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A Microstructural Approach to Self-Organizing: The Emergence of Attention Networks

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Abstract. A recent line of inquiry investigates new forms of organizing as bundles of novel solutions to universal problems of resource allocation and coordination: how to allocate organizational problems to organizational participants and how to integrate participants' resulting efforts. We contribute to this line of inquiry by reframing organizational attention as the outcome of a concatenation of self-organizing, microstructural mechanisms linking multiple participants to multiple problems, thus giving rise to an emergent attention network. We argue that, when managerial hierarchies are absent and authority is decentralized, observable acts of attention allocation produce interpretable signals that help participants to direct their attention and share information on how to coordinate and integrate their individual efforts. We theorize that the observed structure of an organizational attention network is generated by the concatenation of four interdependent micromechanisms: focusing, reinforcing, mixing, and clustering. In a statistical analysis of organizational problem solving within a large open-source software project, we find support for our hypotheses about the self-organizing dynamics of the observed attention network connecting organizational problems (software bugs) to organizational participants (volunteer contributors). We discuss the implications of attention networks for theory and practice by emphasizing the self-organizing character of organizational problem solving. We discuss the generalizability of our theory to a wider set of organizations in which participants can freely allocate their attention to problems and the outcomes of their allocation are publicly observable without cost.

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Introduction

A major line of theoretical development examines organizations as systems of coordinated activities performed by multiple participants to solve multiple problems (March and Simon 1958, Cohen et al. 1972, Puranam 2018, Raveendran et al. 2020). Typically, this line of research starts with the assumption that individual goals are often ambiguous or simply untraceable, links between actions and consequences are weak, and participation in problem solving is fluid and evolving (March and Olsen 1976). Consequently, organizations are viewed as striving to implement coordination mechanisms that reduce uncertainty, stabilize problem-solving routines, and allow organizations to function effectively (Cohen et al. 1972, Padgett 1980, Nadler and Tushman 1997, Padgett et al. 2003, Ocasio 2012).

Extant research documents a variety of stabilizing coordination mechanisms, including hierarchy-based structures (Mintzberg 1979), exogenous distribution of tasks and activities (Galbraith 1973), organizational routines (Becker and Knudsen 2005), systems of formal incentives (Kretschmer and Puranam 2008), and decision-making architectures (Christensen and Knudsen 2010). All these examples assume that organizations are purposefully designed to exert direct managerial control over basic organizing principles, such as division of labor, integration of effort, and exercise of authority.

Perhaps because the concepts of "organization" and "hierarchy" are frequently used as synonyms (Bradach and Eccles 1989, Williamson 1991), we know less about how problem-solving activities may self-organize under conditions characterized by little or no hierarchical control (Puranam et al. 2014, Lee and Edmondson 2017). In recent developments of organizational theory and design, the term "self-organizing" describes the emergence of organizational structure as the result of spontaneous, evolving, and interdependent interactions among participants and problems in a condition of decentralized, loose, or even absent authority (Lee and Edmondson 2017, Massa and O'Mahony 2021). Examples of self-organizing dynamics are frequent in today's work arrangements, ranging from crowdsourcing (Majchrzak et al. 2021) to digital encyclopedias (Arazy et al. 2016, 2020; Klapper and Reitzig, 2018; Lerner and Lomi 2020a), corporate experiments with "holacracy" (Robertson 2015), and open-source online software platforms (Conaldi et al. 2012)—the specific setting that we examine in this study (von Krogh and von Hippel 2006).

How do open organizations control the process of problem allocation to participants in the absence of a formal hierarchy providing an exogenous source of authority? How do organizations provide information to participants to guide them in coordinating their work in the absence of a formal workflow system? We seek to answer these questions by examining how coordination emerges endogenously to stabilize the relation between fluid streams of participants and problems (Cohen et al. 1972). We argue that, in new forms of organizing, which are often driven by distributed open communities (Gulati et al. 2012), built on architectures for decentralized collaborations (Fjeldstad et al. 2012), and populated by problems seeking the attention of problem solvers (Haas et al. 2015, Piezunka and Dahlander 2015), activities are coordinated through visible, public, and transparent acts by which active participants allocate attention to available problems.

We conceptualize organizational attention allocation as determined by a concatenation of self-organizing, microstructural mechanisms based on the mutual interdependence between participants and problems. Whereas traditional views of organizational design treat interdependence as a condition involving participants (or agents) and problems (or tasks) as separate entities (Puranam et al. 2012), our work draws from a more general view of participants and problems in organizations as standing in a dual relation of mutual constitution (Breiger 1974, Breiger and Mohr 2004, Tasselli and Kilduff 2021). At any given moment, acts of attention allocation linking participants to problems generate information signals and create contingencies that influence how other actors might allocate their own attention. Rather than the design of explicit mechanisms for integration of effort between participants, attention allocation itself is the stimulus triggering further behavioral responses from other participants such that organizations are coordinated by the very same processes that their members perform (Padgett and Powell 2012).

Conceptually, this process of allocation of attention may be seen as embedded in a relational structure involving two classes of interdependent entities: "participants"—the carriers of organizational solutions—and "problems" (Carley 1991). We represent this system as a rectangular array in which rows are participants, columns are problems, and individual cells contain information about participants allocating attention to problems. We call this system an *attention network*. Unlike prior attempts to understand organizational networks as the informal representation of social or workflow relationships between participants (e.g., Kilduff and Brass 2010), the focus of our argument is that attention networks capture the emergence of self-organizing, interdependent mechanisms that stabilize emergent patterns of attention allocation. We propose that the emergence of attention networks is generated by the concatenation of four basic microstructural mechanisms, nested within one another in increasing order of complexity: attention *focusing*, attention *reinforcing*, attention *mixing*, and attention *clustering*. Attention focusing captures the tendency of participants to allocate attention repeatedly to the same issues, following a logic of familiarity. Attention reinforcing captures the tendency of participants to allocate attention to problems that already attracted a high degree of attention, following a logic of popularity. Attention mixing captures the interaction between the activity of participants and the popularity of problems so that a disassortative mixing effect indicates that participants that are more active are less attracted by popular problems, following a logic of devaluation. Finally, attention clustering captures the tendency of participants to extend their attention to future problems located in the vicinity of current problems, following a logic of proximity. We frame these mechanisms as theoretically grounded hypotheses to improve our understanding of attention networks in organizations as emergent coordination infrastructures.

We test these arguments through an empirical analysis of the evolutionary dynamics of organizational attention networks within a large open-source software project actively developed and maintained by a global community of participants. Given the "anarchistic" character of open-source productions (Lerner and Tirole 2001, p. 821), this empirical setting is appropriate and uniquely useful for our current purpose. Because development platforms that support open-source productions are explicitly designed to shape the allocation of collective attention, information on problems (called "software bugs") is reported (in a page called "bug report") and stored in virtual spaces (called "bug repositories" or "bug trackers") that participants (volunteer "software developers") may access freely at any time. An attention allocation event is recorded whenever a participant allocates attention to a problem by intervening on (or "touching") the corresponding bug report.

Our work contributes to contemporary research on organizations in at least three ways. First, we contribute to the literature on the microstructural perspective of organization design (Barney and Felin 2013, Puranam 2018) by identifying organizational attention allocation as a self-organizing microstructure that replaces classic coordination mechanisms in traditional bureaucracies. A growing body of research investigates how participants follow self-organizing principles to collaborate (Fjeldstad et al. 2012, Deichmann et al. 2021), increase creativity (Majchrzak et al. 2021), and mobilize collective resources (Massa and O'Mahony 2021). However, extant research typically does not specify the structural micromechanisms through which visible acts of attention allocation allow participants to solve the organizing problems of division of labor and integration of effort to achieve work coordination. Our empirical analysis—conducted at a very high level of temporal resolution—sheds light on the self-organizing dynamics by which visible acts of attention allocation produced by problem-solving agents provide necessary information to other agents that are self-selecting into problems to solve, revealing crucial complementarities between the solutions to the problems of task allocation and provision of information (Puranam 2018).

Second, we add to the scholarly debate on new forms of organizing (Puranam et al. 2014, Lee and Edmondson 2017) by focusing on open-source software communities as a theoretically meaningful setting that reveals how the universal problem of task allocation is solved in absence of direct managerial control by the information produced by visible acts of individual attention allocation. Our study shows that the mechanisms of attention allocation that we postulate remain stable and clearly detectable after controlling for formal structures imposed by software modules, which help participants to search for problems that are better aligned with their interests and skills (von Krogh et al. 2003). Furthermore, the results of our study address the known problem of under-provision of effort to resolve "mundane but necessary" tasks that may easily escape collective attention in systems in which a few popular problems attract a disproportionate share of attention (Lakhani and von Hippel 2003, Puranam 2018). We argue that the tendency of very active participants to divert their attention away from popular problems is fueled by a logic of devaluation, whereby some problems become less interesting to the highly engaged participants once a threshold of popularity is crossed.

Third, we contribute to advancing an attention-based view of organizations (Ocasio 1997, 2011; Ocasio et al. 2022) by extending the original behavioral intuition that individual choices in organizations are influenced by the focus of attention of visible and relevant others (March and Olsen 1976, Ocasio 2011). We show that attention allocation is the product of "socially endogenous inferences" (Zuckerman 2012, p. 227) giving rise to an attention network, shaping the relation between participants and problems (Cohen et al. 2012, Ocasio 2012), an intuition originally articulated in the context of the garbage can model (Cohen et al. 1972).[1] When organizations are characterized by fluid participation that involves a constant churning of people and problems (March and Olsen 1984), we show that the cumulative structural dynamics that we hypothesize leave traces that contribute to stabilize the link between participants and problems to form the attention network that we observe.

Microstructural Mechanisms of Self-Organizing

The notion of organizations as systems of interdependent activities connecting participants to problems is explicit in classic theories of organizations (e.g., Cyert and March 1963, Cohen et al. 1972) and is still central in contemporary theories of organization design (e.g., Puranam et al. 2014, Puranam 2018, Raveendran et al. 2020). As March and Simon (1993, p. 2) clarify, "Organizations are systems of coordinated action among individuals and groups whose preferences, information, interests, or knowledge differ." Classic theories of organizations emphasize the idea that boundedly rational participants make decisions based on information characterized by a high degree of ambiguity (March and Olsen 1976). For example, goals are often ill-defined and inconsistent across different organizational levels, causal connections between actions and their consequences are difficult to clarify, and participation in problem-solving activities is variable and associated with correspondingly variable outcomes (Cohen et al. 1972). Within this perspective, the "universal problem of organizing"—comprising division of labor and integration of effort—constitutes a continuous process by which information is made less ambiguous as a result of coordinated actions of individual organizational participants (Puranam et al. 2012).

Traditionally, organization design scholars have focused on authority and hierarchical ordering as solutions to the problem of organizing (Keren and Levhari 1979, Mintzberg 1979, Padgett 1980). The provision of authority embedded in a hierarchical structure provides an effective mechanism for dividing work, allocating tasks, and making available the necessary information for workflow coordination. However, the nature of work has changed considerably in recent years. Organizational structures have become flatter, managerial control has become more decentralized, and digital technology now allows for a greater variety of coordination mechanisms (Lee and Edmondson 2017, Raveendran et al. 2020, Reitzig 2022). Controlling the allocation of attention becomes crucial whenever decentralization increases the freedom of organizational participants to self-assign to organizational problems or tasks (Ocasio 1997, 2011; Ocasio and Joseph 2005).

Organization theories acknowledge that attention is one of the bases for shaping individual behavior (March and Olsen 1976; see also recent developments in attention-based views, e.g., Ocasio 2011). This line of behavioral research claims that what organizational participants do depends at least partly on the problems to which they devote their attention (Ocasio 1997). However, this literature typically emphasizes characteristics of problems competing for attention, such as length and breadth (Haas et al. 2015), urgency (Sullivan 2010), and degree of supplied information (Hansen and Haas 2001). Alternatively, the emphasis of previous work is on the costs of (mis)coordination that (sub)optimal communication between participants involves (for a recent review of this literature, see Prat and Dessein 2016). The self-organizing mechanisms of attention allocation that we introduce emphasize, the fundamental dependence among individual acts of attention allocation connecting multiple participants to multiple problems. This interdependence arises because, at any given moment, the set of potential attention allocation opportunities is too large to be searched exhaustively by any individual participant (Simon 1978). Under assumptions of information transparency, individual acts of attention allocation also produce signals that may be interpreted as informational cues (Podolny 2001) to guide further attention allocation decisions by other participants (Puranam et al. 2014, Puranam 2018).

What structural mechanisms regulate these interdependent acts of attention allocation in organizations? Building on Schelling (1998), we define a mechanism as a plausible hypothesis that explains the effect of a collective phenomenon (attention allocation in our case) in terms of interaction between elementary agents (organizational participants and problems in our case). We provide a theoretical narrative in which these mechanisms concatenate to form a dynamic attention network linking organizational participants to organizational problems.[2] We derive a set of hypotheses connecting micromechanisms of attention allocation to the macrostructure of the organizational attention network.[3]

Attention Focusing

In an organizational world increasingly characterized by constant change in the sets of participants, problems, and decision opportunities, attention allocation cannot be reduced to a stable set of individual preferences (March 1991) because the choice set of organizational decision makers cannot be completely defined ex ante (Knudsen and Levinthal 2007).[4] Allocating attention involves investing "energy, effort, and mindfulness" (Ocasio 1997, p. 189) on a limited sample selected from a larger population of problems. As an investment decision, the allocation of attention is only partially reversible because of the inertia determined by cognitive costs related to search, information acquisition, and learning (Simon 1978, Conlisk 1996, Gabaix et al. 2006). These problem-specific costs increase the likelihood that organizational participants allocate their attention to more familiar problems. In consequence, the allocation of attention depends also on the degree of familiarity of organizational participants with the problem at hand. According to this "logic of familiarity," attention tends to become more focused over time as organizational participants distribute attention over a progressively narrower and relatively well-known set of issues (Levinthal and March 1993, p. 97). This expectation is consistent with available evidence on the effects of familiarity and experience on ease of recall of instances produced by classic experimental studies of choice under uncertainty (Tversky and Kahneman 1974).

