can explain these results thusly: organizational structure moderates the speed of information diffusion throughout the organization. Centralized structures allow for faster overall information exchange, whereas modular structures, comprising many weakly connected subunits, are generally slower to diffuse information. The key insight is that when organizational structure results in excessively rapid information dissemination, relative to the demands of the environment, a higher RWI can help slow down information diffusion. In this way, remote work can complement or even substitute for organizational structure in modulating the speed of information exchange and balancing organizational exploration and exploitation (March, 1991).

Finally, our results suggest that *asynchronous and synchronous hybrid work can both be viable approaches*. Across the four organizational structures, either purely on-site (RWI = 0/5) or purely remote (RWI = 5/5) dominate in most environmental conditions. We observe nine situations in which hybrid work conditions provide the best results. Among these, synchronous configurations are more frequently optimal, emerging as the best choice in six out of nine cases. The remaining three favor asynchronous arrangements, but the advantage they offer over synchronous alternatives is marginal and tends to come with higher average on-site presence demands (i.e., lower RWI levels). For example, in the centralized structure in an environment with

low turbulence and medium interdependence, the optimal asynchronous setup with RWI = 1/5 produces almost identical performance as a synchronous approach with RWI = 2/5. The intuition for this is straightforward: Two employees who come to the office on two random days a week (i.e., asynchronous hybrid) have only ⅖ * ⅖ = 16% chance to meet. As a result, since asynchronous interactions slow down the knowledge transfer rate, organizations might need to reduce RWI to compensate. While this may make asynchronous hybrid setups appear less favorable overall, it is important to note that our analysis focuses solely on learning outcomes. Managers may favor asynchronous remote work for other reasons; for example, to reduce office space requirements or facilitate worker life-work balance.

This result prompts a follow-up question: Given that task environments are generally exogenous (organizations can't easily change their industry or institutional characteristics), which type of structure is best for a given RWI and task environment? We explore this question next.

4.2 Reorganization as an answer to changing RWI

In this section, we analyze and compare how different organizational structures fare within different types of task environments and levels of RWI. For interpretative clarity, we focus on two edge cases, RWI = 5/5 (high) and RWI=0/5 (low) to investigate which of the four canonical structures (random, scale-free, connected caveman, and small-world) is most advantageous given specific RWI levels and task environment characteristics.

Figure 2 presents the simulation results for different combinations of interdependence and turbulence. Surprisingly, for both high and low RWI, the caveman archetype remains best under negligible complexity and turbulence. Thus, varying RWI does not require reorganization. However, in task environments with low to medium interdependence and turbulence, the optimal structure shifts: small-world networks perform best in low RWI, whereas more random structures

become preferable under high RWI. Focusing on cases with high RWI, as task-environment complexity increases, small-world structures become the most effective choice so long as turbulence is low. Centralized structures (i.e., scale-free networks) emerge as the most favorable in highly turbulent, but moderately interdependent environments, as well as in settings characterized by medium turbulence and high interdependence.

[Insert Figure 2 Here]

Surprisingly, the caveman structure performs best with high RWI in two very different situations: when the task environment is both simple and stable, and when it is complex and turbulent. At first glance, this seems puzzling, yet a deeper analysis of the model reveals surprising dynamics of knowledge diffusion in this type of organization. Recall that the caveman structure consists of several smaller, densely connected groups, where members of each group are well connected with the members of their own group, but only loosely with other groups. In such a structure, learning occurs in two waves. At the team level, members quickly arrive at a shared solution. However, in the presence of interdependencies, the initial solutions that each team adopts may be different. In other words, each team finds and adopts its own *good-enough* solution. This first wave of learning occurs quickly, with over 90% within-team convergence at $t = 25$, averaged for all levels of K. However, after each team finds a solution, the weak links between teams start to exert influence. As the knowledge of team members converges, some of them become aware of different, but superior, solutions adopted by other teams. Slowly, these superior solutions are disseminated across the other teams, further increasing organizational performance. This second wave of learning takes time, however, and we only see 75% organization-wide convergence at $t = 400$. In highly complex and turbulent environments, the connected caveman structure performs well because it enables parallel search. Its semi-isolated teams can simultaneously explore the same rugged landscape. When turbulence is high and there are many peaks, any peak will suffice, and

each team climbing their local peak quickly improves performance. In simple environments where time is not an issue, the structure's benefit of parallel search remains, and its loose connectivity helps preserve diversity of beliefs across teams while still allowing some cross-fertilization of ideas. This balance supports both broad exploration and eventual convergence.

Interestingly, under high RWI, structures with a random pattern of connections produce the highest performance in environments with modest interdependence and turbulence or when only one of these features of the task environment is significant. This means that there is something other canonical structures do not capture that allows the random structure to achieve superior performance. Both findings suggest that the process of organizational learning in the presence of remote work is more nuanced and goes beyond simple throttling of learning speed by different organizational structures. To explore which specific features of these networks pair well with different levels of RWI, we need to go beyond the four canonical structures. We turn to this next.

4.3. Finding an optimal structure for remote work

In this section, we push beyond the four canonical types. Interestingly, the robust performance of the random structure in the prior set of results suggested that in many cases, three of the four archetypes were suboptimal. This prompts further questions: What would be the ideal organizational structure for a given task environment if the organization designers were not constrained to strict archetypes or if structures were allowed to emerge naturally through repeated experimentation? What features of the organizational structure would be important for higher levels of RWI? What if we allowed the structure to freely assume the best possible shape?

One way to answer these questions would be to evaluate every possible structure across all types of task environments and compare their performance to identify the optimal configuration. However, the number of all possible configurations, even for as few as 20 organizational members,

is computationally infeasible to evaluate exhaustively, given that the problem is NP-complete (see Rivkin, 2000, for a detailed discussion). In fact, with 20 employees, there are $1.57*10^{57}$ possible networks to consider. However, we can approximate the optimal solution by using a genetic algorithm (GA), which allows effective structures to naturally emerge through an iterative process of mutations and selection (Holland, 1975; Goldberg, 1989).

