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Learning to search collaboratively: How dyads overcome complexity and misaligned incentives in imperfect modular decompositions

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Abstract

We investigate the search processes that dyads engage in when each human agent is responsible for one module of a complex task. Our laboratory experiment manipulates global vs. local incentives and low vs. high cross-modular interdependence. We find that dyads endogenously learn to coordinate their joint search efforts by engaging in parallel and sequential searches that, over time, give rise to coordinated repeated actions. Such collaborative search emerges despite complexity and misaligned incentives, and without a coordinating hierarchy.

1. Introduction

Modularity is a fundamental concept (Baldwin and Clark, 2000) for organizing work within firms (Sanchez and Mahoney, 1996; Brusoni *et al.*, 2001; Karim, 2006) as well as between them (Schilling, 2000; Jacobides, 2005; Kapoor, 2013). Modularity is of particular importance when firms engage in search and problem solving, as it is typical for the design of new products (Ulrich, 1995; Fleming, 2001; MacCormack *et al.*, 2001) or platform architectures (Kretschmer *et al.*, 2020). As a result, much research on modularity has focused on product and organizational structures (Brusoni and Prencipe, 2001; Campagnolo and Camuffo, 2010), on whether and how these two structures are aligned, and on how they allow reaping the benefits of modularity by the various agents involved (Henderson and Clark, 1990; Baldwin and Clark, 2000; Tee *et al*. 2019). At the same time, however, many organizations experience substantial challenges when implementing modularity, for instance in large projects (Denicol *et al.*, 2020), because interdependencies between tasks are often nontrivial and imperfectly understood (Zirpoli and Becker, 2011) and even an alignment of incentives does not necessarily result in an alignment of actions (Kretschmer and Puranam, 2008; Heath and Staudenmeyer, 2000). When multiple agents search for improvements to the modules of an imperfectly decomposed system, their decisions need to be coordinated to account for interdependencies that span across modules.

Prior research highlights three sets of mechanisms for dealing with these coordination challenges: (i) lateral communication that allows the agents to increase information processing and develop shared understanding and predictive knowledge (Puranam et al., 2012; Knudsen and Srikanth, 2014); (ii) managerial hierarchy in the sense of a higher-level "systems integrator" (e.g., Dosi et al., 2003; Rivkin and Siggelkow, 2003; Baumann and Siggelkow, 2013) that ensures the fit of the different modules; and (iii) global incentives that align the interests of the agents around system-level, rather than module-level, performance (e.g., Rivkin and Siggelkow, 2003; Gulati et al., 2012). Most studies examining these mechanisms are theoretical in nature, often relying on computational models, and they assign a prominent role to hierarchy and global incentives and thus are less applicable to organizational contexts in which these mechanisms are less prominent or even absent, as is the case for less-hierarchical organizing (Lee and Edmondson, 2017; Billinger and Workiewicz, 2019). Hence, despite substantial research, we still lack empirical evidence of how human agents coordinate their search when the key mechanism they can rely on is information processing through lateral communication. *We therefore ask: how do human agents, in the absence of hierarchy, rely on lateral communication to search the different modules of an imperfectly decomposed system?*

Building on recent advancements in the modularity literature, we conceptualize an imperfectly modular decomposition as one involving more or less dense technical interdependencies across boundaries (Colfer and Baldwin, 2016). For the smallest unit of analysis for which such interdependencies can result in coordination challenges, the two-person dyad, prior research suggests that lateral communication can lead to the emergence of coordinated repeated action sequences based on procedural memory that is developed jointly by the two human agents (Cohen and Bacdayan, 1994). In the absence of hierarchy, coordinated repeated action sequences allow for mental activity–inactivity with simplified choices and procedures that the individual agent can rely on when interacting with another agent (March and Simon, 1958; Cohen *et al.*, 1996; Becker, 2004). While enhancing coordination, however, these coordinated repeated action sequences can also prove maladaptive if agents fall prey to joint myopia (Knudsen and Srikanth, 2014) or competency traps (Levitt and March, 1988) that make them unwilling to abandon established but suboptimal solutions (Gulati *et al.*, 2012). Moreover, we do not know how these learning processes are shaped by the degree of cross-module interdependence or by misaligned incentives that human agents may face.

To address these issues, we conduct a laboratory experiment in which 112 dyads engage in combinatorial multi-attribute decision making (Billinger et al., 2014) in a task with 10 binary decision attributes split equally between the 2 participants, both of whom are free to make changes to the 5 binary decision attributes that make up the organizational module that they are assigned to. Over a 24-trial period, every participant can fully observe their partner's choices and receives feedback about both module-level (disaggregate) and system-level (aggregate) performance. Moreover, before making decisions regarding their module, both participants can talk to each other via a chat function. In four between-subject treatments, our experimental design then contrasts global vs. local incentives and low vs. high cross-modular interdependence, thus exposing the dyads' search efforts to various "stress tests," especially in the treatment with high complexity (cross-modular interdependence) and misaligned (local) incentives. In our analysis, we focus on the role of the system-level (aggregate) and module-level (disaggregate) performance feedback that participants receive, as well as on the search distance that characterizes participants' active search behavior (i.e., narrow vs. broad search). In addition, we consider the 4401 chat messages from the lateral communication in our study, which we code to capture the kind and extent of coordination that the dyads rely on during the search process. In combination, these data allow us to test a set of hypotheses aimed at comparing human behavior in the lab with predictions from prior research.

We find that dyads in all conditions endogenously develop joint behavior that allows them to coordinate their search efforts and improve performance. Coordinated joint behavior emerges despite high levels of cross-module interdependence and despite misaligned incentives — and without a hierarchical function that would be able to coordinate the actions taken in the organizational modules. Moreover, our results show that the establishment of coordinated repeated actions has a positive effect on performance. However, they can become detrimental unless they are abandoned at some point. Overall, our study offers novel insights into the ability of dyads to learn to search collaboratively and thus to overcome complexity and misaligned incentives in the absence of managerial hierarchy. The study has implications for the design of less-hierarchical organizations and our understanding of the emergence of routines and capability development in modular structures.

2. Theory and hypotheses

Modularity research often takes Simon (1962) as a central point of departure: problem solving by boundedly rational agents can benefit from decomposing problems into smaller modules, which are then solved independently before being integrated into overall solutions. Building on these foundations, modularity has developed as a problem-solving approach based on a set of design principles to manage complex systems in the presence of human agents with bounded rationality (Baldwin and Clark, 2000; Baldwin, 2020). It involves partitioning a complex system into discrete modules so that the division of labor within and across modules is consistent with the technical interdependences of the work being performed (mirroring principle; Henderson and Clark, 1990; Von Hippel, 1990). Ideally, each module is also as independent from other modules as possible, so that individuals, groups, or organizations can independently focus on innovation within their individual modules while at the same time contributing to system-level improvements (information hiding principle; Parnas, 1972, 1978). As a result, modularity allows mitigating the complexity of the problem and preserving scarce cognitive resources while improving the speed and flexibility of the problem-solving process (Baldwin and Clark, 2000; Brusoni et al., 2007).

When the problem is characterized by a low degree of complexity, an optimal decomposition (i.e., one consistent with the mirroring and information hiding principles) can only be designed by a decision maker with perfect knowledge of the problem (Simon, 1962). When the problem is highly complex, however, an optimal decomposition is technically infeasible (Schaefer, 1999). It follows that boundedly rational agents can, at best, hope to reach near-decompositions that entail a partitioning into quasi-independent subproblems such that interdependencies within modules are stronger than interdependencies between modules

(Simon, 1962). Since couplings between modules can range from loose to very tight (e.g., Zirpoli and Becker, 2011; Denicol et al., 2020), changes made to one module can have a little or great impact on the other module (MacCormack et al., 2007). Great impact on other modules is particularly relevant in situations in which organizations deliberately design modules that (fully) "break the mirror" by allowing for dense cross-module interdependencies and thereby encourage coordination and collaborative development of technically demanding products or services (Colfer and Baldwin, 2016).

Imperfectly decomposed systems tend to give rise to epistemic interdependence, i.e., a "situation in which one agent's optimal choices depend upon a prediction of another agent's actions" (Puranam et al., 2012: 420). In such a setting, the coordination of actions taken by two or more agents must be achieved through individual adaptation in response to feedback (March and Simon, 1958; Cyert and March, 1963) and mutual adjustments (Thompson, 1967) that rely on a joint problem-solving process (Knudsen and Srikanth, 2014) and that seek to strike a balance between co-exploration and co-exploitation (Parmigiani and Rivera-Santos, 2011). Agents pursuing such collaborative search must increase information processing to develop the shared understanding and predictive knowledge necessary to achieve successful coordinated actions (Gailbraith, 1973; Tushman and Nadler, 1978). This requires organizations to design modules that put agents in a situation in which they can observe each other's actions and outcomes, as is the case when the organization (partially) "breaks the mirror" and thereby defines knowledge boundaries that extend over and above task boundaries (Colfer and Baldwin, 2016).