In the presence of problem-specific (cognitive and learning) costs, the higher the participants' focus on familiar problems, the lower the cognitive cost of processing problem-specific information and recognizing problem-specific solutions (Reagans et al. 2005). Repeated attention to familiar problems gives rise to routines and related forms of recurrent behavior and habitual problem solving, which contribute to narrow the focus of attention and stabilize the relation between organizational problems and solutions (Cohen 2012). Our first hypothesis is consistent with classic predictions of behavioral theories of the firm about the reinforcing effects of familiarity on problem-solving behavior (Cyert and March 1963) and with more recent studies inspired by this theoretical tradition that investigate endogenous specialization as sustaining the division of labor in organizations (Christensen and Knudsen 2020). In the empirical context of our study, for example, this prediction is exemplified by a situation in which participants (software developers) display a preferential tendency to focus on a given set of problems (software bugs), thereby increasing task specialization rather than seeking to engage new problems. Hypothesis 1 provides the baseline expectation—based on a logic of familiarity—for the hypotheses that we develop next.

Hypothesis 1 (Attention Focusing Hypothesis). *Organizational participants are more likely to allocate attention to organizational problems that have attracted their attention in the past.*

Attention Reinforcing

Attention focusing explains why participants are more likely to allocate their attention to familiar problems, but it does not explain which problems are more likely to attract attention in the first place, or how attention as a sampling mechanism operates. Theories of selective attention have long recognized that salience affects the likelihood that a problem receives attention (Taylor and Fiske 1978, DiPrete and Eirich 2006). Salience is partly an outcome of frequency-dependent social dynamics activated by the number of others who are visibly paying attention to the same problem or issue (Salganik et al. 2006). In situations in which acts of attention allocation performed by others are directly observable, attention allocation is subject to the tendency of popularity to breed popularity, that is, to the law of accumulative advantage (Powell et al. 2005).

Attention-based accumulative advantage arises because popularity is interpreted as a signal of intrinsic interest, worth, attractiveness, and appropriateness. As Smith (2011, p. 64) observes, "Increasing instances of a particular and, importantly, observable outcome signal the appropriateness of that outcome." The consequence of cumulative advantage of this kind is that attention allocation becomes progressively more concentrated on a limited number of issues or cases. The structural signature of this attention-reinforcing process is a skewed distribution of attention: few problems tend to attract the attention of many, and most problems tend to attract limited or no attention at all. Similar forms of preferential attachment are investigated in a variety of settings (Barabási and Albert 1999, Powell et al. 2005, Dahlander and McFarland 2013). Studies of preferential attachment in social networks demonstrate that popular individuals are more likely to attract ties from other individuals and, hence, become more popular (Merton 1968, Rivera et al. 2010).

In the more specific context of organizational attention, this general insight helps identifying two meaningful sources of attention reinforcing or cumulative advantage of popular problems. The first relates to the fact that the number of organizational participants allocating their attention to a problem increases the visibility of the problem. Participants may decide to allocate their attention to already popular problems to demonstrate their expertise, increase their reputation, or claim legitimate membership in their reference community (Tajfel and Turner 1986, Shah 2006, Dahlander and O'Mahony 2011). For example, in our empirical context popular software problems may become public arenas in which software developers become recognized as trustworthy and willing and able to contribute to problems of general interest for the project. A second source of attention reinforcing derives from the fact that participants engaging popular problems gain access to a larger and more diverse pool of knowledge. For example, in our empirical context allocating attention to popular problems allows software developers to access the experience of a larger sample of peer developers and learn from their experience and problem-solving practices (Reagans et al. 2005, Boh et al. 2007). Hypothesis 2—based on a logic of problem popularity—summarizes this argument.

Hypothesis 2 (Attention Reinforcing Hypothesis). *Organizational participants are more likely to allocate attention to popular organizational problems.*

Attention Mixing

However reasonable as a general tendency describing the allocation of collective attention, reinforcing does have mitigating factors. Empirical studies document individual tendencies to ignore popular issues because popularity is frequently interpreted as a signal of their faddish character, which ultimately makes these issues transitory and short-lived (Berger and LeMens 2009). Empirical studies also document the systematic tendency of individuals to reduce their interest in an issue when the interest expressed by others in that same issue peaks (Berger and Heath 2008).

We argue that attention reinforcing is mitigated by a logic of devaluation of popular problems and the extent to which this happens depends on a specific characteristic of organizational participants, that is, their level of activity. This argument hinges on assumptions about the mixing properties of attention networks, that is, about the correlation between the relational characteristics of problems and participants. In our case, we expect attention allocation patterns to exhibit a disassortative mixing dynamic[5] as the attention of active participants spreads over less popular problems, compensating, in part, for the tendency toward concentration induced by attention reinforcing.

Evidence of disassortativity in bipartite networks (for example, networks connecting individuals and issues) is widespread. Shang et al. (2010) find evidence of disassortative mixing in the bipartite network affiliating participants in an internet-based recommender system website to music they play: very active consumers of music tended to listen to music tracks that few other users would select. Along similar lines, Grujić et al.

(2009) report evidence of disassortative mixing in the bipartite network affiliating users and movies in a popular internet-based movie database: users who recommend many movies recommend movies that are not recommended by many other users. In a recent study of Wikipedia—the open, online encyclopedia—Lerner and Lomi (2020b) find that particularly active contributors (i.e., individuals responsible for a high volume of editing activity) are less likely to modify articles that receive many edits from other contributors. In consequence, more active users seem to dedicate a larger share of their attention to less popular articles than less active users. These empirical studies report patterns of disassortative mixing in large bipartite systems composed of individuals and items competing for their attention, such as music tracks, movies, and web pages.

In organizational attention networks, we expect disassortative mixing to be the outcome of a tendency whereby active people (i.e., people who pay attention to many items) are likely to devalue popular items that become less interesting after a given threshold of popularity is reached (Berger and Heath 2008, Kovács and Sharkey 2014). In the context of organizational problem solving, the decline of interest in popular problems following devaluation is likely to be more pronounced for active participants whose available attention is more severely constrained by the intensity of their engagement (Kahneman 1973). Whereas popularity of problems may be attractive to the average participant because of the potential increase in learning opportunities—as postulated in our attention reinforcing hypothesis (Hypothesis 2)—it may also trigger effort-reducing cognitive heuristics (Tversky 1972) in more active participants. Popularity of problems may also strengthen social psychological effects, such as diffusion of responsibility that depends directly on the number of participants already attracted to an issue (Darley and Latané 1968). Active participants with limited attention may then divert away from engaging with problems that (i) require more intense computation and sense-making efforts to integrate a multitude of contributions from different participants (Castellaneta and Zollo 2015, Criscuolo et al. 2017) and (ii) seem to garner sufficient attention to guarantee their eventual resolution. Participants with extensive experience and limited attention might, thus, be more likely to focus on issues on which their marginal contribution has higher impact. Consequently, active participants are likely to divert their attention away from popular problems.

More generally, our third hypothesis identifies a specific class of mechanisms that may be responsible for the endogenous emergence of division of labor and roles in organizations—a core concern in contemporary behavioral theories of organizations (Knudsen and Srikanth 2014, Christensen and Knudsen 2020). Hypothesis 3—following a logic of devaluation—summarizes this argument.

Hypothesis 3 (Attention Mixing Hypothesis). *Active organizational participants are less likely to allocate attention to popular organizational problems.*

Attention Clustering

Thus far, we have concentrated on behavioral tendencies of individuals (focusing, Hypothesis 1), characteristics of problems (reinforcing, Hypothesis 2), and the direct interaction between individuals and problems (mixing, Hypothesis 3). But organizational participants are linked to each other also indirectly through their joint affiliation to problems that attract their attention (Carley 1991, Conaldi and Lomi 2013). It is possible, therefore, that the indirect connection between problems and participants makes other proximate problems more likely to attract attention in the future. Our reasoning on this issue is firmly rooted in the classic behavioral insight that decision makers actively construct their choice set, and search is indeed a central aspect of organizational problem solving (Knudsen and Levinthal 2007). Organizational participants are more likely to allocate their attention to issues located in the neighborhood of issues that attracted their attention in the past (Simon 1959, Cyert and March 1963). Building on this view, more recent research identifies a number of powerful factors that contribute to constrain the range of problemistic search in the neighborhood of current problems and solutions (Jung and Lee 2016). This view of search requires the definition of some notion of "neighborhood" so that the concept of "local search" may be specified (Stuart and Podolny 1996). Suppose, for example, that two participants i_1 and i_2 are attracted by (i.e., allocate their attention to) the same problem m_2 at time t_1. Suppose, further, that i_2 (but not i_1) is also attracted by a second problem m_1. In this situation (i.e., at time t_1), problem m_1 is in the neighborhood of participant i_1 because i_1 can reach m_1 indirectly through the path $\{i_1 — m_2 — i_2 — m_1\}$.[6] If, at time t_2 ($>t_1$), participant i_1 decides to allocate attention to problem m_1 located in the neighborhood thus defined, then participant i_1 generates a closed structure or a "cluster" of two participants connected to the same two problems.[7] Unlike the more common forms of clustering, or "closure," in social networks involving three nodes (Faraj and Johnson 2011, Bearman et al. 2014, Shore et al. 2015), attention clustering involves pairs of participants allocating their attention jointly to the same pairs of problems, forming a localized and, thus, proximate attention cluster (for a similar conceptualization, see Prato and Stark 2023).

We establish that the extent to which a problem may be considered proximate to a participant depends on the reachability of that problem through indirect connections with other participants. Attention clustering captures precisely the preferential tendency of participants to allocate their attention to more proximate problems—problems present in their neighborhood.

This argument provides an operational network-based definition of the concept of "local search" that is central in behavioral theories of organizations (Cyert and March 1963, Levinthal and March 1993, Knudsen and Levinthal 2007). In the context of our study, this prediction translates into a situation in which (pairs of) developers are more likely to extend prior collaborations to future bugs. In our context, once two developers allocate attention to the same bug, they develop a shared understanding of that problem and a common ground for allocating shared attention to further problems (Lin et al. 2014). In consequence, they tend to find new bugs attracting their shared attention, thereby extending their prior problem-solving collaboration to future problems (Feld 1981). Hypothesis 4—following a logic of problem proximity—summarizes our discussion.

Hypothesis 4 (Attention Clustering). *Organizational participants tend to form attention clusters by allocating their attention to future problems in the neighborhood of their current problems.*

Tables 1 and 2 summarize the substantive implications of our mechanisms in the modern organizational environment, providing contextual examples in contemporary business and society as well as underlying behavioral logic and resulting structural configurations. These examples suggest the possibility to generalize the interpretation of our mechanisms and hypotheses to multiple types of organizations beyond the specific empirical context. Table 3 instead summarizes from a formal perspective the four constructive mechanisms underlying our hypotheses. For each hypothesis, the table reports the antecedent configuration (at time t_1) in the left column, the change (next event) prediction consistent with each mechanism in the central column, and the resulting (predicted) final configuration (at time t_2) in the right column.

Table 1. Summary of Attention Network Mechanisms with Examples

Attention network micromechanism	Description	Behavioral logic	Contextual example	Structural outcome
Attention focusing	Acts of attention allocation are directed to problems that are familiar (i.e., addressed in the past by the focal participant).	Logic of familiarity: people manifest a preferential tendency to allocate their attention to problems that already captured their own attention because of the dynamics of habituation.	A software developer is more likely to focus on contributing repeatedly to solve a specific bug rather than spreading attention to different bugs.	Attention is repeatedly allocated to the same problems (attention stabilization).
Attention reinforcing	Acts of attention allocation are directed to problems that are popular (i.e., addressed by many others).	Logic of popularity: people manifest a preferential tendency to allocate their attention to problems that already captured the attention of other people because of a perception of increased interest, importance, and opportunities.	A software developer is more likely to attend to bugs that exhibit a wealth of prior activities by other developers rather than to less attended bugs.	Attention becomes progressively more concentrated on a limited number of problems (skew distribution of attention).
Attention mixing	Acts of attention allocation by participants who are highly active are progressively diverted away from popular problems.	Logic of devaluation: people's preferential tendency to allocate their attention to popular problems weakens as participants become more active because of a decreased interest for popular issues.	As a software developer becomes progressively more engaged in problem solving activities, the developer also becomes more likely to dedicate attention to bugs left unattended by the rest of the community.	Attention of active participants spreads over less popular problems, compensating, in part, for the tendency toward concentration of attention to already popular problems (disassortative allocation of attention).
Attention clustering	Acts of attention allocation are directed to problems that are situated in the neighborhood of already attended problems.	Logic of proximity: people manifest a preferential tendency to allocate their attention to proximate problems in their neighborhood because of a behavioral tendency toward local search.	A software developer tends to extend previous collaborations with other developers to future bugs.	Attention develops around a neighborhood of participants who collaborate by allocating their attention to the same sets of problems (stable communities of collaborating participants).