To execute the GA, we initialized a population of 1,000 organizations, each represented by an independently generated random graph defining connections among 20 employees. Each organization was then subjected to the learning procedure outlined in the first experiment. Specifically, we ran each of the 1,000 organizations on 1,000 randomly generated NK landscapes of a given level of interdependence (K) and averaged each organization's performance to arrive at a performance value in time *t*, which was determined by the respective turbulence level.

We then generated a second generation of organizations. First, we selected the 50 best-performing organizations to be carried over unchanged to the second generation. This so-called "elitist selection" prevents genetic drift, which can occur when mutation and crossover operations fail to preserve the advantageous features of high-performing structures (De Jong, 1975). Without elitist selection, a population may lose its beneficial traits. By preserving the best-performing performers, we maintain continuity while allowing the algorithm to explore potentially superior solutions in subsequent generations.

Next, using crossover and mutation, we generated the remaining 950 organizations in the second generation by mutating the structures of those from the previous generation. Specifically, we selected 475 pairs of parents by using a rank-based roulette wheel procedure, where organizations with higher performance in the previous round had a higher chance of being selected and could enter the pool multiple times. For each pair of parents, we generated two child organizational structures, each representing an average of the two parent structures. We then

introduced small random mutations in the child organizations' structures by rewiring some of the connections between employees. Setting a maximum probability of mutating a given connection at 5% ensured that the evolution did not stop prematurely, allowing us to explore the maximum number of configurations.

This evolutionary process continued until the elite pool of top-performing organizations remained unchanged for ten consecutive generations, signaling that the algorithm had converged. At that point, we recorded the structures of the top-performing organizations. To obtain the results, we ran this procedure for each of the 32 combinations of parameters (4 levels of complexity x 4 levels of turbulence x 2 levels (low and high) of RWI)[8].

To measure the differences between the organizational structures best adapted to low and high RWI, we recorded the *average_degree* (the average number of connections per employee), *path_length* (average geodesic distance between any pair of employees), and *modularity*. Specifically, to obtain the *modularity* measure, we ran a community detection algorithm to partition the graph using the Louvain method (Blondel et al., 2008). The resulting *modularity* measure is the observed fraction of connections inside subgroups minus the expected value for such a fraction in equivalent random graphs (Newman, 2006). In our case, *modularity* ranges from 0 to 1, where 1 means the structure is fully modular with no connections between the subgroups (isolated teams), and 0 represents a random structure with no discernible clusters. The detailed numerical results can be found in Figure 3. Figure 4 in turn presents examples of optimal organizational structures.

[Insert Figure 3 Here]

[Insert Figure 4 Here]

[8] Since the results are monotonic with regard to turbulence and/or complexity, in the following analysis we present the GA's results for four corner cases of environmental conditions, corresponding to the possible combinations of negligible and high levels of turbulence and complexity.

The results offer several interesting insights. First, under negligible levels of interdependence and turbulence, a structure consisting of a few semi-isolated teams is optimal for both low and high RWI cases, as *average_degree*, *path_length*, and *modularity* remain roughly the same (Figure 3).[9] Correspondingly, there is little visible difference between the examples in Figure 4, panel a.

With increasing interdependence (Figure 4, Panel b), the number of connections rises for both work modes compared with a stable and simple environment, but there is also a more pronounced decrease in modularity when RWI is high, as reflected in both Figure 3 and Panel b of Figure 4. Notably, structural adaptation largely offsets the impact of high RWI on learning, with *fitness* decreasing only marginally from 0.84 to 0.83). This shows that changing organizational structure can help managers adopt a wide range of RWI.

A similar situation emerges in simple but turbulent environments (Figure 4, Panel c). In this case, the optimal organizational structure is much more connected for high RWI, with a pronounced increase in *average_degree*, a reduction in *path_length*, and a sharp decrease in *modularity* (Figure 3). Again, adapting organizational structure preserves performance levels for low RWI (*fitness* of 0.99 vs. 0.98).

Under high interdependence and turbulence (Figure 3, and Figure 4, Panel d), optimal structures for both work modes exhibit high connectivity (high *average_degree* and short *path_length*), and a high level of structural integration (low *modularity*). However, in a turbulent and interdependent environment, even the best possible structure cannot offset the lower *p* characteristic of high RWI. As a result, performance drops from 0.78 to 0.70.

[9] In our discussion of the results, we will use "optimal" to denote the best organizational structure obtained through the GA. This is a simplification, as these are approximations of the optimal structure. Identifying the optimal structure is an NP complete problem, i.e., the optimal solution cannot be determined algorithmically due to a huge number of possible permutations (Rivkin, 2000).

Overall, these results suggest that in simple and stable environments, *few or no interventions to organizational structure may be needed to accommodate an increase in RWI*. From an organizational learning perspective, some of the *ad hoc* approaches implemented by firms and proposed by scholars, to boost knowledge sharing among remote workers, such as mixers and get-togethers (e.g., Choudhury et al., 2020), may have to be reconsidered. However, in the presence of interdependence, organizations that rely on distinct, well-defined, and well-integrated teams may need to break some of those boundaries to create additional avenues for knowledge flows between them. The biggest challenge, however, arises in highly turbulent environments where many more connections must be added to offset the lower learning rate produced by higher RWI. While the distributed structures of semi-connected on-site teams are superior in turbulent environments, much more interconnected structures must be induced for higher levels of RWI. This result suggests that organization designers should go beyond simple restorative actions and consider reducing the isolation of different subunits and flattening their organizational structures while increasing connectivity to maintain learning performance.