Prior research suggests that lateral communication through which dyads coordinate their actions will likely result in coordinated patterns of action (Cohen et al., 1996, Pentland and Feldman, 2005). These action patterns can be repeated more frequently over time (Cohen and Bacdayan, 1994) and evolve into operating procedures to which the agents conform. However,in the case of misaligned incentives, individual decision makers may not always adhere to coordinated action sequences but instead focus on actions to improve the outcome of their own module rather than the overall system. It is therefore questionable whether a dyad's action sequences can be characterized as standardized operating procedures (Nelson and Winter, 1982, Becker, 2004), routinization of joint engagement with a task (Lazaric and Denis, 2005; Bapuji et al., 2012; Cacciatori, 2012), or actual routines that involve routine dynamics (Pentland and Feldman 2005, Feldman et al., 2016, 2021). For the present study, we therefore focus on coordinated repeated action sequences as the core unit of analysis that allows for an examination of whether lateral communication results in collaborative search, conditional on the type of incentive scheme, and the level of interdependence between the agents.

Coordinated repeated action sequences are likely to be developed by participating agents who learn about their partners and the task they perform, developing a shared understanding, procedural memory, and predictive knowledge of coordination requirements and of how their respective actions can complicate or help resolve coordination problems (Cohen and Bacdayan, 1994; Reuer et al., 2002). Much of this learning unfolds through trial and error and is therefore informed by insights from coordination failures (Gulati et al., 2012) and lateral communication (Knudsen and Srikanth, 2014). The enhancement of shared understanding and predictive knowledge supports the mapping of individual actions into collective outcomes (Kogut, 2000) that are likely to be incorporated into relationship-specific repeated action sequences that smoothen coordination (Reuer and Arino, 2007). Yet, both misaligned incentives and high cross-module interdependence are likely to provide challenges to the smoothing of coordination. Moreover, we can expect agents to eventually abandon active search as soon as a mutually satisfactory solution is found (Simon, 1955; MacLeod and Pingle, 2005; Schunk, 2009). In the following, we thus develop hypotheses that investigate whether such satisficing occurs and where dyads search during their collaborative search effort. To capture these aspects of search, we investigate active search (whether to search) and search distance (where to search), which allows for the examination of narrow vs. broad search behavior (Billinger et al., 2021).

2.1. Lateral communication

High levels of lateral communication foster the development of the shared understanding and predictive knowledge necessary for successful coordination (March and Simon, 1958; Lawrence and Lorsch, 1967; Galbraith, 1973; Tushman and Nadler, 1978). This relationship has been documented for a variety of settings, such as sequencing and synchronizing, technological choices, or strategic complementarities (see Weber, 2018 for a review). Its performance effects, on the other hand, are less clear. Extensive work in organizational psychology suggests that, in interdependent tasks, group members are prone to exchange information and expertise (Susman, 1976; Cummings, 1978), engage in coordination efforts and cooperative endeavors to improve their work (e.g., Bachrach et al., 2006; Griffin et al., 2007; Mesmer-Magnus and DeChurch, 2009; Lewicki and Brinsfield, 2017), and produce novel insights and high-quality solutions (see Brown and Eisenhardt, 1995; De Dreu et al., 2008; Krishnan and Ulrich, 2001; Stasser and Abele, 2020 for a review). On the other hand, a substantial literature on product design has shown that higher levels of communication and knowledge sharing may lead to the pursuit of objectives that are minimally acceptable for all team members, thereby resulting in poor innovative outcomes (e.g, Bettenhausen, 1991; Hauptman and Hirji, 1996; Song and Montoya-Weiss 1998; Davis and Eisenhardt, 2011).

Knudsen and Srikanth (2014) addressed these issues using a computational model of joint search where, due to epistemic interdependence, feedback to one agent's actions is confounded by the actions of the other agent. Central to this model is that agents are unable to determine whether positive or negative feedback outcomes are the fruit of their own actions or those of the interdependent others (Lounamaa and March, 1987; Puranam and Swamy, 2016). This leads to increasing mutual confusion, as incorrect mental models held by one agent engender mistakes that, in turn, confuse the other agents by perturbing their mental models, and so forth. High levels of communication counter mutual confusion by fostering the development of shared understanding and predictive knowledge. The subsequent alignment of mental models can, however, lead to increasing joint myopia, since agents tend to reinforce each other into the exploration of a progressively narrower portion of the problem space. This can lead to premature lock-ins on inferior solutions and therefore impair performance. That is, while higher levels of lateral communication reduce mutual confusion, they come at the risk of increasing joint myopia, and vice-versa. Thus, for the joint search to be effective, the agents involved must balance these two effects. In a related computational model, Baumann (2015) finds that, relative to constant communication, temporary communication neglect allows for a broader exploration of the search space, resulting in superior long-run performance. Correspondingly, communication must be dosed to balance broad search with the need to hold on to good solutions.

Overall, this suggests that lateral communication serves as a foundation for the development of coordinated repeated actions that, over time, can become detrimental for the overall performance of collaborative search. Correspondingly, we hypothesize:

H1a. *Higher levels of lateral communication increase the likelihood of search.*
H1b. *Higher levels of lateral communication reduce system-level performance.*

2.2. Local and global incentives

Several studies shed light on the role of local and global incentives in various organizational structures. Using a computational model, Cohen (1984) examined the effect of local and global incentives on the performance of organizational search strategies, finding that local incentives outperform global incentives in all variants of the problem. Burton and Obel (1988) compared the effects of local and global incentives across M-form and U-form organizations in a laboratory experiment, finding that global (local) incentives in M-form (U-form) organizations yield greater cooperative (opportunistic) behavior and higher (lower) total profit. Wageman and Baker (1997) assessed the joint effects of incentive schemes and task interdependence in a longitudinal, quasi-experimental field study, finding that subjects in more interdependent tasks engage in greater pro-social behavior regardless of the incentive scheme. Interestingly, only those provided with group-wide incentives reap the benefits of pro-social behavior, which then enhances performance in more interdependent tasks.

While much prior research assumes the presence of a higher-level decision maker that coordinates search in modular systems, more organic (Burns and Stalker, 1961) and less-hierarchical forms of organizing (Lee and Edmondson, 2017) are required to find alternative coordination solutions. Using a computational model of joint search, Rivkin and Siggelkow (2003) examined the effect of different incentive schemes in organizations with an active or passive hierarchy. They find that global incentives tend to increase system-level stability by narrowing the search when the Chief Executive Officer (CEO) is passive. This is due to specialized agents having to find solutions that benefit the organization as a whole. In contrast, local incentives tend to reduce system-level stability and broadening the search when the CEO is passive, since specialized agents are then given unrestricted freedom to act independently. Siggelkow and Rivkin (2006) refined these results showing that, when cross-module interdependence becomes very high, increased module-level exploration can backfire. Particularly, organizations can fall prey to a status-quo trap that increases system-level stability but reduces search.

Building on these insights, we anticipate that, in a task with no hierarchy, global incentives will enhance the stability of collaborative search, as the alignment of interests induces agents to refrain from taking actions that might adversely affect each other and, possibly, impair joint performance. In a context with imperfect modular decompositions, we expect this to reduce the likelihood for subjects to continue searching, and to induce them to seek new alternatives closer to the status quo. Therefore, we hypothesize:

H2a. *Global (local) incentives reduce (increase) the likelihood of search.*

H2b. *Global (local) incentives reduce (increase) search distance.*

Incentives also affect the long-term vs. short-term effects of collaborative search. Dosi et al. (2003) explored the relationship between incentive schemes, search behavior, and performance in complex organizations using a computational model. They found that, under low level of interdependence, global incentives are often most effective in the short term, since the attempt to implement solutions beneficial to the whole organization allows reaching a local maximum more rapidly. Conversely, local incentives may yield superior long-run performance, as implementing solutions that are beneficial to one's own module can allow the organization as a whole to move away from a poor local maximum and toward a better one. If cross-module interdependence is high, however, collaborative behavior (with global incentives) tends to be more advantageous again.

Mihm et al. (2003) studied local and global optimization processes under different communication regimes using a computational model that mirrored the development of complex products with a high level of cross-module interdependence. The results suggested that immediate, local optimization under delayed knowledge sharing induces a longer time for the system to settle on a local optimum, resulting in inferior overall performance, whereas global incentives dramatically improve system-level performance.

These findings suggest that, when the level of cross-module interdependence is low, the pursuit of collaborative search is more efficient, leading to superior organizational performance in the short run. And yet, the pursuit of opportunistic local solutions aimed to enhance module performance can lead to superior performance in the long run. When the level of cross-module interdependence is high, however, the pursuit of collaborative search is advantageous also in the long run. We hypothesize:

H3a. *Under low cross-module interdependence, the positive influence of global (local) incentives on system-level performance decreases (increases) over time*.

H3b. *Under high cross-module interdependence, the positive influence of global (local) incentives on system-level performance increases (decreases) over time*.

2.3 Joint adaptation and learning in collaborative search

A central claim of the Behavioral Theory of the Firm is that organizations learn by adapting their behavior to performance feedback (Cyert and March, 1963). Prior experimental work showed that search by individuals is adaptive to performance feedback (Busemeyer et al., 1986; Hoeffler et al., 2006; Billinger et al., 2014, 2021). The general evidence suggests that failure (success) decreases (increases) the likelihood for subjects to continue searching and prompts them to broaden (narrow) their search relative to the region of the problem space where they have experienced performance improvements. Existing models of adaptive search, however, incompletely consider the joint pursuit of actions by interdependent agents (Knudsen and Levinthal, 2007). This is critical for problems of coordination, where agents need to learn how to integrate their joint search efforts to establish a successful collaboration.