Table 2. Generalizability of Attention Network Mechanisms to Other Settings

Setting	Attention focusing	Attention reinforcing	Attention mixing	Attention clustering
Distributed software development (e.g., GitHub)	Software developers repeatedly focus their attention to specific projects rather than spreading it across many different projects.	Software developers contribute attention to projects that are well attended by other developers rather than to less popular projects.	When accumulating activity, software developers increasingly divert their attention away from popular to less popular projects.	Software developers extend previous collaborations by attending to the development of proximal projects in their attention network.
Crowdsourced innovation (e.g., idea generation platforms)	Platform participants concentrate their attention on contributing repeatedly to the same ideas.	Platform participants allocate attention to ideas that received a high volume of contributions from other participants.	When accumulating activity on the platform, participants diversify their scope, diverting their attention away from popular ideas.	Participants extend their collaboration with other participants by allocating attention to proximal ideas in their attention network.
Bossless organizations (e.g., holacracy)	Employees in self-managing teams focus their attention on repeatedly engaging the same type of tasks.	Employees allocate their attention to tasks that received a high volume of attention by peer employees.	When accumulating activity, employees divert their attention away from popular tasks to less popular ones.	Employees extend their collaboration across teams by engaging in proximal tasks in their attention networks.
Scientific research production	Researchers accumulate specialized knowledge by focusing their attention repeatedly on specific topics.	Researchers are attracted by topics that are well attended in their scientific community.	When accumulating activity, researchers broaden their expertise by engaging with topics that are less popular in the scientific community.	Researchers extend collaboration with other researchers to proximate topics in their attention network.

Materials and Methods

Empirical Setting

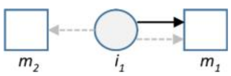
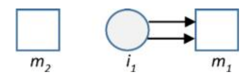
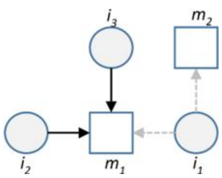
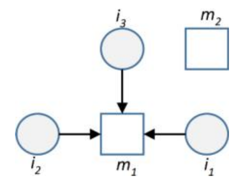
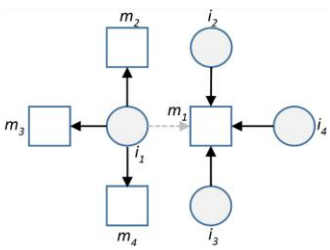
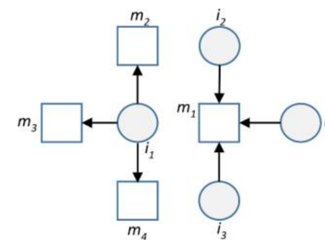
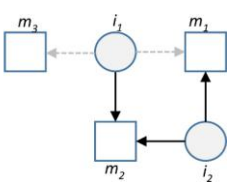
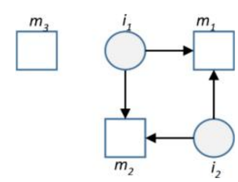
We study the dynamics of attention allocation in the Apache HTTP server, a large and successful free/open-source software (F/OSS) project. The term F/OSS typically refers to software products released under a license that allows inspection, use, modification, and redistribution of the original software source code (Crowston et al. 2012). Developing teams (Lee and Cole 2003, Crowston and Scozzi 2008) contribute private effort to the production of what is effectively a public good (Spaeth et al. 2008, von Krogh et al. 2012). Developers can be unpaid volunteers (Hars and Ou 2002, Lakhani and Wolf 2005) or paid by third parties (Henkel 2006, Stam 2009, Rolandsson et al. 2011). Their motivations vary widely and change over time (von Krogh et al. 2012), ranging from ideological belief (Haruvy et al. 2003, Stewart and Gosain 2006) to pure enjoyment-based, intrinsic motivation (Lakhani and Wolf 2005) and to labor market signaling (Bitzer et al. 2017). Coordination happens mostly—if not only—online (Raymond 1999, Crowston and Scozzi 2008), and the distribution of attention is typically affected by the modular nature of the software (Lerner and Tirole 2002, Baldwin and Clark 2006) with developers concentrating their attention and activities on specific modules better aligned with their interests and skills when not overviewing the overall code structure.

Open-source projects use instant messaging and mailing lists for technical discussions and support, code repositories for storing shared versions of the source code, and bug tracking systems for monitoring and tackling problems with the software (commonly referred to as software bugs). We consider the tackling of bugs—that is, the actions aimed at resolving software problems that cause computer programs to behave in unintended and undesirable ways—as one of the most important activities affecting the quality of the software development process (Zhang and Kim 2010).

We are interested in understanding the mechanisms regulating the allocation of attention to organizational problems, an essential precursor to problem solving. Bug fixing absorbs a considerable amount of participants' attention (Crowston and Scozzi 2008). Indeed, the collective attention allocated to software bugs represents an important quality and reliability signal of the project (Crowston et al. 2003). Given the absence of centralized control and direct access to bug reports, developers typically self-manage the allocation of attention. Bug repositories provide an occasion for coordinating the highly decentralized activities of developers and channeling collective attention.

Apache HTTP server is one of the most popular web server softwares, serving approximately 33% of all existing websites.[8] The development and maintenance of Apache HTTP server is overseen by a project management committee chaired by a vice president. Members of the committee are appointed among the developers who have acquired significant merit in the project with

Table 3. (Color online) Summary of Hypotheses

Time = t_1	Predictions	Time = t_2 (> t_1)
	Attention focusing (Hypothesis 1) Preferential tendency of a participant *(i1)* to allocate attention to a problem *(m1)* at time *t2* that has attracted attention at time *t1.*	
	Attention reinforcing (Hypothesis 2) Preferential tendency of a participant *(i1)* to allocate attention at time *t2* to problems *(m1)* that attracted a higher level of collective attention at time *t1.*	
	Attention mixing (Hypothesis 3) Preferential tendency of a participant *(i1)* that is very active at time *t1* against allocating attention to problems that are very popular *(m1)* at time *t2.*	
	Attention clustering (Hypothesis 4) Preferential tendency of a participant *(i1)* to allocate attention to a problem (*m1*) at time *t2*, if that problem is in its neighborhood—that is, it is reachable through a three-path *(i1– m2 – i2 – m1)* indirectly connecting *i1* to *m1.*	

Notes. Grey circles are participants (*i1*, *i2*). White squares are problems (*m1*, *m2*, *m3*, *m4*). Arrows represent the relation "allocate attention to." Dashed gray arrows denote potential opportunities of attention allocation. Solid black arrows denote observed attention allocation events. Therefore, potential opportunities can only be present at time *t1* (i.e., in the left column of the table).

their contributions. More generally, within Apache HTTP server—and all other projects overseen by the Apache Software Foundation (ASF)—the right of contributors to modify the software is assigned by the community of developers and earned by showing commitment and active engagement. The ASF clarifies that all developers contribute to the project in their personal capacity regardless of work affiliation (Apache Software Foundation 2022a,b). Newcomers looking for ways to contribute to a project are explicitly encouraged by the Apache Software Foundation (2022a) to tackle a problem reported in the bug repository that stimulates their own interest. Given the freedom that developers experience when contributing to solve tasks in a very modular structure, the extensive reliance on volunteer participants, and the complete transparency of their attentional processes, we think Apache represents a particularly apt environment for testing our hypotheses.

Data

We extracted the complete sequence of attention allocation events connecting project participants to software bugs stored in the official bug repository of the Apache HTTP server. Our sample includes all the bugs ever reported on releases 2.X of the software from the first bug report (March 2001) until the end of the observation period (March 2013). During the observation period, a total of 13,526 actions by 4,338 unique developers on 6,000 distinct bug reports were recorded. Information on each individual event is exact to the second. Thus, the data set we constructed contains information on real-time attention allocation events observed throughout the life history of the project.[9]

We adopt the definition of "developer" provided by ASF as individuals who "contribute to a project in the form of code or documentation. They take extra steps to participate in a project, are active on the developer mailing list, participate in discussions, provide patches, documentation, suggestions, and criticism" (Apache Software Foundation 2022b). In the rest of the paper, we use the generic term organizational "participants" to refer to developers and the term organizational "problems" to refer to software bugs. We collected the raw data by parsing the individual, publicly available web pages of all bug reports included in the repository with the web-crawler software Bicho (Robles et al. 2009). In detail, a participant encountering a problem when running or developing the software usually starts the bug reporting process and opens a bug report that is included as a new page in the bug repository. The repository provides the tracking infrastructure for describing, triaging, and resolving software bugs. A bug report is organized into a collection of predefined fields supplying information, such as the name of the module, operating system, and release number that the bug affects. Bug reports also make the history of past actions visible and accessible to all participants. Fields in a bug report are populated when the report is first generated and then updated by individual developers.

Dependent Variable

An attention allocation event linking participant i to problem m at time t is recorded whenever participant i modifies a field in (touches) the bug report associated with problem m. The set of all observed attention allocation events represent the organizational attention network. What makes the organizational attention network a "network" is the aggregate structure of dependences linking individual acts of attention allocation. Our analysis focuses on the modeling of the time to the next observed attention allocation event conditional on the sequence of past events. More precisely, the dependent variable is the instantaneous probability of observing an attention allocation event linking a participant to a problem conditional on (i) characteristics of the participant; (ii) characteristics of the problem, and (iii) the history of interaction between participants and problems within the project.

Independent Variables

It is possible to identify three broad sets of covariates included in our model. The first set includes covariates specifying the effect of direct theoretical interest that take the form of network statistics directly linked to our hypotheses. These covariates are defined exclusively in terms of sequences of attention allocation events linking participants and problems. Attention allocation sequences are inherently dynamic; thus, the covariates of theoretical interest vary over time. The second set includes control covariates that account for a variety of other factors that may affect the probability of observing attention allocation events. Control covariates may refer to characteristics of participants or problems and may be time constant or change over time in a way that does not depend on the history of attention allocation events. The third set of covariates includes interaction effects between control covariates and network effects.

Attention Allocation Mechanisms. We provide a verbal description of the statistics connected to the attentional mechanisms specified in the hypotheses. Then we describe the covariates included in the model to control for additional factors affecting the attention allocation events. Following the formal definition of attention network, in Appendix A we develop the mathematical notation necessary to provide the formal definition of all the effects included in our empirical model specifications, which we now describe informally.

We start by defining Cumulative attention as a default attention allocation mechanism that serves as the basis for identifying the more specific mechanisms linked to our hypotheses. *Cumulative attention* simply involves a positive feedback mechanism regulating individual patterns of attention allocation. This generic baseline mechanism frequently operates in systems of social interaction characterized by increasing inequality in activities, outcomes, and attainment (Merton 1973, Powell et al. 2005). *Cumulative attention* provides a useful baseline mechanism for modeling attention networks: it captures participants' average propensity to change their current level of attention to the project as a function of their history of participation (see Equation (A.1) in Appendix A). A positive effect of *Cumulative attention* provides evidence of self-reinforcing motivation to contribute attention: participants currently contributing a high level of attention to the project are more likely to contribute an even higher level of attention in the future.[10]

According to the *Attention focusing* hypothesis (Hypothesis 1), participants are more likely to allocate their attention to a problem if they have allocated their attention to the same problem in the past. A positive effect of *Attention focusing* indicates that the greater the number of attention allocation events connecting a participant to a specific problem, the higher the likelihood of observing additional events reinforcing this connection (see Equation (A.3)).

According to the *Attention reinforcing* hypothesis (Hypothesis 2), popular problems are more likely to attract further attention and, hence, become even more popular. To test this hypothesis, we define *Attention reinforcing* as a positive feedback effect driving the tendency of high levels of attention to generate further attention (see Equation (A.4)). A positive effect of *Attention reinforcing* indicates that higher levels of attention received by a problem in the past lead to a higher likelihood of receiving even more attention in the future—a sort of "popular for being popular" effect.

Attention mixing is defined as an interaction between cumulative attention and attention reinforcing (see Equation (A.5)). A negative effect of *Attention mixing* implies disassortativity, according to which active participants are less likely to allocate attention to more popular problems. At the project level, the consequence of disassortativity is to divert the attention of active participants away from popular problems to less popular ones. This is the specific prediction summarized in Hypothesis 3.

The fourth hypothesis involves *Attention clustering* (Hypothesis 4), a mechanism that stabilizes the association between participants and problems by "locking" the flow of attention within local clusters. We represent *Attention clustering* as the number of bipartite four-cycles (see Equation (A.6)). A positive effect of *Attention clustering* implies that participants tend to cluster their attention around shared problems over time. We call this effect attention clustering because bipartite systems cannot have closed cycles of odd length, such as, for example, the closed triangles that are commonly used to measure clustering tendencies in social networks (Newman and Park 2003).[11] As we explain, attention clustering captures the local character of search by predicting that participants are more likely to extend their attention to problems located in the neighborhood of problems that are currently attracting their attention.

Control Factors. The probability of observing an attention allocation event may be affected by a number of additional factors related to (i) characteristics of participants, (ii) characteristics of problems, (iii) organization structure, and (iv) interaction between these various factors and the observed sequences of attention allocation events. In our models, we include control variables at each of these levels. We define *Experienced participants* as an indicator variable taking value one for participants that were already active during previous release cycles of the project and zero otherwise. Other conditions being equal, a positive effect provides evidence that experienced participants are more likely to allocate their attention to problems. The variable *Institutional participants* is introduced to capture formal role differentiation. Participants are considered "institutional" if they use an email address ending with the official Apache domain (i.e., apache.org): in such cases, the *Institutional participant* indicator variable equals one; otherwise, it is zero. There were 86 institutional participants out of 6,193 participants present during the observation period. A positive effect associated with this indicator variable implies that institutional participants are more likely to allocate their attention to problems.