4.4 Robustness checks

To check the robustness of our results to alternative model specifications, we ran the model with different values of p (p = [0.8, 0.2] and p = [0.6, 0.4] for on-site and remote interactions, respectively). We also tested alternative sizes of the organization (m = {6, 20, 60}), other organizational structures (fully connected graph, one- and two-star graphs, random graphs with different edge probability values, lattice and caveman archetypes with different rewiring probability values), and different specifications for the GA (fitness-based vs rank-based, linear vs non-linear probability of selection, different values of mutation rates and elitists). The results reported above were robust to these alternative specifications.

5. DISCUSSION AND CONCLUSION

In this paper we offer new insights on the debate about the tradeoffs that remote work will bring for both individuals and organizations. As of 2024, about 25% of all paid workdays among Americans aged 20–64 were performed from home, and across every major demographic, workers desired more remote work hours than actually performed (Buckman et al., 2025). Our work contributes to this important area at a time when decisions about the nature of the future global workforce are being made around the world.

To our knowledge, this study is the first to provide systematic insights into the debate about the long-term impacts of remote work on learning in knowledge-intensive organizations—arguably one of the most pressing issues facing managers today. The dominant narrative around remote work arose from a tradeoff, catalyzed by a global pandemic, in which autonomy, flexibility, and agency at the individual level were gained but potentially at the cost of organizational fragmentation, knowledge silos, and slower learning. This paper seeks to move beyond that narrative. Rather than asking whether remote work hampers organizational learning or should be implemented, we ask whether its effects are structurally contingent and therefore can be manipulated through design. Using computational modeling, we demonstrate that remote work intensity (RWI) interacts meaningfully with the structure of intra-organizational communication to produce learning outcomes, and that in many cases, performance can be sustained or even improved through structural adaptation. Our findings suggest that the benefits and costs of remote work are not fixed but rather contingent on the properties of the environment in which firms operate and on their organizational structure, making them potentially malleable through organizational redesign.

Much of the public and scholarly discourse around remote work has fixated on a false dichotomy: on-site versus remote. Our approach builds on a conceptualization from personnel psychology that reframes remote work as a continuous variable—a dial, not a switch (Gajendran

& Harrison, 2007; Raghuram et al., 2019). This allows for a more nuanced and managerially tractable view of remote work as a design parameter to be calibrated alongside organizational structure. It also reframes the question entirely. Instead of "Should we go remote?" we ask, "Now given that remote work is already in place, how should we organize our activities to mitigate potential losses in knowledge transfer and learning?". In other words, remote work is not a strategic choice to be justified or defended; it is a design constraint to be optimized against, through levers under the control of managers.

Our findings show that structural features like connectedness, modularity, and path length moderate the impact of RWI on learning outcomes, with some configurations amplifying remote work's downsides and others buffering against them. This challenges the implicit assumption in much of the remote work literature that learning losses are intrinsic to physical separation. They are not. They are emergent outcomes of how information flows or fails to flow through a given structure of interactions.

The modeling approach adopted in this study allows us to isolate structural mechanisms. By using both canonical archetypes and a genetic algorithm to seek the highest-performing structures, we show that organizational learning under remote conditions is highly sensitive to structural design and that no one form dominates. In turbulent and interdependent environments, structural adaptation can partially compensate for the informational frictions of high RWI. In contrast, in stable environments, remote work has a negligible impact on learning, and may even increase performance by staving off premature convergence. These findings are not meant to be conclusive, but rather exploratory. While they help explain why the effects of remote work appear so contradictory in the empirical literature, our goal is to encourage and guide more investigations of how structure and remote work are context-dependent.

It is important to emphasize that our analysis focuses exclusively on the impact of remote work on organizational learning. This is one of an organization's key functions, but clearly not the only one. Consequently, our results must be interpreted with that context in mind. We also acknowledge that the model is stylized and intentionally abstracts from key social and political dynamics such as status, affect, and informal norms, which certainly shape learning in real organizations. This allows us to isolate the role of organizational structure and the specific features of the task environment (which is useful in order to draw generalizable insights). It is likely that the dynamics we document would be additive to those ensuing from interpersonal and social processes. For example, while we use tools developed in the study of networks to analyze canonical organizational structures (see Fang, Lee & Schilling, 2010; Kocak, Levinthal, & Puranam, 2023), these structures represent knowledge pathways, not *social* networks. Our agents, by design, lack social dimensions like trust or homophily. Thus, our study should be viewed as complementary to micro-level investigations or remote work's implications, which should encourage future work to explore whether and how these mechanisms interact with the complex realities of organizations.

Our findings suggest several fruitful directions for future research around structural dynamics. Organizations rarely redesign their structures in one grand deliberate sweep, and understanding how structural adaptations unfold in response to remote pressures, which might be incremental, path-dependent, or moments of punctuated change, is a key theoretical and empirical question. Future work could explore how formal communication structures interact with emergent informal networks, especially under hybrid conditions where trust and shared context may be unevenly distributed, but especially where knowledge transfer matters. These directions point to an urgent need for longitudinal, comparative, and multi-level studies that situate remote work within the broader context of organizational environments and structures. This paper contributes to that effort by offering a framework centered on organizational structure, interaction patterns,

and adaptation to remote work. A wide range of methods, such as qualitative, experimental, archival, longitudinal, quantitative, and lab studies, can help advance this research.

Our paper also contributes to the organizational design literature. While the modeling approach prevents us from predicting the *actual* direction in which the organizational structure will change through informal networks in response to a shift to remote work (which would ultimately be an empirical question), we highlight two important factors. First, our study suggests that the eventual changes in organizational structures will most certainly depend on the initial conditions, such as the nature of the task environment and the original organizational structure. Second, we show the direction in which an organizational designer *should* push the structure of interactions in their organization to counter the effects of decreased knowledge transfer engendered by a shift to RW. Thus, with respect to organizational structure, we do not seek to model what will be, but rather what *ought* to be.