Learning how to search collaboratively is a complex process, and the emergence of coordinated repeated action sequences or routines (Lazaric and Denis, 2005; Bapuji et al., 2012) first requires the development of procedural memory (Cohen and Bacdayan, 1994) and some form of transactive memory system (Kirschner et al., 2011; Miller et al., 2014; Argote and Guo, 2016). It is also well documented that learning to align actions typically involves several developmental phases, for instance, as proposed by the Form–Storm–Norm–Perform model (Tuckman, 1965) and that such phases are required for groups to operate successfully (Bonebright, 2010). As agents learn to search collaboratively, we therefore expect system-level feedback to become more prominent than module-level feedback. Accordingly, the joint search process is likely to resemble the adaptive search process that individuals would rely on if they were undertaking search on their own. Thus, we hypothesize:

H4a. *The likelihood of search decreases (increases) in response to system-level failure (success).*

H4b. *Search becomes broader (narrower) in response to system-level failure (success).*

When several agents search collaboratively in modular structures, it is crucial to fully document and consider module-level and system-level performance feedback (Marengo, 2015). Consequently, researchers have started to explore the implications of interdependent feedback in decomposed systems encompassing multiple organizational levels (e.g., Siggelkow and Rivkin, 2009; Gaba and Joseph, 2013; Joseph and Gaba, 2015; Hu and Bettis, 2018; Levinthal and Workiewicz, 2018). Although we can expect module-level feedback to have some disruptive effect on the association between system-level feedback and search efforts, the prior literature provides no basis for developing specific hypotheses concerning behavioral responses to module-level and system-level performance feedback that occur when agents face imperfect modular decompositions. Additionally, due to epistemic interdependence (Puranam et al., 2012) in such settings, we also expect parallel and sequential searches to emerge during the process of search (Cyert and March 1963; Greve 2008; Levinthal and Posen, 2007), with system-level and module-level feedback leading to coordinated repeated actions. The specific role and outcome of each of these components is unclear ex ante, and we therefore examine them in an exploratory way.

3. Method

3.1 Experimental task

We address our research question using a laboratory experiment that builds on the Alien Game paradigm introduced by Billinger et al. (2014). We rely on a modularized Alien Game, i.e., a combinatorial search task based on the canonical NK model (Kauffman, 1993, 1995; Levinthal, 1997; Baumann et al., 2019), in which the overall problem is divided into two organizational modules (Sanchez and Mahoney, 1996) that are allocated to two subjects. Subjects work on separate computers and do not know each other. Each subject is responsible for one module and can generate alternative solutions by (re)combining the decision attributes that make up her module. Within-module as well as cross-module interdependencies are unknown to the subjects. It follows that, due to epistemic interdependence (Puranam et al., 2012), the optimal course of action for each subject depends upon the prediction of the actions of the other subject. At the beginning of every trial, a chat window opens, allowing the two subjects to communicate and coordinate their actions. While the chat window is open, subjects cannot make changes to the decision attributes. Once the chat window has been closed by both participants, subjects independently make decisions in their modules and submit their choices, which completes the trial.

Each alternative combination of decision attribute is associated with a payoff that is generated based on a standard specification of the NK model, thus resulting in a performance landscape that subjects need to search jointly. The payoff of each overall combination is decomposed to reflect the contributions that the combinations of each of the two modules make to overall performance. We refer to the payoff associated with the overall combination as system-level performance. It is the sum of the payoffs associated with the two module combinations. For each trial, both system-level -errorand module-level performance values are revealed after both subjects have completed their decisions for all attributes in their modules. These decisions are final and could not be revised, which also implies that the evaluation of novel combinations is made in an “online” and trial-and-error manner. Notably, subjects are informed about the decisions made by their partner and the associated module-level performance. The Supplementary Data shows a screenshot of the experimental interface.

The concept of modularity is widely used in the literature and our experimental design builds on two conceptions of modularity; one considers organizational modular designs (Sanchez and Mahoney, 1996) or forms (Schilling and Steensma, 2001), and the other one derives from technical features and modular architectures of products (Baldwin and Clark, 2000). Organizational modular design is a central aspect of our dyadic task allocation, where both participants are unambiguously and permanently assigned to separate organizational modules that determine the overall task's division of labor. Each of these organizational modules contains 5 of the 10 decision-variables, which define the scope of actions available to the individual participant. The second conception of modularity considers the interdependencies between decision attributes and is critical for the design of imperfect decompositions. As there are many gradations of modularity (Baldwin and Clark, 2000), the type of decomposition used in the experimental design needs to serve the purpose of the study, which seeks to investigate dyadic search behavior that faces epistemic interdependence and (mis)aligned incentives.

For the present study, we use one NK landscape with an imperfect modular decomposition that emphasizes interdependence between modules, whereas the other NK landscape is characterized by an equal number of interdependencies within and across the modules. These interdependency structures resemble what is referred to as "breaking the mirror" (Colfer and Baldwin, 2016), i.e., a violation of the idea that organizational structure needs to mirror the underlying (technical) interdependency structure. Several streams of the literature suggest that organizations can benefit from strategically breaking the mirror partially or fully. In partially mirrored systems, "knowledge boundaries are drawn broader than operational boundaries" (Colfer and Baldwin: 710). This has proven an effective design rule to intensify information processing and enforce coordination when problems are complex, and the knowledge of all true, latent interdependences remains elusive even after much effort and many iterations (e.g., Brusoni et al., 2001; Tokumaru, 2006; Kapoor and Adner, 2012). In (fully) unmirrored systems, however, organizations go further and overhaul the extant architecture to arrange “dense technical interdependencies across their boundaries” (Colfer and Baldwin, 2016: 724). This occurs, for instance, in alliances and consortia where two or more organizations collaborate in the development of tightly coupled, technically demanding new products or services (e.g., Staudenmayer et al., 2005; Snow et al., 2011; Tuertscher et al., 2014). The evidence suggests that, if successful, fully breaking the mirror can be a source of competitive advantage and yield radical changes that can disrupt an industry. Our conceptualization of an imperfect modular decomposition and the selection of landscapes captures both perspectives — i.e., broader knowledge boundaries that improve information processing and that partially breaks the mirror, as well as dense technical interdependencies across boundaries that emphasize across module interdependencies, thus fully breaks the mirror. Overall, these choices are motivated by our second independent variable, which compares aligned vs. misaligned incentives. Particularly, the latter requires an experimental design with pronounced imperfect modular structures to ensure sufficient feedback disturbances that should result on differences in search behaviors.

Two further technical aspects of the task are important. First, performance values are normalized using the highest-possible performance (i.e., the global peak in the performance landscape) to facilitate comparison across different performance landscapes; performances are also multiplied by uneven multipliers to rule out anchoring effects. Second, to limit the impact of foreknowledge and thus to prevent subjects from tapping into cognitive priors that might guide their search, the experimental task (the Alien Game) is framed in an abstract way. Specifically, the decision attributes consist of abstract symbols, and the overall combinations of decisions are framed to be sold to an abstract entity (an “alien”), whose willingness to pay a different price for different products reflects the (unknown) structure of the performance landscape. Overall, this setup is particularly apt to shed light on the determinants of joint search and the role of coordination and behavior.

3.2 Experimental design

The combinatorial task consists of 10 decision attributes $N = 10$ partitioned into two modules of five decision attributes each. Because each decision attribute is a binary variable, the overall search space consists of 210 = 1, 024 possible combinations. The number of trials is 24. Since the number of alternatives far exceeds the number of available trials, resources for search are scarce. Drawing upon these assumptions, we implement a 2 × 2 factorial design that distinguishes low and high cross-module interdependencies and local and global incentives.

In the condition with low cross-module interdependence, each of the attributes of the NK-based search task is interdependent with two other decision attributes (i.e., $K = 2$), of which one decision attribute is located in the same module as the focal decision attribute ($KWithin = 1$) and one is located in the other module ($KBetween = 1$). In the condition with high cross-module interdependence, each of the decision attributes of the search task is interdependent with five other attributes (i.e., $K = 5$), of which one decision attribute is located in the same module as the focal decision attribute ($KWithin = 1$) and four are located in the other module ($KBetween = 4$). Both setups capture an imperfect decomposition with tightly coupled modules, such that changes in one module have a great impact on the other module (MacCormack et al., 2007; Colfer and Baldwin, 2016). Consistent with the NK model, as K increases, the performance landscape becomes rugged, or multi-peaked (Levinthal, 1997).

In the local incentives condition, subjects are rewarded based on the performance of the module that they are responsible for. This captures individual goals conductive to conflicting interests. In the global incentives condition, subjects are rewarded based on a 50/50 split of the system-level performance, which aligns interests within the dyad. Final compensation is based on the payoff accumulated over all search trials (Billinger et al., 2021), rather than the payoff associated with the best-performing alternative (Billinger et al., 2014, see also Tracy et al., 2017; Vuculescu, 2017), thereby introducing an opportunity cost for changing the status quo. This is because the performance of a new combination (or sub-combination) could be less than the payoff of the status quo, resulting in a reduction of the payoff accumulated over all search trials.