The community of participants structured around the project has several ways to channel attention on problems. Examples include the assignment of problem priority and severity levels. Participants willing to allocate their attention to a specific problem assign a priority level ranging from one (highest priority problems) to five (lowest priority problem) to it. Assigning a priority level is an attempt to communicate how urgently participants want to fix specific problems and, hence, to direct their attention to them. We use this information to construct an ordinal problem priority indicator that we use to control for the potential differential attractiveness of problems assigned to different levels of priority. A negative effect associated to *Problem priority* indicates that problems with high priority tend to attract additional attention (because problems with priority = 1 are high-priority problems). Participants also assign a severity level to each software bug on a seven-point scale ranging from "enhancement" (a request for new features) to "blocker," a bug that effectively prevents further development of the software. Assigning a severity level is an attempt to communicate how urgently bugs need to be fixed and, hence, to direct attention to crucial problems. For example, if a problem has blocker status, then it must absolutely be fixed before the next release or project milestone. We use this information to construct a *Problem severity* indicator variable taking the value one if the problem is classified as a blocker and zero otherwise. A positive estimate of the parameter associated with problem severity suggests that severe problems tend to receive additional attention.

Problem latency is the age of a problem measured in days, that is, the age of the problem computed for each active problem as the difference between the current time and the last time in which the problem was first reported or reopened (Cohen et al. 1972). *Problem latency* is defined formally in Appendix A (Equation (A.7)). *Problem resolved* takes the value one when a problem status is changed to "resolved" and zero otherwise. When this happens, the problem remains visible but is no longer "active." This time-varying indicator variable allows us to control for the decrease in attention over problems after they are resolved. A negative effect indicates that attention allocation events are less likely to be performed on problems that are collectively considered resolved. Note that our design admits that resolved problems may be reopened in the future. For example, a software bug considered resolved might reappear in a subsequent release of the software. For this reason, attention allocated to resolved problems is likely to decrease but does not necessarily or permanently drop to zero.

Problem recognition counts the number of comments associated with a problem. We include this variable to control for the differential propensity of problems to attract attention as a function of the discussion that problems generate. Many comments left by software users on a problem can signal that a problem is of general interest for the community at large. In turn, that could attract differential attention of the participants. *Problem recognition* is defined formally in Appendix A (Equation (A.8))

F/OSS projects vary greatly in the extent to which they contain formal elements of organizational structure related to modularity. The necessity to adopt a modular structure increases as a function of the size and complexity of a project. Apache HTTP server, for example, is sufficiently large to sustain a formalized modular organization of its code. Examples of such modules include the "core" code, software extensions, and the corresponding software documentation. The software code is devoted to the basic processing of HTTP requests and responses. Each of the modules extends this basic functionality with a specific feature. For example, the module "mod ssl" provides Apache HTTP server with cryptographic capabilities now almost universally used by web servers. Alongside the software code composing core and modules, the code repository of the project contains software documentation that developers write and maintain as the project evolves. A software bug can affect the software as a whole, that is, in multiple areas of the code base, across core and multiple modules. A software bug can affect only the core, one of the modules, or the documentation. Furthermore, a software bug may be reported as affecting the "build"—that is, the compilation of the source needed before execution—as well as the installation procedure of the software. To assess the extent to which the modular structure of the project affects our results, we assigned each software problem to one of five categories representing the different modules. This is the variable *Module*. The first category (omitted) includes all software bugs identified as affecting the software globally and serves as a baseline category. The second category includes all software bugs affecting the core module of Apache HTTP server. The third category includes all software bugs affecting build and installation of the software. The fourth category includes all software bugs affecting software documentation. The fifth category includes all software bugs affecting one of the other noncore modules of Apache HTTP server.

We incorporate information on the modular structure of the project by including *Preferential modularity* as a covariate controlling for the tendency of participants to work preferentially on problems within the same module. The interpretation of organizational structure provided by Cohen et al. (1972) is perfectly consistent with our quasi-experimental representation of *Preferential modularity* as an exogenous constraint on the access that solutions carried by participants have to problems that the project generates. A positive *Preferential modularity* effect indicates that attention allocation events are more likely to occur within the same module in which they occurred in the past. In other words, a positive estimate provides evidence that participants tend to allocate their attention within individual modules. *Preferential modularity* is defined formally in Appendix A (Equation (A.9)). Participant- and problem-specific covariates may affect the probability of observing attention allocation events both directly and indirectly through their interaction with the attention network. For this reason, in the empirical analysis we report in the next section, we control for interaction effects that may reveal specific ways in which attributes of problems and participants interact with one another and with problem solving sequences. We define *Attention clustering within modules* as an interaction effect between *Module* and *Attention clustering* because we want to investigate how formal organizational structure affects attention clustering between participants. A negative estimate of the coefficient associated with *Attention clustering within modules* reveals a tendency of participants to cluster their attention on problems across modules. *Attention clustering within modules* is defined formally in Appendix A (Equation (A.10)).

Finally, *Time inactive* records for each participant i the time difference between the current time and the last time i was active in addressing any problem. We include *Time inactive* to control for participants who are formally in the risk set but do not actively contribute to the collective problem-solving process. *Time inactive* implies that participants with long inactivity time hardly influence the estimation of other model effects. *Time inactive* is formally defined in Equation (A.11).

Table 4 summarizes the control factors included in the empirical model specifications, the class of objects to which factors pertain, the reason for inclusion, and the units of measurement. Mathematical definitions are reported in Appendix A.

Relational Event Models

The relational event model that we implement in the empirical part of the paper exploits the full information contained in the sequence of time-stamped attention allocation events and in their exact time ordering (Butts 2008, Perry and Wolfe 2013). The specific relational event model we adopt is described in detail and tested extensively in Lerner and Lomi (2020a). A more general introduction to relational event models may be found in Butts et al. 2023).

The generating mechanisms represented in the model are defined in terms of event sequences that preserve the temporal information of individual problem-solving attempts. We use a Cox proportional intensity model incorporating both static and history-dependent covariates (Andersen and Gill 1982). We adopt well-established partial likelihood inference procedures to estimate the parameters of interest (Perry and Wolfe 2013). Appendix B provides additional background and information on the specification, estimation, interpretation, and evaluation of the relational event models. The model is estimated using the eventnet software (https://github.com/juergenlerner/eventnet) and the R package "survival" version 3.4-0 (Therneau 2022).

The complete information contained in the history of the attention network during the observation period was used to construct the vector of time-varying statistics, the "effects" described in the prior section. More specifically, a risk set including all participants and all problems recorded in our data set is built and used to draw a sample of nonrealized events needed for estimation (see Appendix B for details). When determining the event sequence used to construct our statistics, we note that some problems enter the risk set as they are reported, but no action is ever taken to solve them. Furthermore, to

Table 4. Variables, Units, and Measures

Effect	Variable type	Unit of measurement	Measure	Included in the model to capture
Institutional participant	Binary	Dimensionless	Indicator variable = 1 if participant's email address ends in "apache.org" and = 0 otherwise	Preferential tendency of institutional participants to become involved in problem solving activities
Experienced participant	Binary	Dimensionless	Indicator variable = 1 if participant was active in prior release cycles and = 0 otherwise	Preferential tendency of experienced participants to become involved in problem solving activities
Problem priority	Ordinal	Dimensionless	Priority level assigned to the problem (five priority levels, 1 = highest priority)	Differential tendency of problems to attract attention as a function of their assigned level of priority
Problem severity	Binary	Dimensionless	Indicator variable = 1 if problem is classified as severe in the bug report and = 0 otherwise	Differential tendency of problems to attract attention as a function of their assigned level of severity
Problem latency	Numerical	Units (days)	Problem age	Differential tendency of problems to attract attention as a function of their age
Problem resolved	Binary	Dimensionless	Indicator variable = 1 if problem is resolved and = 0 otherwise	Differential tendency of problems declared resolved to attract further attention
Problem recognition	Numerical	Units (messages)	Number of comments generated by a problem	Differential tendency of problems to attract attention as a function of the comments they have generated
Time inactive	Numerical	Units (days)	Number of days elapsed since last contribution	Time of inactivity of participants
Cumulative attention	Numerical	Units (events)	Overall number of events connecting participants to problems observed within the observation period	Overall volume of problem solving activity within the project
Module indicators	Binary	Dimensionless	Indicator variable = 1 for problems belonging to one of the five main modules of the project	Tendency of formal organizational structure to channel attention of participants toward specific classes of problems

be defined, the *Time inactive* control factor requires a second action to be taken by a participant at any point during the observation period. Thus, the event sequence used for estimation consists of 11,599 attention allocation events by 1,890 participants on 5,543 problems. The effects we estimate specify how the next attention allocation event (the dependent variable of the model) depends on specific configurations of time-structured sequences of past events. Parameter estimates tell the direction, magnitude, and significance of the theory-based mechanisms and the effect of the control factors.

Results

Analysis

The results of the analysis are reported in Table 5. Model 0 (null model M0) is the benchmark model defined only in terms of cumulative activity for each individual participant. According to model 0, the next attention allocation event depends only on the history of past events. As a null model, model 0 is considerably more challenging for alternative models than a model with no parameters. Model 1 (attribute control model M1) is the baseline model controlling only for attributes of the problems and the participants. According to M1, individual attention allocation events are independent and affected only by attributes of the participants and the problems but do not depend in any specific way from prior events. Model 2 (attention network model M2) introduces the effects of theoretical interest and is the focus of our discussion. Model 3 (organization structure model M3) examines the robustness of the estimates of theoretical interest when we consider elements of formal organizational structure present in the project. Heuristically, the goodness-of-fit diagnostics reported at the bottom of the table indicate that the models estimated are significant and the full model (model 3) improves significantly on the null model (model 0) and on intermediate models after accounting for differences in degrees of freedom.

The effects of control factors included in model 1 are numerically stable across specifications and are generally consistent with our expectations. We discuss them briefly. *Institutional participants* and *Experienced participants* are

Table 5. Cox Regression Model: Partial Likelihood Estimates of Bipartite Relational Event Models (Standardized Estimates)

	Null (M0)	Control (M1)	REM (M2)	Org structure (M3)
Cumulative attention	2.5376 (0.0233)***	0.8813 (0.0144)***	0.7808 (0.0143)***	0.7848 (0.0143)***
Experienced participant		0.9060 (0.0476)***	0.9767 (0.0557) ***	1.0444 (0.0568)***
Institutional participant		1.0971 (0.0361)***	0.9537 (0.0392)***	0.9736 (0.0395)***
Problem priority		−0.0334 (0.0256)	−0.0175 (0.0275)	−0.0341 (0.0279)
Problem severity		0.1409 (0.0323)***	0.1519 (0.0347)***	0.1531 (0.0356)***
Problem latency		−0.0019 (0.0000)***	−0.0017 (0.0001)***	−0.0017 (0.0001)***
Problem resolved		−1.4596 (0.0356)***	−1.7946 (0.0418)***	−1.7897 (0.0420)***
Problem recognition		0.5253 (0.0108)***	0.3430 (0.0143)***	0.3440 (0.0145)***
Time inactive		−0.0163 (0.0003)***	−0.0135 (0.0003)***	−0.0135 (0.0003)***
Attention focusing (Hypothesis 1)			0.2150 (0.0066)***	0.2029 (0.0065)***
Attention reinforcing (Hypothesis 2)			0.1354 (0.0116)***	0.1320 (0.0117)***
Attention mixing (Hypothesis 3)			−0.0320 (0.0028)***	−0.0308 (0.0027)***
Attention clustering (Hypothesis 4)			0.0349 (0.0039)***	0.0452 (0.0070)***
Module 1				−0.1276 (0.0634)*
Module 2				−0.2006 (0.0660)**
Module 3				0.1717 (0.0732)*
Module 4				−0.5103 (0.0557)***
Preferential modularity				0.4094 (0.0243)***
Attention clustering w/in modules				−0.0128 (0.0069)
Log-likelihood	−33,021.85	−12,844.57	−11,434.08	−11,266.95
Akaike information criterion	66,045.7081	25,707.1446	22,898.1567	22,575.9039
LR test	—	40,355	43,176	43,510
Number of events	11,599	11,599	11,599	11,599
Number of observations	1,170,871	1,170,871	1,170,871	1,170,871

Note. *Three-path* effects estimates not reported in table.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

significantly more likely to engage in attention allocation activities. For example, experienced participants are more than 148% more likely than nonexperienced participants to allocate attention to problems within the project ($\exp(0.91) = 2.484$). However, after one month of inactivity, the probability than an inactive participant (*Time inactive*) contributes again drops by approximately 39% (because $\exp(-0.0163 \times 30) = 0.61$).

Problems labeled "high priority" (*Problem priority*) do not have a significantly higher chance of attracting attention from participants. Severe problems (*Problem severity*) are approximately 15% more likely to attract attention. The longer a problem remains in the system (*Problem latency*), the less likely it is to attract attention. Problems resolved are predictably less likely to attract further attention. Because resolved problems may be eventually reopened, however, the odds of attracting further attention decline by almost 80% (because $\exp(-1.4596) = 0.23$) but do not drop to zero immediately—a result echoing a garbage can view of organizational problems as recursive (Cohen et al. 1972) and never quite resolved once and for all (Fioretti and Lomi 2010). Finally, a long list of comments attached to a bug report may be interpreted as a signal that a bug is being recognized by the community as particularly interesting, complex, or worthy of discussion (Hooimeijer and Weimer 2007, Arya et al. 2019). The positive and significant effect of *Problem recognition* confirms this expectation: an increase in one standard deviation in the number of comments increases the hazard of generating additional attention by 41% (because $\exp(0.3430) = 1.41$).