The future of work will not be about whether we return to the office or embrace fully remote work arrangements. It will be shaped by how we structure organizations to enable learning under varying degrees of presence and different modes of synchrony. The stakes of getting this wrong remain as high as ever, and we argue for reconsidering the reluctance to adopt remote work in light of possible interventions that can mitigate its risks.

References

Allen, T. J. (1977). Managing the Flow of Technology. MIT Press, Cambridge, MA.

Allen, T., & Henn, G. (2007). The organization and architecture of innovation. Routledge.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. Organ. Sci., 22(5), 1123–1137.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. Science, 286(5439), 509–512.

Barrero, J. M., Bloom, N., & Davis, S. J. (2021a). Let Me Work From Home, or I Will Find Another Job. Chicago, IL.

Barrero, J. M., Bloom, N., & Davis, S. J. (2021b). Why Working From Home Will Stick. National Bureau of Economic Research No. w28731.

Bartlett, C. A., & Ghoshal, S. (1998). Beyond strategic planning to organization learning: Lifeblood of the individualized corporation. Strategic Leadership, 26(1), 34–39.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. J. Stat. Mech., 2008(10), P10008.

Bloom, N., Han, R., & Liang, J. (2024). Hybrid working from home improves retention without damaging performance. Nature, 630, 920–925.

Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. Q. J. Econ., 130(1), 165–218.

Boudreau, K. J., Brady, T., Ganguli, I., Gaule, P., Guinan, E., Hollenberg, A., & Lakhani, K. R. (2017). A field experiment on search costs and the formation of scientific collaborations. Rev. Econ. Stat., 99(4), 565–576.

Box, G. E. (1979). Robustness in the Strategy of Scientific Model Building. In Robustness in Statistics (pp. 201–236). Academic Press.

Brucks, M. S., & Levav, J. (2022). Virtual communication curbs creative idea generation. Nature, 605(7908), 108–112.

Buckman, S. R., Barrero, J. M., Bloom, N., & Davis, S. J. (2025). Measuring work from home (No. w33508). National Bureau of Economic Research.

Burton, R. M., & Obel, B. (2011). Computational modeling for what-is, what-might-be, and what-should-be studies—and triangulation. Organ. Sci., 22(5), 1195–1202.

Carson, S. J., Madhok, A., Varman, R., & John, G. (2003). Information processing moderators of the effectiveness of trust-based governance in interfirm R and D collaboration. Organ. Sci., 14(1), 45–56.

Catalini, C. (2018). Microgeography and the direction of inventive activity. Manag. Sci., 64(9), 4348–4364.

Choudhury, P., Crowston, K., Dahlander, L., Minervini, M. S., & Raghuram, S. (2020). GitLab: work where you want, when you want. Journal of Organization Design, 9(1), 1–17.

Choudhury, P., Foroughi, C., & Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. Strateg. Manag. J., 42(4), 655–683.

Clement, J., & Puranam, P. (2018). Searching for structure: Formal organization design as a guide to network evolution. Manag. Sci., 64(8), 3879–3895.

Cramton, C. D. (2001). The Mutual Knowledge Problem and Its Consequences for Dispersed Collaboration. Organ. Sci., 12(3), 346–371.

Csaszar, F. A., & Siggelkow, N. (2010). How Much to Copy? Determinants of Effective Imitation Breadth. Organ. Sci., 21(3), 661–676.

Cyert, R. M., & March, J. G. (1963). A Behavioral Theory of the Firm. Prentice-Hall, Englewood Cliffs, NJ.
Dahlander, L., & McFarland, D. A. (2013). Ties that last: Tie formation and persistence in research collaborations over time. *Administrative Science Quarterly*, *58*(1), 69-110.
De Jong, K. A. (1975). An analysis of the behavior of a class of genetic adaptive systems. University of Michigan.
Emanuel, N., & Harrington, E. (2024). "Working Remotely? Selection, Treatment, and the Market for Remote Work." American Economic Journal: Applied Economics, 16(4), 528–59.
Erdős, P., & Rényi, A. (1959). On random graphs. Publicationes Mathematicae, 6, 290–297.
Ethiraj, S. K., & Levinthal, D. A. (2004). Modularity and Innovation in Complex Systems. Manag. Sci., 50(2), 159–173.
Fang, C., Lee, J., & Schilling, M. A. (2010). Balancing Exploration and Exploitation through Structural Design: The Isolation of Subgroups and Organization Learning. Organ. Sci., 21(3), 625–642.
Gajendran, R. S., & Harrison, D. A. (2007). The Good, the Bad, and the Unknown About Telecommuting: Meta-Analysis of Psychological Mediators and Individual Consequences. J. Appl. Psychol., 92(6), 1524–1541.
Gajendran, R. S., Ponnapalli, A. R., Wang, C., & Javalagi, A. A. (2024). A dual pathway model of remote work intensity: A meta-analysis of its simultaneous positive and negative effects. Personnel Psychology, 77(4), 1351–1386.
Galbraith, C. S. (1990). Transferring Core Manufacturing Technologies in High-Technology Firms. Calif. Manag. Rev., 32(4), 56–70.
Galbraith, J. R. (1974). Organization Design: An Information Processing View. Interfaces (Providence), 4(3), 28–36.
Galbraith, J. R. (1977). Organization Design. Addison-Wesley, Reading, MA.
Gibbs, M., Mengel, F., & Siemroth, C. (2023). Work from home and productivity: Evidence from personnel and analytics data on information technology professionals. J. Polit. Econ. Microecon., 1(1), 7–41.
Goldberg, D. E. (1989). Genetic algorithms in search, optimization and machine learning. Addison-Wesley, Reading.
Greenwood, R., & Miller, D. (2010). Tackling design anew: Getting back to the heart of organizational theory. Academy of Management Perspectives, 24(4), 78–88.
Gulati, R., & Puranam, P. (2009). Renewal through reorganization: The value of inconsistencies between formal and informal organization. Organ. Sci., 20(2), 422–440.
Hanaki, N., & Owan, H. (2013). Autonomy, conformity and organizational learning. Administrative Sciences, 3(3), 32-52.
Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. Administrative science quarterly, 44(1), 82-111.
Hansen, S., Lambert, P. J., Bloom, N., Davis, S. J., Sadun, R., & Taska, B. (2023). Remote work across jobs, companies, and space (No. w31007). National Bureau of Economic Research.
Holland, J. H. (1975). Adaptation in natural and artificial systems. University of Michigan Press, Ann Arbor, MI.
Joseph, J., & Gaba, V. (2020). Organizational structure, information processing, and decision-making: A retrospective and road map for research. Acad. Manag. Ann., 14(1), 267–302.
Kane, G. C., & Alavi, M. (2007). Information technology and organizational learning: An investigation of exploration and exploitation processes. Organization Science, 18(5), 796-812.