3.3 Implementation

We conducted our experiment in the behavioral computer laboratory at the Munich Experimental Laboratory for Economic and Social Sciences (MELESSA). The experimental design was approved by the laboratory before the data collection. About 224 subjects were randomly selected using the lab's recruitment system and were incentivized financially. Subjects were on average 24.3 years old and mostly stemmed from the university's general student population. The participants were randomly assigned to the 4 conditions, for a total of at least 28 dyads per condition. Each dyad consisted of a male and a female participant who were randomly and anonymously paired, resulting in a 50/50 gender split, with participants being unaware of the other participants' gender. At the beginning of each session, participants consented to standard laboratory procedures (when signing-in) and then received experimental instructions at the workstation they were assigned to (see Supplementary Data). The supervising instructor read the text aloud and answered questions, if any. To access the experimental task, participants had to correctly answer a set of comprehension questions. The experimental software was specifically developed for the task. It contained an interface that was identical for both participants (see Supplementary Data) and that provided, at all times, information concerning the overall combination, the modules, as well as system-level and module-level performances for both participants. A set of socio-demographic questions completed the session. The experiment lasted about 45 min and participants earned, on average, 20.83€, including a comparatively low 4€ show-up fee that amplified the relevance of the different incentive schemes.

3.4 Measures

We operationalize the four experimental conditions using dummy coding. *Interdependence* between modules takes the value of 1 if *High*, and 0 otherwise. The variable captures the number of interdependencies and their distribution within and between tightly coupled modules. *Low Interdependence* serves as the reference category. *Incentives* take value of 1 if the scheme is *Global*, and 0 otherwise. The variable captures aligned and misaligned interests, respectively. *Local Incentives* serves as the reference category.

Search behavior was coded using two main measures to distinguish whether and where agents search (Billinger et al., 2021). *Active Search* takes the value of 1 if at least one subject within the dyad changes at least one attribute in the current trial, and 0 otherwise. The variable captures decisions on whether to search. *Search Distance* is measured as the

Hamming distance between a novel, overall combination and the best-performing overall combination that a dyad had identified in prior trials, thus consisting of discrete count data and ranging between 1 and 10. The variable captures decisions about where to search. Performance was coded using two measures. *Average Performance* is the cumulative mean of payoffs that the dyad received so far. The variable captures that subjects must balance the exploration of novel combinations with the exploitation of known ones (March, 1991). *Maximum Performance* is the highest performance that the dyad achieved so far. The variable captures the quality of search.

To measure participants' lateral communication and coordination, two research assistants independently coded two variables: lateral communication and coordination. The coding is based on 4401 chat messages that occurred on a trial-by-trial basis before the dyads engaged in search in the four experimental conditions. It resulted in an inter-rater reliability score of 0.96, suggesting a near-perfect agreement (Landis and Koch, 1977). *Lateral Communication* takes a value of 1 if communication is two-way, and 0 otherwise. It captures the information processing through which shared understanding and predictive knowledge are developed. *No Communication* serves as the reference category. *Coordination* takes a value of 1 if subjects agree upon a search procedure and implement it, and of 0 if they agree upon a search procedure but do not implement it, while it is not defined (NA) if they do not agree on a search procedure. The variable captures coordination as the (intended) alignment of the participants' actions (Gulati et al., 2012).

The variable *Coordination* is instrumental for coding joint actions, as specified by the following variables. *Coordinated Repeated Actions* is a binary variable that measures if the dyad repeatedly implements the same agreed-upon procedure for more than one trial. The variable captures relationship-specific repeated action sequences [1] that are an outcome of the coordination process. *No Coordinated Repeated Actions* serves as the reference category. To

[1] Examples of such action sequences include the following: the dyad agrees that everyone makes only one change per round; the dyad agrees to mirror each other's actions (e.g., both change the second attribute from the top of their module's symbol list); the dyad agrees that one agent moves with many changes while the other agent makes only few changes; the dyad agrees "to copy" the other agent's changes in the last round. Overall, the dyads were rather creative and came up with a lot of different patterns of such coordinated actions.

shed light on the nature of search that the dyad is conducting we rely on the variable *Sequential Search*. It takes the value of 1 for *Sequential Search*, that is only one human agent makes at least one change in her or his own module, and the value of 0 for *Parallel Search*, that is both human agents make at least one change in their own module. *Parallel Search* serves as the reference category. The variable captures the allocation of joint search effort over time.

To appraise adaptation to performance feedback in joint search, we coded two measures: system-level performance feedback and module-level performance feedback. *System Failure* takes value of 1 if in the most recent trial the dyad did not manage to achieve a performance improvement relative to the best-performing overall combination that it had identified in prior trials (failure), and 0 otherwise (success). Drawing upon prior models of adaptive search (Billinger et al., 2014, 2021), the variable captures adaptation in response to aggregate performance outcomes. *Module Failure* is the vector obtained through the Multiple Correspondence Analysis (MCA)[2] of the performance feedbacks that the first and the second subjects independently received relative to their own module, each taking value of 1, if in the last trial, the subject of interest did not manage to achieve a performance improvement relative to the best-performing module combination that she or he identified in prior trials (failure), and 0 otherwise (success). In both *System Failure* and *Module Failure*, *Success* serves as the reference category. Finally, in assessing perfomance, we include a count variable for the number of *Trial*, which is necessary to estimate the performance implications of *Incentives* as well as *Coordinated Repeated Action* (and *Sequential Search*) over time. A summary of all variables can be found in Table 1.

Table 1 about here

2 MCA is the counterpart of Principal Component Analysis (PCA) in the analysis of categorical variables. Here, it is used to avoid the collinearity issues that would derive from using Module 1 Feedback and Module 2 Feedback simultaneously (see Abdi and Valentin, 2007 for a review). The first-best dimension (i.e., what in PCA would be the "principal component," namely the best-fitting vector) that we use accounts for 81.1% of the variance in the data.

3.5 Model specifications

To test our hypotheses regarding search behavior, we extend the 2-stage model of adaptive search by individuals, as introduced by Billinger et al. (2021), to joint search. Accordingly, we use a 2-stage Heckman regression (Heckman, 1979) to examine how dyads first make a decision about whether to stop or continue searching, and then about where to search. In the first stage, the Heckman procedure fits a Probit regression to estimate the likelihood of *Active Search*, which is a binary variable. In the second stage, it fits a linear regression to estimate *Search Distance*, which is a continuous variable, conditional on *Active Search*.

In the model of adaptive search by individuals, the exclusion restriction for estimating the first stage is given by the payoffs received in the first three trials, which promotes the early-stage anchoring of expectations relative to feasible or available performance, thereby affecting the decision to stop or continue searching (Wilson et al., 1996; Billinger et al., 2021). This approach is not suitable to joint search, where epistemic interdependence is likely to create mutual confusion and compromise early-stage anchoring. Therefore, in the model of joint adaptive search, we assume that the exclusion restriction for estimating the first stage is given by *Lateral Communication*. The rationale is that, in the presence of cross-module interdependence, communication counters mutual confusion by fostering the development of the shared understanding and predictive knowledge necessary for successful coordination efforts, thereby affecting the decision to jointly stop or continue searching.

To evaluate joint search behavior, in connection with the 2-stage model, we regress Active Search (Stage 1) and Search Distance (Stage 2) on *Incentives*, *System Failure*, *Module Failure*, and the interaction between *System* and *Module Failure*, further controlling for *Sequential Search*, *Coordinated Repeated Actions*, and the interaction between *Coordinated Repeated Actions* and *Sequential Search*. *Lateral Communication* acts as exclusion restriction in the selection equation conveyed by *Active Search*. As for the performance implications, the analysis is conducted on subsamples by splitting observations according to *Low* and *High Module Interdependence*, respectively. This is necessary to test our hypotheses on the effect of *Incentives* over time under *Low* and *High Interdependence* (which would have otherwise required a three-way interaction term between *Incentives, Interdependence,* and *Trial).* On this premise, we regress *Maximum and Average Performance* on *Lateral Communication, Incentives, Trial,* and the interaction between *Incentives* and *Trial,* as well as between *Sequential Search* and *Trial, Coordinated Repeated Action* and *Trial,* and *Coordinated Repeated Actions and Sequential Search*.

Figure 1 about here

To improve interpretability, all scale predictors are standardized by subtracting their mean and dividing by two standard deviations. Subtracting the mean improves the interpretation of main effects when interactions are present while dividing by two standard deviations makes the relevant variables directly comparable to binary variables (Gelman, 2008). Moreover, as independent variables of the experimental design, *Interdependence* and *Incentives* are time-invariant higher-level variables. It follows that the fixed effect model is not relevant to our purpose, as it cannot appraise variables that do not vary within a group. Therefore, we resort to a random effect (RE) model, with random intercepts for each dyad and robust standard errors clustered by dyads.

4. Results

Figure 1 displays the percentage of dyads with jointly active searchers for *Local* and *Global Incentives* under *Low* and *High Interdependence*, respectively. The proportion of dyads with *Local* or *Global Incentives* at the end of the search process is similar regardless of the level of *Interdependence* (*Local*: 62%; *Global*: 32%): under *Low Interdependence*, the search process consists of an average of 10.43 active trials when *Incentives* are *Local,* and 9.84 active trials when *Incentives* are *Global*. The search process stops around trial 17 under *Local Incentives*, and around trial 19 under *Global Incentives*. Under *High Interdependence*, the search process involves on average 10.06 active trials when *Incentives* are *Local,* and 8.65 active trials when *Incentives* are *Global*. Moreover, the search process stops around trial 18 under *Local Incentives*, and around trial 16 under *Global Incentives*. In line with expectations, *Global Incentives* to some degree promote more stability than *Local Incentives*, especially when *Interdependence* is *High*.