We now focus on model 2 in Table 5, which incorporates the effects of theoretical interest. As an aid to interpretation, we note that significantly positive (negative) effects increase (decrease) the rate of events connecting participants to problems according to the mechanism generating the event sequence associated with the effect.[12]

Attention Focusing (Hypothesis 1). We hypothesize that participants working on specific problems are more likely to focus their attention on those problems in the future. We argue that this form of inertia in the attachment of participants to problems is important because it induces specialization and because it stabilizes patterns of organizational attention. Because *Attention focusing* also sustains faster learning, attention focusing helps participants to develop skills that are, at least in part, problem-specific. Estimates support the focusing hypothesis: an increase by one standard deviation in the level of attention that a participant allocates to one specific problem prior to the current decision point increases the odds that the participant decides to pay attention to the same problem again by 24% ($\exp(0.2150) = 1.240$).

Attention Reinforcing (Hypothesis 2). Hypothesis 2 summarizes our prediction that popular problems—problems attracting the attention of many participants—are more likely to attract additional attention in the future. As we discuss, *Attention reinforcing* may be due to uncertainty about the quality of a problem, such as, for example, its level of difficulty, or it may be the consequence of participants' attempts to gain access to a broader pool of knowledge by joining conversations attended by many other participants. We find strong support for the *Attention reinforcing* hypothesis: an increase by one standard deviation in the level of attention that a problem receives within the community increases the odds that the same problem attracts further attention by approximately 15% (because $\exp(0.1354) = 1.145$).

Attention Mixing (Hypothesis 3). The results support our hypothesis for *Attention mixing*: the negative and significant coefficient shows that the attention that active participants allocate to popular problem is reduced, indicating a tendency toward disassortativity. A participant that is by one standard deviation more active than the average participant experiences a decrease in the attention reinforcing effect by approximately 3% ($\exp(-0.0320) = 0.97$). That is, for such a participant, a problem that has received one standard deviation more attention in the past has the odds of receiving attention by that participant increased only by approximately $15\% - 3\% = 12\%$. A participant that is more active than average by approximately 42 events exhibits no preferential tendency to allocate attention to more popular problems ($\exp(-0.0320 \times 6) = 0.83$, offsetting the 15% increase in the attention that a more popular problem receives from a participant with average activity). Other conditions equal, this result shows that very active participants exhibit a preferential tendency against popular problems. Figure 1 provides a graphic examination of this mitigation effect by showing to what extent the marginal effect of *Attention reinforcing* decreases the more *Cumulative attention* increases.

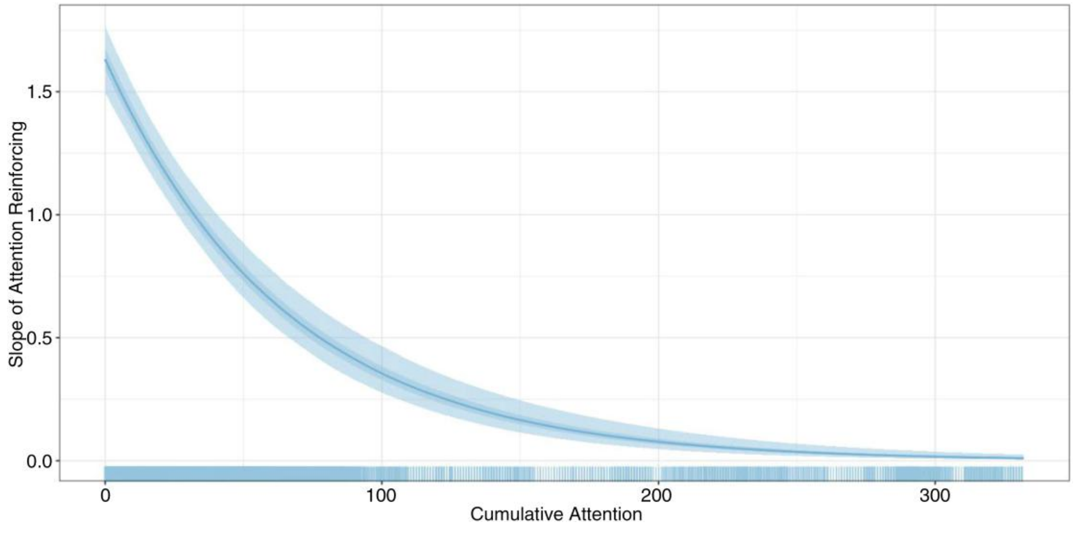
Attention Clustering (Hypothesis 4). We hypothesize that participants are more likely to allocate attention to problems in the neighborhood of their current problems. *Attention clustering* captures the tendency of participants to extend their current collaborative experience to future problems located in their neighborhood. Results provide solid support for the *Attention clustering* hypothesis (Hypothesis 4). An increase by one standard deviation in the number of three-paths indirectly connecting a participant to a problem increases by slightly less than 4% the odds that this participant addresses this problem directly in the future ($\exp(0.0349 = 1.355)$. This effect may seem small, but considering that a participant–problem pair can be indirectly connected by a high number of three-paths, even one extra event closing a three-path can have a large impact on the number of four-cycles, or attention clusters, that are generated.

Table 6 summarizes the qualitative implications of our findings. Hazard ratios in Table 6 are calculated based on the estimates of model 2 in Table 5 under ceteris paribus assumptions. Consequently, the figures discussed in the text and summarized in the table are provided as an aid to a heuristic interpretation of the estimated parameters in the light of our hypotheses.

Supplementary Sources of Structuring in Organizational Attention Networks

Attention focusing, reinforcing, mixing, and clustering may be viewed as intended consequences of attention

Figure 1. (Color online) Johnson–Neyman Plot (with 95% Confidence Interval) of Hypothesis 3 *Attention Mixing* Interaction Term



Notes. The plot shows how the marginal effect (i.e., the slope) of *Attention reinforcing* decreases as the *Cumulative attention* of participants increases. The marginal effect is calculated on the hazard ratio; therefore, values above one on the y-axis denote a positive effect of *Attention reinforcing* (on the probability of an attention allocation event) and values below one a negative effect.

Table 6. Qualitative Implications of Estimates for Parameters of Theoretical Interest

Hypotheses	Hazard ratio (M2, Table 5)	Heuristic interpretation
(Hypothesis 1) Attention focusing	exp(0.2150) = 1.240	One standard deviation increase in the level of attention that a participant has allocated to one specific problem in the past is associated to a 24% increase in the odds that the participant will pay attention to the same problem again in the future (please refer to main text for additional explanation).
(Hypothesis 2) Attention reinforcing	exp(0.1354) = 1.145	One standard deviation increase in the level of attention that a problem has received within the community in the past is associated to a 15% increase in the odds that the same problem will attract further attention in the future (please refer to main text for additional explanation).
(Hypothesis 3) Attention mixing	exp(−0.0320) = 0.969	One standard deviation increase in the level of individual problem-solving activity (approximately seven events) is associated with a reduction in the strength of the attention reinforcing effect by approximately 3% (please refer to main text for additional explanation).
(Hypothesis 4) Attention clustering	exp(0.0349) = 1.036	One standard deviation increase (approximately ten events) in the number of (open) three-paths indirectly connecting a participant to a problem will be associated with an increase of slightly less than 4% in the odds that this participant will pay direct attention to this problem in the future, hence closing the (open) three-path to form a four-cycle (please refer to main text for additional explanation).

structures shaped, at least in part, by formal organization design (Ocasio and Joseph 2005). We entertain this possibility in a supplementary analysis that accounts for the formal elements inherent in the organizational structure of the project. Doing so allows us to assess the role of formal structure in matching interests and skills of participants to characteristics of problems as an alternative explanation for the allocation of attention and, hence, for the self-organizing nature of attention networks. Such structure in open-source software projects takes the form of modularity (Baldwin and Clark 2006).

Modularity allows different functional areas to be developed almost independently, thus accelerating the evolution of the global software system. In more general terms, modularity exemplifies a case of "specialized access—or an attempt to force solutions to specialize in the kinds of problems that can be associated to them" (Cohen et al. 1972, p. 6). In open-source software projects, the primary function of modularity is to help participants search efficiently for opportunities to contribute aligned with their interests and skills (MacCormack et al. 2006). For this reason, modularization is a common organizing principle in open-source software projects (von Krogh et al. 2003), but it is particularly salient in Apache HTTP server, which is one of the largest open-source softwares in existence. Because of its size and complexity, the overall project is parsed into modules that reflect major functional areas of the software.

Model M3 in Table 5 incorporates the effects of modularity. The modularity effects should be interpreted with respect to the omitted baseline category (software bugs affecting the software as a whole). The effect of *Preferential modularity* (ratio of the participant's past contributions that are allocated to problems in the same module as the focal problem) reveals a strong tendency of participants to concentrate their attention on problems within software modules. According to the estimates of model 3, participants are approximately 51% more likely to allocate attention to problems within the same module (exp (0.4094) = 1.51). Interpreted in tandem with the effect of *Attention focusing*, the effect of *Preferential modularity* implies a tendency toward specialization within modules in accordance with the general expectation that participants tend to allocate attention to problems that belong to their area of expertise.

Accounting for elements of formal structure organizing problems by skills and interests of participants does not affect the significance, strength, or direction of the mechanisms underlying our hypotheses. Therefore, our results seem to be extendable to contexts in which the rules of the game (Ocasio 1997) allow for some degree of specialized access to problems, at least in its "upper limits" of who may attend to what (March and Olsen 1976, p. 40), instead of the more general unsegmented access typical of organized anarchies (Cohen et al. 1972, Ocasio 2012). Attention focusing, reinforcing, mixing, and clustering continue to operate once the effect of organizational structure on the allocation of attention is accounted for. Thus, empirical evidence is stacked against the intuitive explanation emphasizing individual interests and personal skills as the main drivers of attention. What our results reveal is that individual interests and skills as reflected in the modular structure of the project do not explain away how software developers allocate their attention to software problems. This conclusion is strengthened further by the effect of *Attention clustering within modules* that we include to account for the tendency of participants with similar interest and skills to be attracted by the same problems within the same module. The effect is far from statistical significance—a noteworthy outcome given the sample size. This means that patterns of extended collaboration captured by *Attention* *clustering* cannot be simply explained away by similarity of individual interests among participants.

Additional Robustness Checks. We consolidate further the validity of our results by performing a series of additional robustness checks representing situations in which the allocation of attention is potentially driven by alternative (self-)organizing logic. Specifically, we tested whether the self-organizing patterns of attention structures are sensitive to different levels of intensity (or effort) in attention allocation. Furthermore, we checked if our results are affected by different empirical interpretations of the theoretical assumption of "attention scarcity" postulated in classic behavioral (Simon 1947), attentional (Ocasio 2012), and garbage can theories (Cohen et al. 1972). We checked whether the attention network mechanisms operate differently in presence of higher problem crowding, which denotes higher scarcity of collective attention (Piezunka and Dahlander 2015). Finally, we checked the sensitivity of our results to some alternative definitions of our sampling strategy by excluding (i) problems that are reopened once solved and (ii) events produced by extremely active participants. In all cases, the main substantive patterns of our results remain unaffected by alternative model specifications. Further details about the specific tests and respective tables of additional results can be consulted in Appendix C.

Discussion

Through the lens of attention networks, the space of possibilities for the allocation of attention in organizations appears as potentially very large but almost completely empty. The attention allocation events that are actually observed cover only a small subspace in the much larger space of possible events that could have happened, but did not. The subspace of observed events is small and is highly structured by the attention allocation mechanisms that we have postulated. This general conclusion resonates clearly with classic behavioral theories of organization (Simon 1947, Cyert and March 1963, Levinthal and March 1993, Ocasio 2011) and also bears important implications for contemporary theories of organizational attention and for future research on the allocation of attention within organizations. We conclude with a discussion of the theoretical contributions of the study, its practical implications, limitations, and directions for future research.

Contributions to Theory and Research

We need theories of organizations that bring renewed focus to the investigation of contemporary organizational environments in which individuals have increasing independence in choosing the tasks and issues to which they contribute and in which their activities are often publicly visible to other organizational members (e.g., Puranam et al. 2014, Alexy et al. 2021). In these contexts, problem-solving activities take place under conditions of high decentralization of authority, fluid participation, and variable attention lent by volunteer participants. Under conditions in which managerial hierarchies and organizational systems of task allocation and control are weak or absent, visible acts of attention allocation become a fundamental stabilization mechanism by which participants provide information to each other about how to coordinate their efforts. Considering attention as a resource that connects participants and problems in a relation of mutual constitution brings to the fore the issue of its role in enabling coordination in self-organizing contexts (Hansen and Haas 2001, Hoffman and Ocasio 2001).