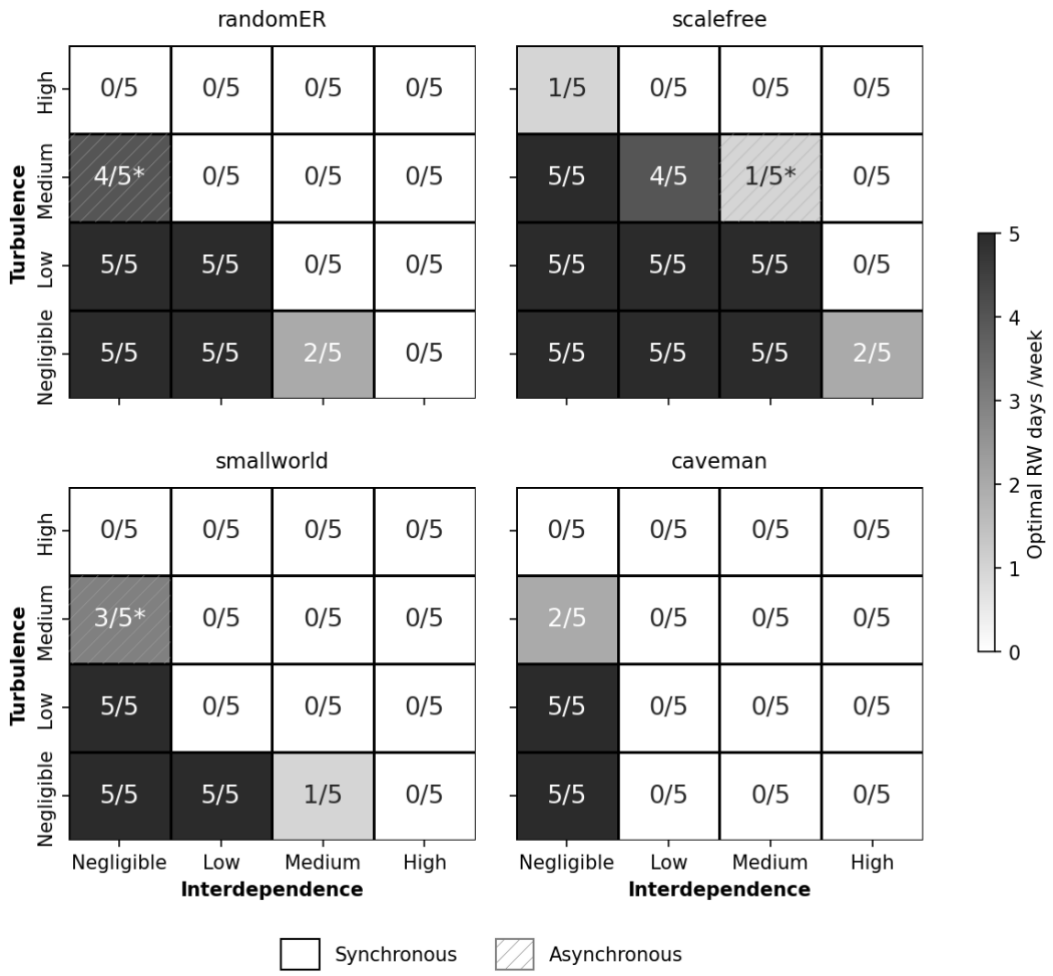
Karim, S., & Kaul, A. (2015). Structural recombination and innovation: Unlocking intraorganizational knowledge synergy through structural change. Organ. Sci., 26(2), 439–455.
Kelly, J. (2021, February 25). Goldman Sachs CEO David Solomon Calls For Workers To Return To The Office. Forbes.
Kiesler, S., & Cummings, J. N. (2002). What do we know about proximity and distance in work groups? A legacy of research. In Distributed Work (pp. 57–80).
Knudsen, T., A. Levinthal, D., & Puranam, P. (2019). A model is a model. *Strategy Science*, *4*(1), 1-3.
Kocak, Ö., Levinthal, D. A., & Puranam, P. (2023). The Dual Challenge of Search and Coordination for Organizational Adaptation: How Structures of Influence Matter. Organ. Sci., 34(2), 851–869.
Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. Organ. Sci., 3(3), 383–397.
Kogut, B., & Zander, U. (1996). What Firms Do? Coordination, Identity, and Learning. Organ. Sci., 7(5), 502–518.
Kossek, E. E., Hill, N. S., Villamor, I., Lautsch, B. A., & Perrigino, M. B. (2025, February). Does Returning to the Office Support Your Company's Strategy? Harv. Bus. Rev..
Kryscynski, D., Coff, R., & Campbell, B. (2021). Charting a path between firm-specific incentives and human capital-based competitive advantage. Strateg. Manag. J., 42(2), 386–412.
Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and Integration in Complex Organizations. Adm. Sci. Q., 12(1), 1–47.
Lazer, D., & Friedman, A. (2007). The Network Structure of Exploration and Exploitation. Adm. Sci. Q., 52(4), 667–694.
Leonardi, P. M. (2020). COVID-19 and the new technologies of organizing: digital exhaust, digital footprints, and artificial intelligence in the wake of remote work. J. Manag. Studies, 58(1), 249.
Levinthal, D. A. (1997). Adaptation on Rugged Landscapes. Manag. Sci., 43(7), 934–950.
Levinthal, D. A., & Workiewicz, M. (2018). When Two Bosses Are Better Than One: Nearly Decomposable Systems and Organizational Adaptation. Organ. Sci., 29(2), 207–224.
Lewis, K. (2004). Knowledge and performance in knowledge-worker teams: A longitudinal study of transactive memory systems. Manag. Sci., 50(11), 1519–1533.
Lin, Y., Frey, C. B., & Wu, L. (2023). Remote collaboration fuses fewer breakthrough ideas. Nature, 623(7989), 987–991.
March, J. G. (1991). Exploration and Exploitation in Organizational Learning. Organ. Sci., 2(1), 71–87.
March, J. G., & Olsen, J. P. (1976). Ambiguity and choice in organizations. Universitetsforlaget.
McEvily, B., Soda, G. & Tortoriello, M. (2014). More formally: Rediscovering the missing link between formal organization and informal social structure. Acad. Manag. Ann., 8(1), pp.299-345.
Miller, K. D., & Martignoni, D. (2016). Organizational learning with forgetting: Reconsidering the exploration–exploitation tradeoff. Strategic Organization, 14(1), 53-72.
Miller, K. D., Zhao, M., & Calantone, R. J. (2006). Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. Acad. Manag. J., 49(4), 709–722.
Mintzberg, H. (1979). The Structuring of Organizations: A Synthesis of the Research. Prentice-Hall, Englewood Cliffs, NJ.
Nadler, D. A., & Tushman, M. L. (1997). Competing by Design: The Power of Organizational Architecture. Oxford University Press, New York, NY.