Figure 2 distinguishes in separate graphs the relative proportion of dyads undertaking *Parallel* and *Sequential Search* when an agreed-upon procedure is implemented only once (i.e., *Coordination* = *1* and *Coordinated Repeated Actions* = 0) and when the same agreed-upon procedure is repeatedly implemented in more than one trial (i.e., *Coordination* = *1* and *Coordinated Repeated Actions* = 1). As evident in all experimental conditions, the overall proportion of dyads implementing one-shot coordinated actions decreases over time, going from over 75% to 10–15% (upper four graphs). In contrast, the proportion of dyads implementing coordinated repeated actions for more than one round rises sharply, going from 0% to at least 75% (lower four graphs). While in the case of one-shot coordinated actions the great majority of dyads make changes in parallel, progressively more dyads agree to make changes sequentially as coordinated repeated actions take over. Still, in the later phase of the search process, the proportion of dyads making changes in parallel picks up again, especially when *Incentives* are *Global*.

Figure 2 about here

Figure 3 displays the mean of full-scale *Search Distance* (from 0 to 10) of *Parallel* and *Sequential Search* when an agreed-upon procedure is implemented only once (i.e., *Coordination* = *1 and Coordinated Repeated Actions* = *0*) and when the same agreed-upon procedure is repeatedly implemented for more than one trial (i.e., *Coordination* = *1 and Coordinated Repeated Actions* = *1*). Overall, the *Search Distance* of one-shot coordinated actions (M = 3.57, SD = 0.96) is significantly broader (Mann–Withney U = 918, $P < 0.001$) than that of coordinated repeated actions (M = 0.83, SD = 1.41). More specifically, for one-shot coordinated actions, the average *Search Distance* of *Parallel Search* is always broader than that of *Sequential Search* under both *Local* and *Global Incentive*s, regardless the level of *Interdependence*. For coordinated repeated actions, the differences between the average *Search Distance* of *Parallel Search* and *Sequential Search* become negligible under *Local Incentives*, which result in slightly-broader-than-incremental changes for both, regardless the level of *Interdependence*.

Discernible differences, however, arise under *Global Incentives*, which promote small incremental changes when *Interdependence* is *Low*, and the sheer stopping of the search process when it is *High*.

Figure 3 about here

Table 2 displays the regression models for search behavior. Odd-numbered models fit the first-step RE Heckman Probit regression for stopping. The dependent variable consists of *Active Search*. Even-numbered models fit the second-step RE Heckman linear regression for the search distance of active searchers. The dependent variable consists of *Search Distance*, ranging between 1 and 10. Starting with the exclusion restriction, the regression results indicate that *Lateral Communication* increases the likelihood of *Active Search* ($P < 0.001$ in models 1 and 3). Importantly, the effect becomes not significant as we control for *Coordinated Repeated Actions* ($P > 0.05$ in models 5 and 7). This suggests that information processing through *Lateral Communication* promotes the development of shared understanding and predictive knowledge, until subjects learn to search collaboratively through coordinated repeated action sequences and thereby identify a way to substitute lateral communication. The results therefore provide evidence in support of H1a, while also adding further nuances to its rationale.

Focusing on experimental conditions, *Global Incentives* reduce the likelihood of *Active Search* ($P < 0.001$ in models 1, 3, 5, and 7). The negative effect on *Search Distance* is in the expected direction, but not significant ($P > 0.05$ in models 2, 4, 6, and 8). This suggests that *Global Incentives* motivate dyads to refraining from taking actions that might hurt them, thereby increasing the likelihood to jointly stop searching. However, *Global Incentives* do not motivate subjects to seek new alternatives close to the status quo. The results therefore provide evidence in support of H2a but not in support of H2b. *High Interdependence* has no significant effect on *Active Search* or *Search Distance*. The same goes for the interaction between *Incentives* and *Interdependence*.

Turning to joint adaptation, the likelihood of *Active Search* decreases in response to *System Failure* given *Module Success* ($P < 0.001$ in models 1 and 3) as well as *Module Failure* given *System Success* ($P < 0.05$ in models 1 and 3), which therefore enhances the main effects of *System Failure* and *Module Failure*, respectively. Further, it decreases in response to the interaction of *System* and *Module Failure* ($P < 0.001$ in models 1 and 3). These effects however disappear as we control for *Coordinated Repeated Actions* ($P > 0.05$ in models 5 and 7). *Search Distance* does not broaden in response to *System Failure* ($P > 0.05$ in all models), but it does in response to *Module Failure* ($P > 0.001$ in all models). Most notably, *Search Distance* narrows in response to the interaction of *System Failure* and *Module Failure* ($P < 0.01$ in model 2 and $P < 0.05$ in model 4), which buffers the main effect of *Module Failure*. These effects are preserved as we control for *Coordinated Repeated Actions* ($P < 0.001$ for all estimates in models 6 and 8), with the interaction between *System Failure* and *Module Failure* even reversing the main effect of *Module Failure*. This suggests that individuals learn to search collaboratively by trial and error, with the selection (stopping) and adjustment (broadening or narrowing search) of agreed-upon procedures being informed by the covariates *System* and *Module Failure*, where the latter is particularly relevant for increasing search distance. Thereafter, dyads settle on *Coordinated Repeated Actions*, which are further adjusted (broadening or narrowing search) in response to the covariate *System* and *Module Failure*. These results provide evidence in support of H4a but not H4b. Overall, the insights that derive from this exploratory analysis shed new light on the role of system-level and module-level feedback in shaping collaborative search in imperfectly decomposed systems.

The regression results further indicate that *Sequential Search* reduces the likelihood of *Active Search* ($P < 0.001$ in model 7), while also narrowing *Search Distance* ($P < 0.001$ in model 8). What is more, *Coordinated Repeated Actions* reduce the likelihood of *Active Search* ($P < 0.001$ in model 7), although they have no immediate effect on *Search Distance* ($P < 0.05$). This notwithstanding, the interaction between *Coordinated Repeated Actions* and *Sequential Search* increases the likelihood of *Active Search* ($P = 0.001$ in model 7), while also broadening *Search Distance* ($P < 0.05$ in model 8). This suggests that, as subjects have established coordinated repeated actions, their collaborative search relies on agreed-upon procedures. If these procedures involve *Sequential Search*, the dyads jointly experiment with incremental changes (see also Figure 3).

Table 2 about here

Figure 4 displays the mean *Maximum Performance* of parallel and sequential searches when an agreed-upon procedure is implemented only once (i.e., *Coordination = 1 and Coordinated Repeated Actions* = *0*) and when the same agreed-upon procedure is repeatedly implemented in more than one trial (i.e., *Coordination = 1 and Coordinated Repeated Actions* = *1*), respectively. In general, the *Maximum Performance* achieved through one-shot coordinated actions (M = 0.82, SD = 0.06) is significantly lower (Mann–Whitney U = 8291, P < 0.001) than that achieved through coordinated repeated actions (M = 0.87, SD = 0.06). This suggests that, as joint active searchers learns to search collaboratively, they tend to settle on an agreed-upon procedure that has proven effective. From a different perspective, this may also imply that, once an effective procedure has been identified, making long jumps through one-shot repeated actions (that, as can be seen in Figure 3, are typically characterized by a higher search distance) can be detrimental. More specifically, for one-shot repeated actions, *Sequential Search* leads to a higher *Maximum Performance* than *Parallel Search*, regardless the *Incentives* or the level of *Interdependence*. For coordinated repeated actions, in contrast, the *Maximum Performance* of parallel and sequential searches appears to be approximately the same in all experimental conditions.

Figure 4 about here

Figure 5 displays the mean *Average Performance* of parallel and sequential searches when an agreed-upon procedure is implemented only once (i.e., *Coordination* = *1 and Coordinated Repeated Actions* = *0*) and when the same agreed-upon procedure is repeatedly implemented in more than one trial (i.e., *Coordination* = *1 and Coordinated Repeated Actions* = *1*). Clearly, *Average Performance* exhibits a similar pattern to *Maximum Performance*. In particular, the *Average Performance* yielded by one-shot coordinated actions (M = 0.64, SD = 0.04) is significantly lower (Mann–Whitney U = 10 288, P < 0.001) than that yielded by coordinated repeated actions ($M = 0.72$, SD = 0.04). This suggests that, as the dyad learns to search collaboratively, settling on an agreed-upon procedure that has proven effective offers the possibility to maximize the average stream of (joint) payoffs. Further, this implies that making long jumps through one-shot coordinated actions (see Figure 3), which deviate from the agreed-upon procedure that has proven effective, is likely to have an adverse effect on *Average Performance*. For one-shot repeated actions, the *Average Performance* of *Sequential Search* is higher than that of *Parallel Search*, regardless the *Incentives* or the level of *Interdependence*. For coordinated repeated actions, parallel and sequential searches lead to no significant differences in *Average Performance* in any of the experimental conditions. This pattern mirrors that of *Maximum Performance*.