In this paper, we address these core theoretical concerns by reframing socially transparent acts of attention allocation as a microstructural coordination mechanism allowing organizational participants to provide information to each other about organizing work around available problems. This study contributes to the scholarly debate on the microfoundations of organization design, that is, "the micro-level processes, behaviors, and interactions that aggregate to yield the organization's overall structure" (Raveendran et al. 2020, p. 829; for further discussion of the microfoundations of social networks, see Tasselli et al. 2015). These microfoundational interactions between participants and problems are not based on exogenous task allocation decisions or predetermined workflows that participants know ex ante. Instead, they emerge from participants' efforts to coordinate work as they face ambiguous task demands and fluid organizational boundaries and observe how their peers operate. In this sense, our analytical framework is consistent with a view of boundedly rational participants who learn about their interests and uncertain future preferences by interacting with actual problems attracting their attention (March and Olsen 1976) in a context in which "contributors do not know if their efforts will result in a suitable working product" (von Krogh et al. 2003, p. 1219). By investigating the emergence of attention networks as the by-product of interdependent acts of attention allocation, our work responds to recent calls for a better "understanding [of] the involvement of agents in the design process … in scenarios in which the tasks are not clear-cut" (Raveendran et al. 2020, p. 829) and resonates with the idea that "interdependence is endogenous to the organization design process … because it arises during agent interactions" (Raveendran et al. 2020, p. 831).

It's worth noting that our study hinges on the assumption that organizational participants have access to transparent information about how others allocate their attention. Observability underlies the formation of socially endogenous inferences (Zuckerman 2012) upon which we base our theorizing and facilitates the emergence of stigmergic coordination—that is, "implicit coordination mediated by changes to a shared work product" (Rezgui and Crowston 2018, p. 1; Moffett et al. 2021). This feature of our study reveals an important implication for the debate on the microstructural approach to organization design insofar as "we would expect the process of search for new forms of organizing to stabilize around clusters of complementary solutions" (Puranam 2018, p. 155). In particular, we show that the transparency of attention constitutes a valuable complementary solution to task allocation via self-selection because it provides the necessary informational cues for participants to coordinate their effort and, thus, for attention networks to self-organize and dynamically emerge in organizations.

We introduce the notion of attention networks to emphasize the self-organizing character of organizational problem solving. Our emphasis, specifically, is not on the static characterization of this network, but on the interdependent mechanisms of its transformation and emergence (Gibson 2012, Padgett and Powell 2012). The operational concept of attention networks that results from our set of hypotheses provides an illustration of how contemporary organizations are to some extent defined and transformed by the very activities that their members perform, resonating with the idea of "autocatalysis" (Padgett et al. 2003, Padgett and Powell 2012, Padgett 2018). Every visible act of attention allocation involves the creation of new connections between participants and problems and, hence, implies change in the organizational structure via change in the activities and issues on which organizational participants choose to focus. Hence, "structure" and "change" are constructs that can only be understood in reference to one another: they represent a duality that entails the concept of organizing itself. If traditional firms and societies are described as "centralized, bureaucratic, and inflexible" (Thompson 1967, p. 108), self-organizing contexts allow individuals to broaden their "range of aspirations" (p. 114) by giving the freedom to allocate time and effort to issues that are prioritized by the individuals themselves. Our set of connected hypotheses shows that the mechanisms linking people to problems and tasks follow a structural logic that, accumulating over time, contributes to shape organizational problem solving.

Interestingly, as shown in the models that we specify and estimate, the microstructural mechanisms associated with each individual hypothesis concatenate to generate the dynamic attention network that we actually observe. Not only, as predicted and tested by structuralist sociologists (e.g., Blau 1960, Freeman 1978), do social interactions between individuals follow network patterning—being subjected to structural properties and regularities—but as we discover, also the very relations connecting organizational participants and the tasks they perform are exposed to structural mechanisms that can be interpreted and measured from a network perspective. We show that this result is unaffected by observable individual characteristics of the participants (e.g., their experience and institutional affiliation), intrinsic features of the problems (e.g., their level of difficulty), and the effect of formal (exogenous) organizational structures that regulate the matching between individual skills and problem characteristics (i.e., the project modules).

Implications for Practice

Our study bears implications for managers and practitioners interested in the design of self-organizing and distributed productions. Far from being confined to the world of open-source software projects, self-organizing is becoming increasingly popular also in the context of traditional corporate organizations, in which the pressure to give employees and managers freedom in self-selecting into tasks is often associated with the aim to stimulate collective creativity and empower idea generation (e.g., Cross et al. 2021; see also Table 2 for concrete examples on the generalizability of our hypotheses). However, attempts to give personnel more independence often find internal resistance from decision makers who are afraid of losing control over their workforce's activities. How can organizations and managers find the right balance between giving freedom to organizational members to self-allocate time and attention to problems and still managing to keep control over decision making and problem solving? As shown by our results, this tension is at least partly misplaced. Attention tends to self-organize following structural patterns, thus finding, in serendipitous ways, its own order. More specifically, our mechanism of attention mixing seems particularly important as it mitigates the effect of attention reinforcing by distributing the attention of active participants over a broader set of problems. Concretely, this mechanism helps the sustainability of crowdsourced production systems, which are characterized by the presence of a large number of diverse issues that may easily escape attention, whereas a limited number of popular issues tend to attract a disproportionate share of collective attention (Huberman et al. 2009). In these settings, survival depends crucially on the willingness of a community of volunteers to allocate attention to "mundane but necessary tasks" (Lakhani and von Hippel 2003, p. 923). Yet these tasks are essential to the survival of the project although they are neither popular nor capable of motivating repeated engagement (Shah 2006). Moreover, the disassortative patterns of attention mixing distribute collective attention over a larger set of problems, tackling well-known problems of under- or over-provision of effort for certain tasks, an outcome that students of organizations struggle to find a solution for despite very detailed and extensive research (Stewart 2005, Faraj and Johnson 2011, von Krogh et al. 2012, Puranam 2018).

Limitations and Conclusions

This study has several limitations, and two deserve special attention as they invite future research along clear new directions. The first limitation relates to the empirical scope of the study, which assumes that acts of attention allocation are transparent to other peer participants. This scope condition applies to most arguments based on social transparency (Stuart et al. 2012) and ambient awareness (Leonardi 2015) or free access to information on the behavior, opinion, orientation, or evaluation that might reveal the preferences of others. The scope of our study is, thus, relevant to a wide range of contexts designed precisely to support information sharing through social media functionalities. Examples of self-organizing forms that rely on transparency as a condition for information provision (Puranam et al. 2014) include external (Piezunka and Dahlander 2015) and internal (Deichmann et al. 2021) crowdsourcing platforms for idea development; enterprise-based systems of collaboration, such as internal communities of practice (Haas et al. 2015), platform-based systems of decentralized problem solving such as open-source software (von Krogh and von Hippel 2006) and distributed innovation (Kogut and Metiu 2001). Clearly, the plausibility of the assumptions underlying our hypotheses decreases as the opacity of information about what others do increases. However, the confidence in the generalizability of our hypotheses derives not only from the growing diffusion of new forms of organizing, but also by the general tendency to make traditional organizations increasingly more open and transparent. These tendencies are diffusing from emergent online communities to established corporate entities (e.g., Dahlander and Magnusson 2005, Fosfuri et al. 2008), including the cases of the Zappos holacracy (Robertson 2015), examples of agile organizational networks (Tasselli and Caimo 2019), or the cases of Valve and Morningstar documented by Lee and Edmondson (2017). Our arguments extend to a wide set of contexts in which participants decide to allocate attention to "many problems seeking solutions" (Haas et al. 2015, p. 681) and in which peer participants can observe their actions and decisions.

A second limitation is inherent in the almost exclusive focus on individual acts of attention allocation, which preclude analysis of possible outcomes of such acts. Whenever participants allocate attention on a bug report, their act contributes an event edge in our attention network. The dynamics of these events are the focus of our analytical interest in this paper. This observation scheme is not inspired by a focus on the real effectiveness of the collective resolution of problems, on how long problems remained unresolved within the project, or on how durable (or stable) were the solutions that contributors implemented (Fioretti and Lomi 2008). Addressing these issues requires a different research design, one oriented toward the consequences of problem-solving behavior rather than on attention as one of its main antecedents. The study says little about attentional selection or the consequences of attention allocation decisions (Ocasio 2011). We hope our study invites further research on issues of problem solving effectiveness that could not be pursued in the context of this study.

Despite its limitations, we believe that our study contributes valuable new elements to the understanding of the self-organizing mechanisms underlying attention allocation in organizations. The world of self-organizing is a world of variable attention, fluid participation, and evolving problems with little, or no centralized control. The rapid diffusion of such new organizational forms forces us to broaden our view of what "organizing" means and our understanding of the conditions under which organizations can exist and operate effectively. Contemporary open-source software projects are probably the organizational archetype of self-organizing contexts that capture the properties of the ideal formulation of "organized anarchy" prophesized by Cohen et al. (1972) more than half a century ago. We present an empirical example of how coordination of efforts may emerge and self-organize out of time-ordered sequences of individual acts of attention allocation connecting organizational participants (software contributors) to organizational problems (software bugs). In the case we present here, the linkages between participants and problems are "less consequential than temporal" because "attention to problems seems to be determined as much by the time of their arrival as by assessment of their importance" (March and Olsen 1984, p. 743). In closing, we note that the theoretical vision that inspires the current study was articulated decades before innovation in information technology made open-source software projects possible or even only conceivable. In this sense, the current study celebrates the success of organization theories and theorists whose insight, vision, and imagination time proved prescient.

Acknowledgments

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Appendix A. Notation and Definitions

Appendix A establishes the basic notation needed for describing with accuracy the effects of theoretical interests and the control factors included in the empirical model specification and discussed in the paper.

A.1. Organizational Attention Networks

Consider an organization as a set of problems $M = \{m_1, m_2, \ldots, m_k\}$ and a set of participants $I = \{i_1, i_2, \ldots, i_l\}$. The models estimated in the paper interpret an individual act of attention allocation as a relational event $e = (t_e, i_e, m_e)$ connecting participant i_e to problem m_e at time t_e. An attention network is the set of all relational events $E = \{e_1, e_2, \ldots, e_n\}$ connecting individuals to problems at the given event times. Membership in the sets M and I is updated at every event time t_e, which in the data we collect is precise to the second.

An attention network is empty (denoted E_0) if no organizational participant ever pays attention to any organizational problem. The attention network is complete (denoted as $E_{m,l}$) if every participant pays attention to every organizational problem at every given time. As Cohen et al. (1972) note, the allocation of attention in organizations typically generates relational patterns that fall within these two extreme cases: some organizational participants attend to some organizational problem some of the times.

A.2. Baseline Attention Allocation Mechanisms

As explained in the main text, *Cumulative attention* provides the basic attention allocation mechanism that we use as a baseline. *Cumulative attention* of participant $i \in I$ is defined as

$$\text{Cumulative attention}(t, i) = \sum_{m \in M} \sum_{e=1}^{N_{im}(t^-)} w(t, T^e_{im}), \tag{A.1}$$

where T^e_{im} is the time stamp associated with event e connecting participant i to problem m. The count $N_{im}(t^-)$ is the number of past events from participant i to problem m that happen strictly before t. The function $w(t, T^e_{im})$ assigns a temporal weight to events so that every event observed has an immediate effect when it is recorded and then a delayed effect on subsequent events that decays over time. The precise definition of the temporal weight for the event e is given by

$$w(t, t_e) = \exp\left(-(t - t_e) \cdot \frac{\ln(2)}{T_{1/2}}\right) \tag{A.2}$$

for a given half-life $T_{1/2} > 0$, where t_e is the time of the event included in the computation of the network statistics, and t is the current time, that is, the time in which the partial likelihood function is evaluated (see Appendix B). Following Brandes et al. (2009) and Lerner et al. (2013), Equation (A.2) assigns a weight that progressively decreases toward zero to events that happened in the more distant past. In this way, current attention allocation events have a continuously decreasing effect on future events. In our models, we set the half-life equal to 10 days.

A.3. Hypotheses

Attention focusing is the cumulative number of attention allocation events connecting participant i to problem j before time t—downweighted by the elapsed time—and is defined as

$$\text{Attention focusing}(t, i, j) = \sum_{e=1}^{N_{ij}(t^-)} w(t, T^e_{ij}), \tag{A.3}$$

where t^- indicates the complete history of the event network up to t and the time-weighting function $w(t, T^e_{ij})$ is defined in Equation (A.2).

Attention reinforcing is defined simply as the current number of attention allocation events performed on a problem downweighed by the elapsed time:

$$\text{Attention reinforcing}(t, j) = \sum_{g \in I} \sum_{e=1}^{N_{gj}(t^-)} w(t, T^e_{gj}), \tag{A.4}$$

where T^e_{gj} is the time stamp of attention allocation event e from participant g to problem j and the function $w(t, T^e_{gj})$ defined in Equation (A.2) assigns a temporal weight for the event e.

To examine mixing patterns (or assortativity), *Attention mixing* is simply the interaction of cumulative attention and attention reinforcing:

$$\text{Attention mixing}(t, i, j) = \sum_{m \in M} \sum_{e=1}^{N_{im}(t^-)} w(t, T^e_{im}) \cdot \sum_{g \in I} \sum_{e=1}^{N_{gj}(t^-)} w(t, T^e_{gj}). \tag{A.5}$$

In a bipartite data structure, such as the one we analyze, closure cannot involve an odd number of links. Therefore, *Attention clustering* takes the form of a bipartite four-cycle and can be formally defined as follows:

$$\text{Attention clustering}(t, i, j) = \sum_{m \neq j} I[N_{im(t^-)} > 0] \cdot \sum_{g \neq i} I[N_{gj(t^-)} > 0] \cdot I[N_{gm(t^-)} > 0], \tag{A.6}$$

where $I[x]$ is an indicator function that equals one if statement x is true and otherwise $I[x] = 0$. In Equation (A.6), g and m index participants and problems, respectively. *Attention clustering* gives the number of three-paths indirectly connecting the participant i of the focal dyad with its problem j via another participant g different from i and another problem m different from j; these three-paths are closed to four-cycles by an event on (i, j). This statistic is contingent on the number of three-paths attached to participant i and the number of three-paths attached to problem j, defined in Equations (A.7) and (A.8), respectively.