Newman, M. E. J. (2006). Modularity and community structure in networks. Proceedings of the National Academy of Sciences of the United States of America, 103(23), 8577–8582.
Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. Organization Science, 5(1), 14-37.
O'Leary, M. B., & Mortensen, M. (2009). Go (Con)figure: Subgroups, Imbalance, and Isolates in Geographically Dispersed Teams. Organ. Sci., 21(1), 115–131.
O'Reilly, C. A., & Tushman, M. L. (2004). The Ambidextrous Organization. Harv. Bus. Rev., 82(4), 74–83.
Oldham, G. R., & Brass, D. J. (1979). Employee Reactions to an Open-Plan Office: A Naturally Occurring Quasi-Experiment. Adm. Sci. Q., 24(2), 267–284.
Piezunka, H., Aggarwal, V. A., & Posen, H. E. (2022). The Aggregation-Learning Trade-off. Organ. Sci., 33(3), 1094–1115.
Posen, H. E., & Levinthal, D. A. (2012). Chasing a Moving Target: Exploitation and Exploration in Dynamic Environments. Manag. Sci., 58(3), 587–601.
Puranam, P. (2018). The microstructure of organizations. Oxford University Press.
Puranam, P., Alexy, O., & Reitzig, M. (2014). What's "new" about new forms of organizing? Acad. Manag. Rev., 39(2), 162–180.
Puranam, P., & Maciejovsky, B. (2017). Organizational structure and organizational learning.
Puranam, P., Raveendran, M., & Knudsen, T. (2012). Organization design: The epistemic interdependence perspective. Acad. Manag. Rev., 37(3), 419–440.
Puranam, P., Stieglitz, N., Osman, M., & Pillutla, M. M. (2015). Modelling Bounded Rationality in Organizations. Acad. Manag. Ann., 9(1), 337–392.
Raghuram, S., Hill, N. S., Gibbs, J. L., & Maruping, L. M. (2019). Virtual work: Bridging research clusters. Acad. Manag. Ann., 13(1), 308–341.
Ren, Y. (2020). Learning in virtual teams. In L. Argote & J. M. Levine (Eds.), Oxford Handbook of Group and Organizational Learning (pp. 623–634). Oxford University Press, New York, NY.
Ren, Y., & Argote, L. (2011). Transactive memory systems 1985–2010: An integrative framework of key dimensions, antecedents, and consequences. *Academy of Management Annals*, *5*(1), 189-229.
Rivkin, J. W. (2000). Imitation of complex strategies. Manag. Sci., 46(6), 824–844.
Rivkin, J. W., & Siggelkow, N. (2007). Patterned interactions in complex systems: Implications for exploration. Manag. Sci., 53(7), 1068–1085.
Sauermann, H., & Cohen, W. M. (2010). What makes them tick? Employee motives and firm innovation. Manag. Sci., 56(12), 2134–2154.
Schilling, M. A., & Fang, C. (2014). When hubs forget, lie, and play favorites: interpersonal network structure, information distortion, and organizational learning. Strateg. Manag. J., 35(7), 974–994.
Schilling, M. A., & Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. Manag. Sci., 53(7), 1113–1126.
Schumpeter, J.A. (1942). Capitalism, Socialism and Democracy. Harper & Brothers, New York, NY.
Siggelkow, N., & Rivkin, J. W. (2005). Speed and Search: Designing Organizations for Turbulence and Complexity. Organ. Sci., 16(2), 101–122.
Siggelkow, N., & Rivkin, J. W. (2006). When exploration backfires: Unintended consequences of multilevel organizational search. Acad. Manag. J., 49(4), 779–795.