Figure 5 about here

Table 3 displays the regression models on performance. Odd-numbered models fit the RE linear models for *Maximum Performance*. The dependent variable is the cumulative maximum of the best-performing combinations from the first to the last trial. Even-numbered models fit the RE linear models for *Average Performance*. The dependent variable is the cumulative mean of the payoffs from the first to the last trial. The regression results indicate that *Lateral Communication* increases *Maximum Performance* under both *Low Interdependence* ($P < 0.01$ in model 1) and *High Interdependence* ($P < 0.05$ in model 3). The negative effect on *Average Performance* is in the expected direction but not significant ($P > 0.05$ in models 2 and 4). This suggests that information processing through *Lateral Communication* supports the discovery of better-performing alternatives, while it has no immediate influence on the maximization of the average stream of (joint) payoffs. The results therefore provide evidence against H1b relative to *Maximum* as well as *Average Performance*.

Global Incentives increase *Maximum Performance* under *Low Interdependence* ($P < 0.001$ in model 1). Notably, the interaction between *Global Incentives* and the number of *Trial* reduces *Maximum Performance* under the same condition. Although in the expected direction, the relevant effect is not significant ($P > 0.05$ in model 1). Even so, the interaction between *Global Incentives* and the number of *Trial* increases *Average Performance* under *High Interdependence* ($P < 0.05$). Combined, these findings suggest that *Global Incentives* facilitate the discovery of better-performing system-level alternatives over the short run when the level of *Interdependence* is *Low*. Further, under *High Interdependence*, *Global Incentives* enhance the maximization of the stream of (joint) payoffs over the long run. The results therefore provide evidence in (partial) support of H3a and in (full) support of H3b.

Finally, *Sequential Search* increases *Maximum Performance* ($P < 0.01$ in model 1 and $P < 0.001$ in model 3) as well as *Average Performance* ($P < 0.01$ in models 2 and 4), with the effect being stronger under *High Interdependence*. Most notably, *Coordinated Repeated Actions* increase *Average Performance* ($P \leq 0.001$ in models 2 and 4), with the effect again being stronger under *High Interdependence*. Still, the interaction between *Coordinated Repeated Actions* and the number of *Trial* reduces *Maximum Performance* ($P < 0.001$ in models 1 and 3) as well as *Average Performance* ($P < 0.001$ in models 2 and 4). Once more, the relevant effects are stronger under *High Interdependence*. This suggests that the repetition of the agreed-upon procedure that has proven effective hinders the ability to uncover better-performing combinations. Nonetheless, search based on *Coordinated Repeated Actions* enables subjects to maximize their average stream of (joint) payoffs. The maximizing effect of collaborative search through *Coordinated Repeated Actions* however decays over time with the effect still being stronger when the degree of interdependence is higher. This indicates that, although search based on coordinated repeated actions initially helps improve performance, the involved joint myopia can lead to a competency trap and make it detrimental unless the effective and yet suboptimal procedure that is embraced is abandoned at some point. These dynamics are most pronounced when the level of *Interdependence* between modules is *High*.

Table 3 about here

5. Robustness tests

We confront results from the two-stage RE Heckman models on search behavior with those from (i) single-equation RE Probit models on *Active Search*; (ii) single-equation RE Poisson on

Search Distance (from 1 to 10); and (iii) unified linear models on the full-scale *Search Distance* (from 0 to 10) of joint searchers. For each of the above classes, we fit two main models: before and after the introduction of *Coordinated Repeated Actions* (and their interaction with the *Parallel Search*). All the models produce qualitatively similar results to the RE Heckman models.

However, as a standalone, the single-equation RE Probit model is less appropriate to assess the decision of whether to stop or continue searching (*Active Search*). Indeed, this decision would be better investigated using a Cox Survival model, which does not allow introducing random effects while also clustering standard errors. The impossibility to use a Cox Survival model therefore strengthens the robustness of the estimates produced through the RE Probit model in the context of the first stage of the RE Heckman approach.

Regarding search distance, the RE Poisson model is in principle more suited than a linear model to assess the decision of where to search. The compatibility of the results from the Poisson model therefore strengthens the robustness of the estimates produced through the linear model in the context of the second stage of the RE Heckman approach.

As per the unified linear model, it does not allow disentangling whether the effects of the explanatory variables impact the decision of whether to search (*Active Search*) or the decision of where to search (*Search Distance*). As a consequence, the results from the unified linear model are causally ambiguous, thereby hinting to the methodological superiority of the RE Heckman approach.

We also confront the results from the RE linear models on performance with alternative specifications of the models of interest. In particular, to probe possible nonlinearities in the effect of *Lateral Communication*, we test models in which we interact the relevant variable with the number of *Trial*. However, the introduction of this interaction term prevents some models from converging. [3]

[3] Future research may investigate the issue of nonlinearities in the effect of *Lateral Communication* through purposefully designed

In addition, to further survey the effect over time of *Incentives*, *Sequential Search*, and *Coordinated Repeated Actions*, we test further models in which their interaction with the number of *Trial* is replaced with a quadratic term for each of the variables in question. Although converging, the models drop the squared terms due to collinearity.

The results from the robustness tests strengthen the findings of the baseline specifications reported above.

6. Discussion and conclusions

We conducted a laboratory experiment to investigate the search behavior of dyads who operated in imperfectly decomposed systems without a coordinating hierarchy. Using a 2 × 2 factorial design that varied local vs. global incentives and high vs. low levels of cross-modular interdependence, we examined how both factors shape joint search and performance. We found that, in all experimental conditions, dyads learn to search collaboratively by coordinating their actions—even in conditions with many cross-modular interdependencies and misaligned incentives. This finding is unexpected, as it highlights the potential efficacy of bilateral coordination, which develops endogenously and is different from coordination by a higher-level decision maker. Our analysis shows that most dyads initially search in parallel, then sequentially, and eventually terminate their search by settling on a well-performing solution. Dyads typically develop and experiment with coordinated joint actions using one-shot attempts that they assess for their viability. If a coordinated action is effective, they then adjust to repeat the search procedure. The result is a coordinated repeated action that both agents pursue as they collaboratively search an imperfectly decomposed system.

These findings have several implications. First, our results highlight that poor modular decompositions may prove effective even in the absence of hierarchy. Much prior work has pointed to authority and top-down decision making to facilitate coordination across modules.

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experiments, in which no communication is contrasted, for example, with low, moderate, and high levels of communications.

We show that coordination can endogenously emerge and provide the basis for the joint action. This finding offers a basis for explaining why less-hierarchical structures (Lee and Edmondson, 2017; Billinger and Workiewicz, 2019) may be effective despite the challenges they face. Moreover, the fact that dyads are not only able to overcome coordination problems but also cooperation problems is pivotal. Even when dyads were exposed to misaligned incentives and frequently faced situations in which one agent's module-level performance was inferior to that of the other agent, we identified noncooperative behavior in only 0.44% of all trials. The human agents clearly understood that the task involved imperfect decompositions that required trial-and-error search that may have detrimental effects on their own (module-level) performance. This raises important questions for the design of modularity and the limits of coordination, and more specifically, the amount of negative feedback that individual human agents are willing to accept in an imperfectly decomposed system.

Second, the findings suggest that dyads engaging in collaborative search develop coordinated repeated actions by endogenously and jointly developing search procedures that they test with one-shot experiments. Such coordinated repeated actions are likely to be crucial for the dyad to develop procedural memory (Cohen and Bacdayan, 1994) or a transactive memory system (Kirschner *et al.*, 2011; Miller *et al.*, 2014; Argote and Guo, 2016) that can become the basis for routinization (Lazaric and Denis, 2005; Bapuji *et al.*, 2012; Cacciatori, 2012). It is worth noticing that the dyads, on average, progressively develop these joint operating procedures over time without going through distinct stages such as, for example, the ones described by the Form– Storm–Norm–Perform model (Tuckman, 1965; Bonebright, 2010). It is also unclear when a coordinated repeated action becomes a *standardized* operating procedure (Nelson and Winter, 1982). Some human dyads in our experiment, before settling on one coordinated repeated action sequence, were instantly ready to abandon an identified operating procedure (and 6.25% of the dyads even temporarily abandoned a coordinated repeated action, i.e., a procedure they even identified as effective earlier on!). These findings suggest that the establishment of standardized operation procedures, or the emergence of routines, may involve rather fragile processes that need further investigation.

Third, search that is conducted by two independently acting human agents is typically confronted with epistemic interdependence (Puranam *et al.*, 2012), which creates mutual confusion (Knudsen and Srikanth, 2014). Our findings show that dyads manage to eliminate mutual confusion by adopting sequential search. One would expect that especially local incentives would inspire individual human agents to engage in search independent of the other agent. However, we find that sequential search becomes the predominant way to engage in collaborative search after an initial period of parallel search. It seems that transparency, and in particular module-level *and* system-level feedback, denote a powerful way to make a human agent realize that individual isolated action, without consideration of the other agent, is detrimental for everyone involved. These findings shed novel light on the role of transparency in imperfectly modular systems, and the need to better understand mechanisms capable of instilling forms of discipline without hierarchal intervention.