The number of three-paths attached to participant i of a given dyad (i, j) is defined as follows:

$$\text{3path.participant}(t, i, j) = \sum_{j'} \sum_{m \neq j'} I[N_{im(t^-)} > 0] \cdot \sum_{g \neq i} I[N_{gj'(t^-)} > 0] \cdot I[N_{gm(t^-)} > 0]. \tag{A.7}$$

In contrast to the four-cycle statistic, *3paths.participant* does not require that the three-paths starting at participant i end at problem j of the focal dyad, but instead allows that these three-paths can end at any problem j' that may but does not have to be different from j. The statistic *3paths.participant* is one of the two antecedents of the four-cycle statistic because it gives the three-paths that may be closed to a four-cycle in the next event initiated by i. The other antecedent of the four-cycle statistic is the number of three-paths attached to problem j of the given dyad (i, j) defined by

$$\text{3paths.problem}(t, i, j) = \sum_{i'} \sum_{m \neq j} I[N_{i'm(t^-)} > 0] \cdot \sum_{g \neq i'} I[N_{gj(t^-)} > 0] \cdot I[N_{gm(t^-)} > 0]. \tag{A.8}$$

Similar to *3paths.participant*, the statistic *3paths.problem* does not require that the three-paths ending at problem j start at participant i of the focal dyad, but instead allows that these three-paths can start at any participant i' that may but does not have to be different from i. The statistic *3paths.problem* is the second of the two antecedents of the four-cycle statistic because it gives the three-paths that may be closed to a four-cycle in the next event received by j.

A.4. Control Factors

Problem latency records the age of each problem and is defined as

$$\text{Problem latency}(t,j) = t - T_j^{\text{opened}}, \tag{A.9}$$

where T_j^{opened} is the time when problem j is first reported—or reopened if it had already been declared resolved in the past.

Problem recognition is defined as

$$\text{Problem recognition}(t,j) = \sum_{i=1}^{l} \sum_{e=1}^{C_{ij}(t^-)} w(t, T_{ij}^e), \tag{A.10}$$

where $C_{ij}(t^-)$ is the set of comment events from participant i to problem j before time t, T_{ij}^e is the time stamp of comment event e, and the time-weighting function $w(t, T_{ij}^e)$ is defined in Equation (A.2).

Preferential modularity is defined as

$$\text{Preferential modularity}(t,i,j) = \frac{\sum_m I[z(m) = z(j)] \cdot I[N_{im}(t^-) > 0]}{\sum_m I[N_{im}(t^-) > 0]}, \tag{A.11}$$

where $z(j)$ is the module index of problem j. The statistic is the proportion of problems in the same module as problem j out of all problems addressed by participant i.

Attention clustering within modules for participant i to problem j at time t is defined as follows:

$$\text{Attention clustering w.m.}(t,i,j) = \sum_{m \neq j} I[z(m) = z(j)] \cdot I[N_{im(t^-)} > 0] \cdot \sum_{g \neq i} I[N_{gj(t^-)} > 0] \cdot I[N_{gm(t^-)} > 0], \tag{A.12}$$

where the first indicator equals one if problems j and m are in the same module; otherwise, $I[z(m) = z(j)]$ is zero. The effect described in Equation (A.12) is used to examine the preferential tendency of attention to cluster within software modules, that is, to examine the extent to which formal organizational structure affects the joint allocation of attention to the same problems.

Finally, *Time inactive* records for each participant i the time difference between the current time and the last time i was active in addressing any problem. It is defined as

$$\text{Time inactive}(t,i) = t - T_i^{\text{last active}}(t), \tag{A.13}$$

where $T_i^{\text{last active}}(t)$ is the maximum time stamp, strictly before the current time t, when participant i addressed any problem; time inactive(t,i) is undefined for participants i that have never been active before t. Indeed, we define that participants enter the risk set right after their first event (first events of participant are not modeled). Once they have entered the risk set, participants never leave it again, but the time inactive provides an important control mechanism that lets the probability that participants initiate any further event tend to zero as their time inactive increases. Participants with long time inactive hardly influence the estimation of other model effects; they are almost out of the risk set. This is a more principled way to deal with participants who apparently have decided not to contribute again than defining an arbitrary crisp cutoff after which participants are removed from the risk set. Strictly speaking, even after a prolonged time of inactivity, participants could still decide to become active again even though it is increasingly unlikely.

Appendix B. Model Estimation, Interpretation, and Evaluation

B.1. Point Process Models for Bipartite Networks

The model we implement in the empirical part of the paper is based on a bipartite extension of the point process models for directed social interaction networks proposed by Perry and Wolfe (2013). Introduced by Butts (2008) as a strategy for the analysis of social networks, this class of models is also known as relational event models. The advantage of this approach over more conventional models for networks is its ability to analyze sequences of relational events directly rather than as aggregate network ties. Our data require that the model be adapted to two-mode networks—networks containing two classes of nodes with relations defined only between nodes in different classes (Everett and Borgatti 2013). The counting process framework developed in the analysis of repeated events within event history analysis provides the statistical foundation for the models that we develop (Aalen et al. 2008).

Modeling the evolutionary dynamics of an attention network connecting participants to problems starts by defining a counting process $N_{ij}(t)$ on the dyad linking participant i and problem j. The counting process $N_{ij}(t)$ increases (or "jumps") by one unit whenever participant i allocates attention to problem j at time t. When we have l participants and k problems, the total number of counting processes is $l \times k$. Following Perry and Wolfe (2013), each process is modeled by a conditional intensity function $\lambda_{ij}(t)$ taking the form of the Cox proportional intensity model (Cox 1972, Cook and Lawless 2007):

$$\lambda_{ij}(t \mid H_{t^-}) = R_{ij}(t)\lambda_0(t) exp[\theta^T s(t,i,j)], \tag{B.1}$$

where H_{t^-} is the complete network history right before time t, $s(t,i,j)$ is the vector of time-varying statistics, and θ is a vector of coefficients to be estimated from data; $R_{ij}(t)$ is the "at-risk" indicator, which equals one if participant i can perform actions on problem j at time t. This happens when the participant is active (that is, right after the participant's first event), and the bug report is opened so they are both in the risk set at time t. Otherwise, $R_{ij}(t) = 0$. The at-risk indicator function plays a central role in our models because it records the continuous change in the flow of problems and participants, thus controlling what actions are possible at any given moment, that is, the "opportunity set." When all elements of $s(t,i,j)$ are set to zero, the intensity equals the baseline rate $\lambda_0(t)$. To account for potential baseline rate changes during the observation time, we assume a nonparametric form of $\lambda_0(t)$, a flexible and widely used approach in survival and event history analysis

(Andersen and Keiding 2002, Vu et al. 2011, Perry and Wolfe 2013).

B.2. Model Estimation

Thanks to the nonparametric choice of the baseline rate $\lambda_0(t)$, the effects associated with the network statistics discussed in the paper can be estimated by maximizing the partial likelihood (Andersen et al. 2012):

$$PL(\theta) = \prod_{e \in E} \frac{\exp[\theta^T s(t_e, i_e, j_e)]}{\sum_{(i,j) \in R(t_e)} \exp[\theta^T s(t_e, i, j)]}, \tag{B.2}$$

where E is the set of attention allocation events and $R(t_e)$ contains every dyad (i,j) for which the indicator $R_{ij}(t_e)$ is equal to one. Perry and Wolfe (2013, appendix B) provide a proof of the consistency of inference based on maximum partial likelihood for this model.

Defining a counting process for events on each participant–problem pair makes computation unfeasible because the number of events may also be very large. To alleviate this computational constraint, we employ the nested case-control sampling approach (Borgan et al. 1995). Under this sampling method, for each event included in the sample, we randomly select a subset of nonevents (case controls) from the current risk set $R(t)$ to compute the denominator sum in the partial likelihood (B.2). This results in the sampled partial likelihood of the form (Borgan et al. 1995)

$$\widetilde{PL}(\theta) = \prod_{e \in E} \frac{\exp[\theta^T s(t_e, i_e, j_e)]}{\sum_{(i,j) \in \tilde{R}(t_e)} \exp[\theta^T s(t_e, i, j)]}, \tag{B.3}$$

where $\tilde{R}(t_e)$ includes the case and only the sampled controls at the event time t_e. For our current analysis, we sample up to 100 controls for each observed event (Lerner and Lomi 2020b). This results in a final data set of 11,599 cases and 1,170,868 nested controls for the estimation. Most commercial or open-source statistical software can be used for parameter estimation based on this sampled partial likelihood. The results that we report are based on the *survival* package (Therneau and Grambsch 2013) in the R software for statistical computing.

B.3. Parameter Interpretation

We interpret estimated network effects in terms of hazard ratios, a common concept in survival analysis (Aalen et al. 2008). The hazard ratio Π_p of a network statistic s_p is defined as the ratio of the intensity function for dyads with the statistic value $s_p(t,i,j) = v + 1$ to the intensity function of those with one unit smaller in that network statistic, that is, $s_p(t,i,j) = v$, holding all other statistics constant. It can also be thought of as the odds that attention allocation events occur on dyads with $s_p(t,i,j) = v + 1$ over those with $s_p(t,i,j) = v$, all other statistics being equal. The hazard ratio can be estimated by the formula $\Pi_p = \exp(\beta_p)$, where β_p is the maximum likelihood estimate of the parameter corresponding to the network statistic $s_p(t,i,j)$.

Appendix C. Robustness Checks

C.1. Attention Intensity Levels.

In constructing our data set, we record an attention allocation event whenever a developer chooses to allocate attention to and, thus, visibly "touch" a bug report without distinguishing between the varying levels of effort required. All actions leave visible cues potentially catching the attention of other participants; thus, our modeling approach reflects the fact that the intensity of the effort behind each specific act of attention allocation does not directly affect the theoretical arguments that underlie our hypothesized mechanisms. However, could it be that attention allocation patterns do vary significantly depending on the level of effort put into the acts visible to participants? To answer this question, we estimate new models, including interaction effects between the four variables capturing the attention mechanisms we hypothesize and a new variable called *High attention effort.* In our empirical setting, the intensity of attention acts can be inferred by considering the nature of the bug report modification that each act represents. We consider acts that involve the direct production or review of software code—intended as a patch for the focal bug—as a proxy for high attention effort. Conversely, low attention effort acts are those addressed at more mundane tasks contributing to the description, general classification, and maintenance of software bugs (Lakhani and von Hippel 2003). The results of these additional tests show that all four main effects are still significant and consistent with our hypotheses (see Table C.1). *Attention focusing* and *Attention mixing* show significant interactions going in the same direction of their respective main effect, thus representing a reinforced effect for high attention effort events. Our additional findings suggest that the dynamics that underlie the self-organizing properties of the attention structures that we investigate are substantively similar for high and low attention efforts.

C.2. Crowding.

In our modeling approach, the idea that attention is limited is just assumed—in line with our theoretical framework—and, thus, not directly tested. However, within that assumption, to which problem a participant allocates attention could depend on the amount of choice opportunities available, a concept referred to as "crowding" in related literature (e.g., Piezunka and Dahlander 2015). According to this view, attention could become more limited as there are more choice opportunities available, and individuals could become more selective in allocating their limited attention to competing issues. Do crowding levels have a significant effect of the mechanisms of attention allocation we hypothesize? To answer this question, we coded a new variable *Crowding*—similarly to that done by Piezunka and Dahlander (2015)—by counting, for each attention allocation event recorded, all problems at risk of attracting attention acts. We also applied an exponential decay function to the count with a 60-day half-life, thus giving more emphasis to newer problems (we tested alternative specifications of 30 and 90 days with similar results). We then interacted *Crowding* with the four variables capturing the attention mechanisms we hypothesize. The results in Table C.2 show that all four main effects are still significant and consistent with our hypotheses. Whereas all new interaction effects are statistically significant, our main effects maintain the same direction and significance once the moderator is included in the model with crowding only affecting the relative magnitude of the effects. These results suggest that the mechanisms underlying our