Simon, H. A. (1947). Administrative Behavior: a Study of Decision-Making Processes in Administrative Organization. Macmillan, New York, NY.
Simon, H. A. (1962). The architecture of complexity. Proceedings of the American Philosophical Society, 106(6), 467–482.
Simon, H. A. (1991). Bounded rationality and organizational learning. Organ. Sci., 2(1), 125–134.
Smith-Doerr, L., & Powell, W. W. (2010). Networks and economic life. In Handbook of Economic Sociology (pp. 379–402).
The Economist. (2022, March 12). Is Hybrid Work the Worst of Both Worlds.
The Economist. (2023, June 28). The working from home illusion fades.
Thompson, J. D. (1967). Organizations in Action. McGraw-Hill, New York, NY.
Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. Acad. Manag. Rev., 3(3), 613–624.
Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. Am. J. Sociol., 111, 447–504.
Watts, D. J. (1999). Networks, dynamics, and the small-world phenomenon. Am. J. Sociol., 105(2), 493–527.
Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. Nature, 393(6684), 440–442.
Williams, C. (2021, November 8). The fight over the hybrid future of work. The Economist.
Winter, S. G. (1987). Knowledge and competence as strategic assets. In Strategies for Industrial Innovation and Renewal, Teece DJ (ed.). Harper & Row.
Yang, L., Holtz, D., Jaffe, S., Suri, S., Sinha, S., Weston, J., Joyce, C., et al. (2022). The effects of remote work on collaboration among information workers. Nat. Hum. Behav., 6(1), 43–54.
Yayavaram, S., & Ahuja, G. (2008). Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. Adm. Sci. Q., 53, 333–362.

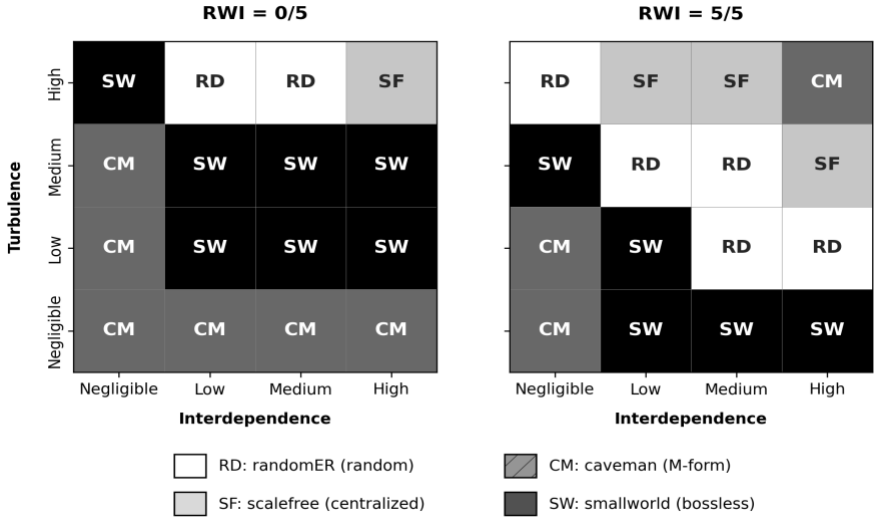
FIGURES

Figure 1. Optimal levels of RWI for different organizational structures and environments



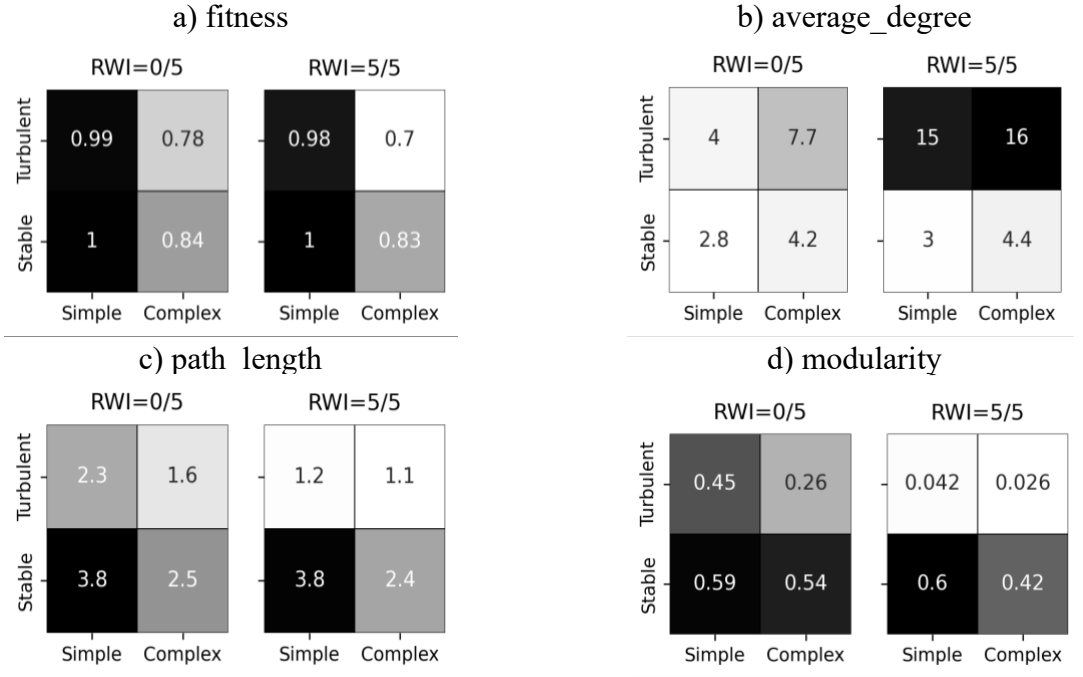
Note: This figure presents the best RWI across four archetypal structures. For each panel, the x-axis represents the level of interdependence, from K=0 for Negligible, to K=11 for High. The y-axis shows turbulence, from t=400 for Negligible level to t=25 for High. The key insights are that remote work is best in environments characterized by lower levels of interdependence and turbulence, but even when operating in the same task environment, organizations may benefit from different *RWIs* depending on their organizational structures. An asterisk (*) indicates cases where the performance difference between the optimal asynchronous and optimal synchronous configurations is statistically indistinguishable, even with high iteration counts.