Finally, our study provides some evidence suggesting that endogenously emerging joint action may offer an initial step toward capability development. Prior literature already highlights the importance of mutually-agreed transactions (Baldwin, 2008), and puts an emphasis on transaction costs and the role of hierarchal or institutional structures (Jacobides, 2006, Jacobides and Winter, 2005). We show that agents facing a nonhierarchical situation in which gains and losses cannot be attributed unambiguously within a modular structure, ultimately have to rely on coordinated joint action and collaborative search to navigate in the modular structure. Our results suggest that agents who pursue this collaborative search are, by doing so, also taking initial steps toward capability development on the microlevel. Our setting is characterized by a predefined given division of labor in which a static assignment of tasks to agents resembles a core aspect of the modular structure and thereby becomes a starting point for endogenously emerging joint action and capability development.

In concluding, our paper is concerned with imperfectly implemented decompositions in modular structures and human agents who operate within these structures. The picture the findings paint of this challenging situation, however, is quite positive. For ensuring that joint search in similar conditions is coordinated, canonic strategies suggest either to minimize the degree of interdependence ex ante by decomposing complex systems into larger modules (Ethiraj and Levinthal, 2004) or to deal with them ex post by employing a coordinating "systems integrator" or providing global incentives (Rivkin and Siggelkow 2003; Siggelkow and Rivkin, 2005). Adding to these basic solutions, our paper provides evidence for an additional approach—teams or groups of module-level agents learning to search jointly by endogenously developing joint repeated actions. The fact that these patterns occur endogenously underscores an underappreciated ability of humans to interact in imperfectly decomposed modular systems and to use it as an opportunity to overcome coordination and cooperation challenges.

Supplementary data

Supplementary data are available at *Industrial and Corporate Change* online.

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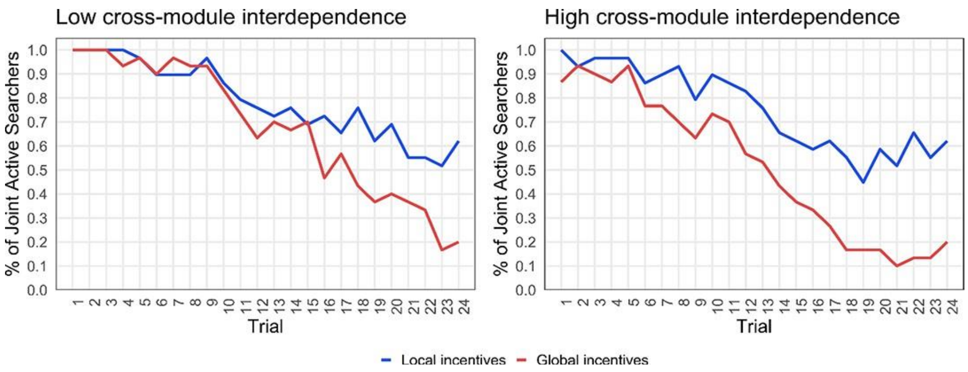

Figure 1. Percentage of joint active searchers

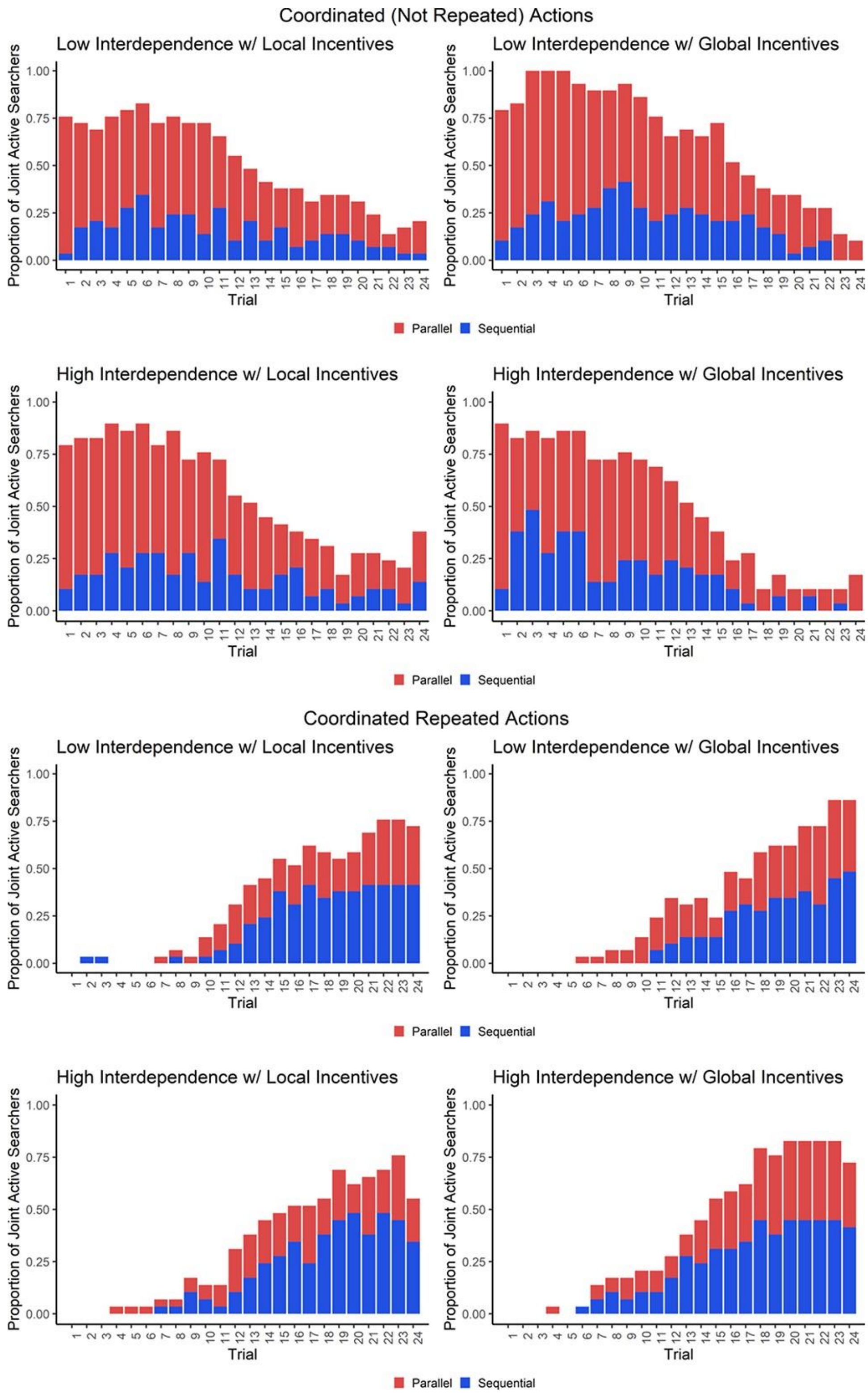
Coordinated (Not Repeated) Actions
Low Interdependence w/ Local Incentives
Low Interdependence w/ Global Incentives
High Interdependence w/ Local Incentives
High Interdependence w/ Global Incentives
Coordinated Repeated Actions
Low Interdependence w/ Local Incentives
Low Interdependence w/ Global Incentives
High Interdependence w/ Local Incentives
High Interdependence w/ Global Incentives
Proportion of Joint Active Searchers
0.00
0.25
0.50
0.75
1.00
Trial
Parallel
Sequential

Figure 2. Relative proportion of active searchers undertaking parallel and sequential searches