Table C.1. Cox Regression Model: High vs. Low Attention Effort

	Model 1	Model 2
Cumulative attention	0.9125 (0.0147)***	0.8098 (0.0142)***
Experienced participant	1.4348 (0.0554)***	1.2900 (0.0556)***
Institutional participant	1.1685 (0.0373)***	1.1428 (0.0377)***
Problem priority	−0.0250 (0.0270)	−0.0223 (0.0275)
Problem severity	0.1710 (0.0347)***	0.1498 (0.0350)***
Problem latency	−0.0020 (0.0000)***	−0.0018 (0.0000)***
Problem resolved	−1.9565 (0.0412)***	−1.8208 (0.0411)***
Problem recognition	0.3474 (0.0153)***	0.3340 (0.0151)***
Time inactive	−0.0170 (0.0003)***	−0.0155 (0.0003)***
Attention focusing (Hypothesis 1)	0.2357 (0.0067)***	0.2096 (0.0066)***
Attention reinforcing (Hypothesis 2)	0.1608 (0.0119)***	0.1448 (0.0120)***
Attention mixing (Hypothesis 3)	−0.0342 (0.0028)***	−0.0322 (0.0027)***
Attention clustering (Hypothesis 4)	0.0449 (0.0070)***	0.0444 (0.0070)***
Module 1	−0.1431 (0.0609)*	−0.1132 (0.0616)
Module 2	−0.1652 (0.0640)**	−0.1386 (0.0645)*
Module 3	0.1328 (0.0709)	0.1175 (0.0719)
Module 4	−0.5976 (0.0542)***	−0.5334 (0.0547)***
Preferential modularity	0.4003 (0.0232)***	0.3830 (0.0234)***
Attention clustering within modules	−0.0055 (0.0069)	−0.0045 (0.0069)
High attention effort		−3.0232 (0.0849)***
Attention focusing × High attention effort		0.1266 (0.0208)***
Cumulative attention × High attention effort		−0.4138 (0.0990)***
Attention reinforcing × High attention effort		−0.0442 (0.0402)
Attention clustering × High attention effort		−0.0287 (0.0289)
Attention mixing × High attention effort		−0.2865 (0.0931)**
Akaike information criterion	29,255.1392	24,287.3073
Number of events	11,599	11,599
Number of observations	2,330,137	2,330,137

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table C.2. Cox Regression Model: Interacting Attention Crowding with Effects of Interest

	Model 1	Model 2
Cumulative attention	0.7706 (0.0139)***	1.0765 (0.0240)***
Experienced participant	1.2818 (0.0560)***	1.2079 (0.0589)***
Institutional participant	1.1832 (0.0377)***	1.2699 (0.0389)***
Problem priority	−0.0526 (0.0276)	−0.0446 (0.0287)
Problem severity	0.1494 (0.0349)***	0.1579 (0.0357)***
Problem latency	−0.0017 (0.0000)***	−0.0018 (0.0001)***
Problem resolved	−1.7850 (0.0407)***	−1.7857 (0.0424)***
Problem recognition	0.3223 (0.0154)***	0.2941 (0.0154)***
Time inactive	−0.0150 (0.0003)***	−0.0139 (0.0003)***
Attention focusing (Hypothesis 1)	0.2112 (0.0066)***	0.2513 (0.0077)***
Attention reinforcing (Hypothesis 2)	0.1298 (0.0117)***	0.1815 (0.0126)***
Attention mixing (Hypothesis 3)	−0.0285 (0.0027)***	−0.1173 (0.0067)***
Attention clustering (Hypothesis 4)	0.0509 (0.0067)***	0.0416 (0.0081)***
Module 1	−0.1247 (0.0614)*	−0.1120 (0.0631)
Module 2	−0.1498 (0.0641)*	−0.1098 (0.0653)
Module 3	0.1419 (0.0713)*	0.1515 (0.0730)*
Module 4	−0.5139 (0.0543)***	−0.4888 (0.0554)***
Preferential modularity	0.3780 (0.0234)***	0.3843 (0.0239)***
Attention clustering within modules	−0.0052 (0.0067)	−0.0040 (0.0070)
Attention focusing × Crowding		0.0636 (0.0063)***
Cumulative attention × Crowding		−0.4220 (0.0244)***
Attention reinforcing × Crowding		−0.0531 (0.0121)***
Attention clustering × Crowding		0.0273 (0.0077)***
Attention mixing × Crowding		0.0857 (0.0062)***
Akaike information criterion	23,256.4512	22,405.9749
Number of events	11,599	11,599
Number of observations	1,170,870	1,170,870

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table C.3. Cox Regression Model: Exclusion of Problems Attracting Attention of Developers After Resolution

	Model 1	Model 2 (excluding resolved problems)
Cumulative attention	0.8171 (0.0144)***	0.7604 (0.0137)***
Experienced participant	1.2219 (0.0558)***	1.2506 (0.0559)***
Institutional participant	1.1508 (0.0379)***	1.1406 (0.0380)***
Problem priority	−0.0447 (0.0274)	−0.0133 (0.0284)
Problem severity	0.1379 (0.0351)***	0.1734 (0.0351)***
Problem latency	−0.0018 (0.0000)***	−0.0018 (0.0001)***
Problem resolved	−1.8088 (0.0412)***	−1.8164 (0.0416)***
Problem recognition	0.3507 (0.0153)***	0.3192 (0.0156)***
Time inactive	−0.0148 (0.0003)***	−0.0153 (0.0003)***
Attention focusing (Hypothesis 1)	0.2054 (0.0065) ***	0.2090 (0.0067)***
Attention reinforcing (Hypothesis 2)	0.1255 (0.0117)***	0.1424 (0.0123)***
Attention mixing (Hypothesis 3)	−0.0310 (0.0027)***	−0.0284 (0.0029)***
Attention clustering (Hypothesis 4)	0.0465 (0.0069)***	0.0527 (0.0067)***
Module 1	−0.1408 (0.0622)*	−0.0717 (0.0624)
Module 2	−0.1968 (0.0650)**	−0.1304 (0.0646)*
Module 3	0.1266 (0.0719)	0.1274 (0.0723)
Module 4	−0.5065 (0.0550)***	−0.4660 (0.0548)***
Preferential modularity	0.3562 (0.0237)***	0.3556 (0.0236)***
Attention clustering within modules	−0.0040 (0.0069)	−0.0059 (0.0066)
Akaike information criterion	23,022.6114	22,901.9335
Number of events	11,599	11,369
Number of observations	1,170,871	1,147,640

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

hypotheses are robust to this "ecological" conceptualization of limited attention.

C.3. Returning Problems.

In our modeling approach, problems that are considered solved remain in the risk set as they could be reopened at a later stage and still attract the attention of participants. It is, however, reasonable to expect a reduced attractiveness of problems marked as resolved, and our control variable *Problem resolved* confirms this intuition consistently in our models. However, distinct attention mechanisms pertaining to problems resolved and reopened could exist and potentially confound our results. To address the point, we reestimated our models, excluding problems from the

Table C.4. Cox Regression Model: Observations Above the 90% Quantile of *Cumulative Attention* Removed

	Model 1	Model 2 (excluding observation > 90% quantile of *Cumulative attention*)
Cumulative attention	0.8171 (0.0144)***	1.2232 (0.0204)***
Experienced participant	1.2219 (0.0558)***	1.0198 (0.0584)***
Institutional participant	1.1508 (0.0379)***	1.1627 (0.0407)***
Problem priority	−0.0447 (0.0274)	−0.0536 (0.0291)
Problem severity	0.1379 (0.0351)***	0.1519 (0.0378)***
Problem latency	−0.0018 (0.0000)***	−0.0018 (0.0001)***
Problem resolved	−1.8088 (0.0412)***	−2.0719 (0.0465)***
Problem recognition	0.3507 (0.0153)***	0.3597 (0.0163) ***
Time inactive	−0.0148 (0.0003)***	−0.0129 (0.0003)***
Attention focusing (Hypothesis 1)	0.2054 (0.0065)***	0.2272 (0.0071)***
Attention reinforcing (Hypothesis 2)	0.1255 (0.0117)***	0.1746 (0.0121)***
Attention mixing (Hypothesis 3)	−0.0310 (0.0027)***	−0.1164 (0.0062)***
Attention clustering (Hypothesis 4)	0.0465 (0.0069)***	0.0442 (0.0082)***
Module 1	−0.1408 (0.0622)*	−0.1033 (0.0670)
Module 2	−0.1968 (0.0650)**	−0.1749 (0.0699)*
Module 3	0.1266 (0.0719)	0.1733 (0.0771)*
Module 4	−0.5065 (0.0550)***	−0.4707 (0.0595)***
Preferential modularity	0.3562 (0.0237)***	0.3598 (0.0253)***
Attention clustering within modules	−0.0040 (0.0069)	−0.0087 (0.0082)
Akaike information criterion	23,022.6114	20,078.9980
Number of events	11,599	10,439
Number of observations	1,170,871	1,169,235

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

risk set after they were marked as resolved once. The number of bugs excluded from the analysis is not high (approximately 200), and the estimates are stable and fully consistent with our previous results (see Table C.3).

C.4. Extreme Outliers.

In our empirical setting, the number of recorded attention allocation acts varies significantly across participants and is not normally distributed. Indeed, we expect the mechanisms underlying our hypotheses to produce an uneven concentration in attention allocation, and our modeling approach is suited to handle this skew. Nonetheless, could it be that the results we find are only driven by the actions of the most active participants? To answer this question, we reestimated our models, excluding the more severe outliers among the participants. We computed the 90% quantile of cumulative attention over all events and removed all observations above that threshold from the data set. The results in Table C.4 show that the new estimates are stable and consistent with our previous results.

Endnotes

[1] The self-organizing nature of attention networks that we introduce is deeply rooted in the basic behavioral premises of the garbage can model (Cohen et al. 1972, March and Olsen 1976). First, a key element of our theory hinges on the constant churning ("fluid participation" in the Cohen et al. work) of organizational participants and problems and, hence, opportunities for attention allocation. Second, participants in self-organizing contexts are likely to face a high degree of goal ambiguity ("problematic preferences" in the Cohen et al. work) given the marginal role that managerial hierarchies and formal incentive structures play in the model. When these two conditions prevail, "attention focus, rather than utility, seems to explain much of the behavior" (March and Olsen 1976, p. 15). In line with our hypotheses, decision making becomes, therefore, less dependent on traditional rational choice logic and more dependent on context-specific and situated attention allocation dynamics (Ocasio 2012). As March and Olsen (1976, p. 26) state, "What happens depends on how the situation fits into a mosaic of simultaneous performances involving other individuals, other places, other concerns, and the phasing of other events." Our theorizing of attention networks builds on this seminal work to provide a precise operational specification of the network principles and mechanisms of situated attention according to which attention allocation decisions are sensitive to the situational and structural context (Ocasio 1997).

[2] Our notion of attention network differs from previous attempts at conceptualizing attention using a network perspective. For example, Rhee and Leonardi (2018) look at communication networks (i.e., social networks in which nodes are people and edges are communication instances between people) and conceive attention as an actor-based attribute (i.e., a concentration index capturing the degree to which social actors pay uniform attention to all communication edges to which they are tied or concentrate their attention on a subset of these edges). On the contrary, our conceptualization of attention network entails a bipartite relation connecting participants to problems, and our structural micromechanisms define exactly in what ways participants allocate attention to problems.

[3] To facilitate exposition, the four hypotheses are introduced and discussed sequentially. In the empirical models, the four mechanisms concatenate to generate the organizational attention network that is actually observed. A useful way to interpret the hypotheses, thus, is as an interdependent set of interdependent claims about the relational microstructures that regulate observed patterns of association between multiple participants and problems.

[4] As March (1991, p. 109) usefully explains, "Individuals attend to some things and thus do not attend to others. The attention devoted to a particular decision by a particular potential participant depends on alternative claims on attention. Since those alternative claims are not homogenous across participants and change over time, the attention every particular decision receives can be both quite unstable and remarkably independent of the properties of the decision."

[5] Reference to well-established network analytic concepts might help to describe efficiently the mixing properties of attention networks (Pastor-Satorras et al. 2001; Newman 2002, 2003; Newman and Park 2003). An attention network is assortative if active participants (participants who pay attention to many problems) are attracted by popular problems (problems that attract the attention of many participants). On the contrary, an attention network is disassortative if active participants allocate their attention to less popular problems. We note that the concept of assortativity we adopt is specific to two-mode networks—networks defined only between distinct classes of objects (Lerner and Lomi 2020a)—and differs from the more common concept of assortativity or assortative mixing as used in game theory (Bergstrom 2003) in which networks are typically social, that is, they connect objects within the same class. In the empirical context of our research, disassortativity characterizes the consequence of the structural mechanism of mixing that we introduce.

[6] This path indirectly connecting a participant to a problem through another participant is called a three-path in the analysis of bipartite networks (Wang et al. 2013). A three-path is the shortest possible indirect path linking a participant and a problem in a bipartite network. As such, the notion of three-path provides the analytical basis for an unambiguous definition of neighborhood (see also Pattison and Robins 2002 for a similar discussion in the context of social networks).

[7] The closed structure connecting two participants to the same two problems is called a four-cycle in the analysis of bipartite networks (Wang et al. 2013). The four-cycle is the analytical analogue of triadic closure in social networks.

[8] Based on information reported by W3Techs (last access on January 30, 2023): https://w3techs.com/technologies/overview/web_server.

[9] A dynamic visualization of the data we analyze in the empirical part of the study may be accessed by following the link https://zenodo.org/record/7564503. The actual data we collected and used in the analysis are publicly available and may be found at the following address: https://github.com/juergenlerner/eventnet/tree/master/data/apache.

[10] All the statistics are time-weighted according to a time decay parameter defined in Equation (A.2). In this way, more recent events have a heavier weight on the prediction of the next event—a weight that progressively decreases for events in the more distant past.

[11] As with clustering defined for one-mode (social) networks, clustering for bipartite networks involves path shortening behavior (or closure): the difference is that, in bipartite networks, path shortening closes an open three-path connecting a participant indirectly to a problem through another problem and another participant (see Equation A.7 for the formal definition of three-path. See also Table 1, bottom left panel, for an intuitive graphic representation). Four-cycles are the most basic form of closure in bipartite systems (Wang et al. 2013).

[12] Because the network-dependent effects are standardized, the interpretation of their magnitude is carried out in terms of standard deviations from mean. Standardization is useful in this case because the sample size and the way the covariates are constructed makes statistical significance alone unhelpful to evaluate the magnitude and strength of the effects of theoretical interest.

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