Figure 2. Comparison of optimal structural archetypes between low and high RWI modes



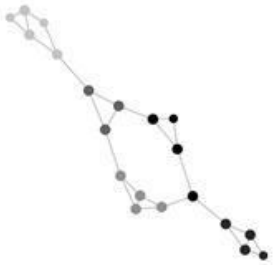
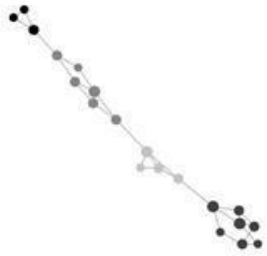
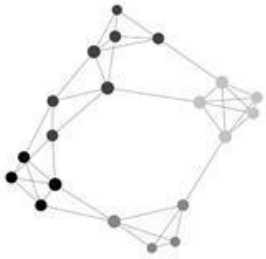
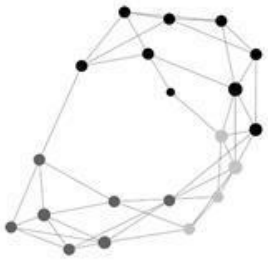
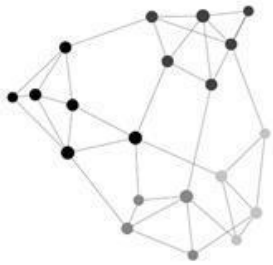
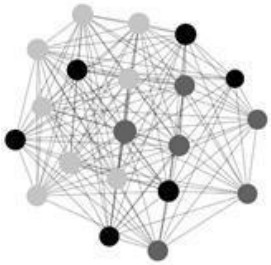
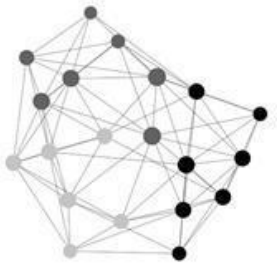
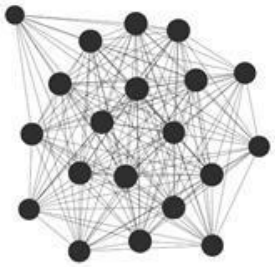
Note: This figure shows which of the four archetypes yields superior learning efficacy with high and low RWI. The key observation is that for many cases, changes in RWI often require reorganization.

Figure 3: Selected structural metrics from GA analysis



Note: The figure shows the fitness and main measures of the optimal structures for low and high RWI conditions, which are the best performers in the last generation of our GA. *Fitness* (panel a) is the normalized organizational performance at the end of *t* periods, with 1 representing all employees having converged on the global peak. *Average_degree* (panel b) is the average number of edges per node (in this experiment, the GA is not limited in terms of edges it can create). *Path_length* (panel c) is the average geodesic distance between all possible pairs of nodes. Finally, *modularity* (panel d) captures the relative density of intra-subgroup links versus inter-subgroup links (Newman, 2006), when subgroups are detected with the Louvain modularity-greedy method (Blondel et al., 2008). With this 2-staged method, *modularity* score can range from 0 to 1, with 0 representing a non-modular structure, and 1 representing a fully-modular one.

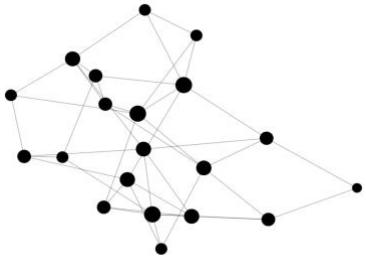
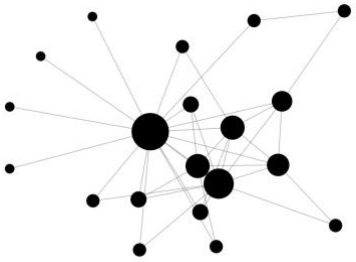
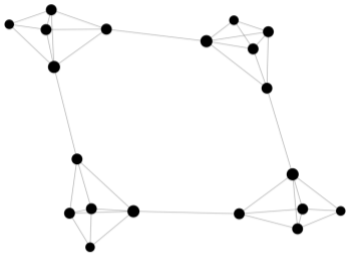
Figure 4: Optimal structures generated by the GA algorithm

Task Environment	RWI=0/5	RWI=5/5
a) Stable & Simple		
b) Stable & Complex		
c) Turbulent & Simple		
d) Turbulent & Complex		

Note: The figure compares representative examples of optimal structures (as identified by the GA) for low (RWI = 0/5, fully on-site) and high (RWI = 5/5, fully remote) levels of remote work intensity across four types of task environments. Duration for learning is set at $t = 25$ for the turbulent condition, and $t = 400$ for the stable condition. For simple environments $K = 0$, while for complex ones $K = 11$. The sizes of the nodes are set proportional to their degrees. For graphs with modularity scores larger than 0.05, node colors are based on the grouping detected by Louvain method, otherwise all nodes have the same color representing the common membership of a single group.

TABLES

Table 1: Descriptions of selected structural archetypes

Structure	Description	Visualization
Random graph (Erdős & Rényi, 1959)	Random graphs where edges are created with a pre-defined probability.	
Scale-free (Barabási & Albert, 1999)	Graph dominated by a few central hubs, degree distribution follows a power law as the result of preferential attachment algorithm. These features correspond to a centralized organization with a few central actors who have significantly more connections than an average employee.	
Connected Caveman (Watts, 1999)	Graphs with several nearly isolated subgroups. This structure corresponds to an organizational structure with multiple semi-isolated project teams.	
Small-world (Watts & Strogatz, 1998)	Graphs where nearest neighbors are connected and most nodes are not neighbors but can reach any other node via a few edges. These attributes could be found in flat or bossless organizations where employees freely join and leave projects.	