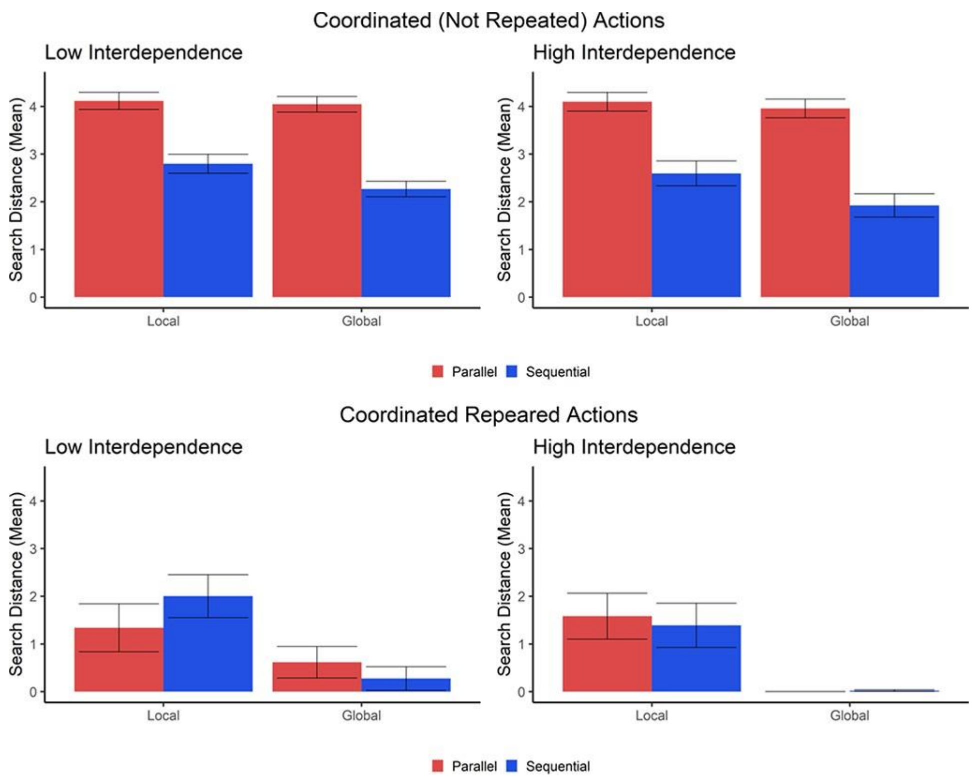

Figure 3. Search distance under parallel and sequential searches

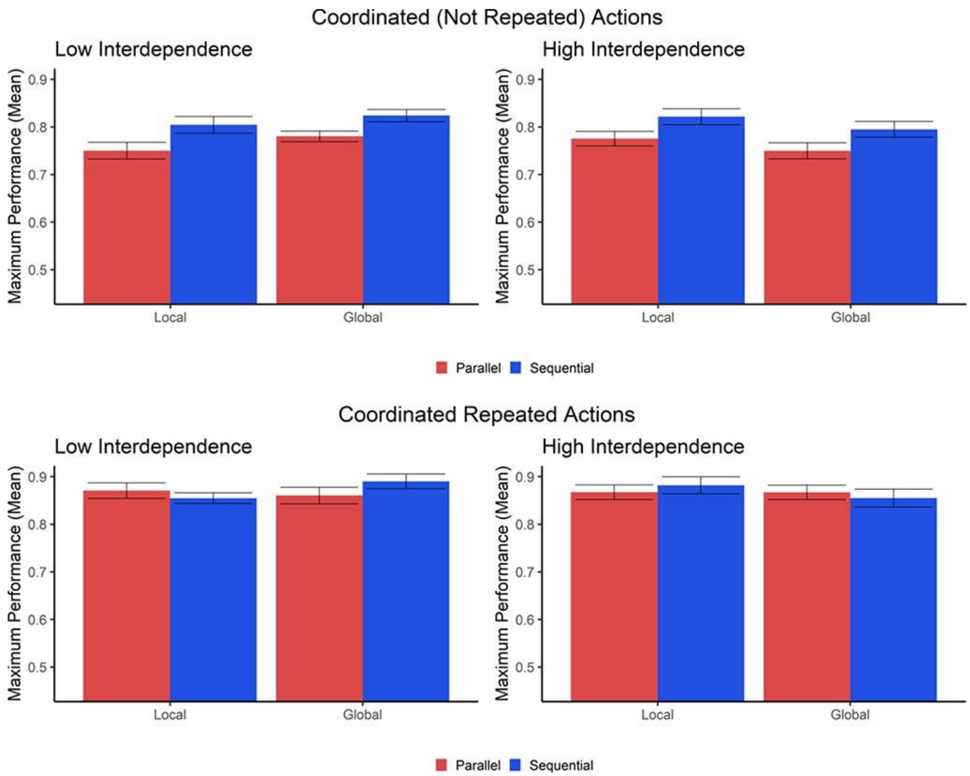

Figure 4. Maximum performance under parallel and sequential searches

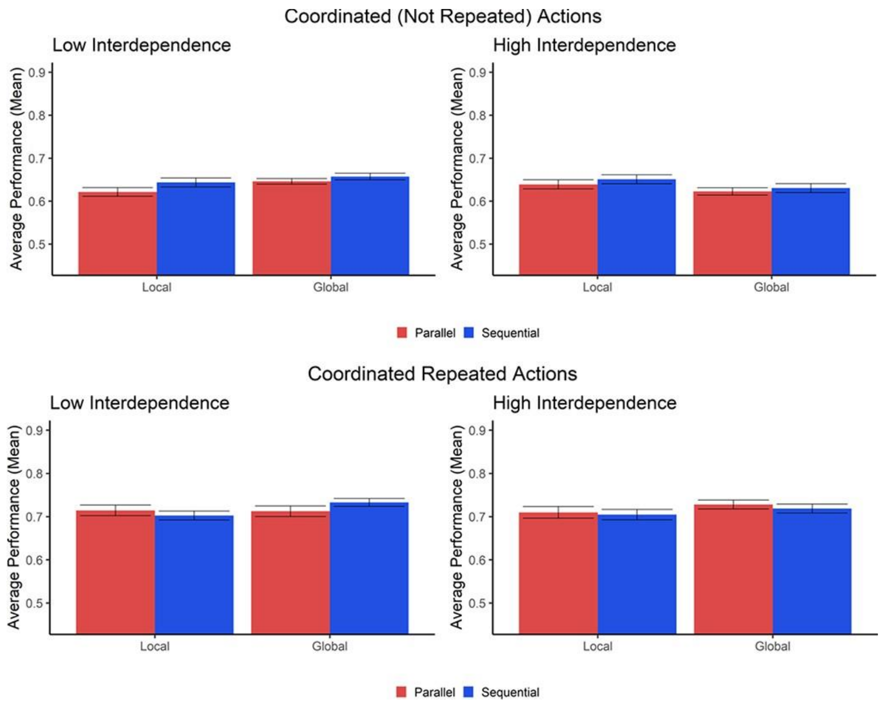

Figure 5. Average performance under parallel and sequential searches

Table 1. Main Variables

Name	Type	Min	Max	Mean	SD	Explanation
Interdependence	Dummy	0	1	-	-	Low cross-module interdependence (K_{Within} = 1, $K_{Between}$= 1) is coded with 0; High cross-module interdependence (K_{Within} = 1, $K_{Between}$= 4) with 1
Incentive	Dummy	0	1	-	-	Local incentives are coded with 0; Global incentives with 1
Active Search	Dummy	0	1	0.70	0.20	Positive search distance in any subsequent round is coded with 1; otherwise 0
Search Distance	Count	0	10	2.48	1.14	Number of changed attributes relative to status quo (Hamming distance)
Average Performance	Scale	0.33	1	0.65	0.04	Cumulative average of payoffs from the first to the last trial
Maximum Performance	Scale	0.33	1	0.82	0.05	Highest payoffs from the first to the last trial
Lateral Communication	Dummy	0	1	-	-	Two-way communication is coded with 1; otherwise 0
Coordination	Dummy	0	1	-	-	Alignment of actions is coded with 1 when a search procedure is agreed-on and implemented; 0 if agreed-on but not implemented; NA if not agreed.
Coordinated Repeated Actions	Dummy	0	1	-	-	Implementation of the same agreed-on search procedure is coded with 1; otherwise 0
Sequential Search	Dummy	0	1	-	-	Sequential search (i.e., only one agent makes one or more changes) takes value of 1; parallel search (i.e., both agents make one or more changes) of 0
System Failure	Dummy	0	1	0.20	0.06	Failure to improve status quo is coded with 1; success with 0
Module Failure	Scale	-	-	-	-	First-best dimension minimizing information loss from the MCA of the Module 1 and Module 2 Failure
# Trial	Count	1	24	-	-	Number of the current trial

Table 2. RE Heckman Regression Models on Search Behavior

	(1) Active Search	(2) Search Distance	(3) Active Search	(4) Search Distance	(5) Active Search	(6) Search Distance	(7) Active Search	(8) Search Distance
Lateral Communication	1.058***		0.985***		0.218		0.232	
	(0.137)		(0.139)		(0.144)		(0.141)	
	[0.000]		[0.000]		[0.131]		[0.099]	
Global Incentives	-0.720***	-0.157	-0.743***	-0.254	-1.111***	-0.162	-1.051***	-0.094
	(0.207)	(0.233)	(0.203)	(0.225)	(0.214)	(0.195)	(0.221)	(0.188)
	[0.000]	[0.500]	[0.000]	[0.258]	[0.000]	[0.406]	[0.000]	[0.618]
High Interdependence	-0.277	-0.097	-0.258	-0.131	-0.303	-0.113	-0.278	-0.066
	(0.234)	(0.261)	(0.239)	(0.256)	(0.284)	(0.254)	(0.269)	(0.238)
	[0.236]	[0.712]	[0.279]	[0.609]	[0.285]	[0.656]	[0.301]	[0.781]
Global Inc. * High Interdep.	0.072	-0.194	0.073	-0.115	0.031	-0.097	-0.011	-0.147
	(0.300)	(0.349)	(0.298)	(0.316)	(0.326)	(0.320)	(0.319)	(0.306)
	[0.812]	[0.578]	[0.806]	[0.715]	[0.925]	[0.762]	[0.972]	[0.630]
System Failure	-0.487***	-0.225	-0.437**	-0.142	0.130	-0.235	0.167	-0.221
	(0.137)	(0.152)	(0.142)	(0.145)	(0.168)	(0.135)	(0.170)	(0.135)
	[0.000]	[0.139]	[0.002]	[0.328]	[0.439]	[0.082]	[0.325]	[0.100]
Module Failure	-0.272*	0.663***	-0.314*	0.559***	-0.178	0.561***	-0.184	0.551***
	(0.127)	(0.123)	(0.140)	(0.104)	(0.147)	(0.103)	(0.158)	(0.102)
	[0.031]	[0.000]	[0.025]	[0.000]	[0.224]	[0.000]	[0.245]	[0.000]
System.Failure* Module Failure	-1.097***	-0.587**	-1.064***	-0.504*	-0.242	-0.633***	-0.344	-0.621***
	(0.231)	(0.201)	(0.233)	(0.204)	(0.291)	(0.184)	(0.297)	(0.185)
	[0.000]	[0.003]	[0.000]	[0.013]	[0.405]	[0.001]	[0.247]	[0.001]
Sequential Search			-0.575***	-1.167***	-0.332*	-1.239***	-0.762***	-1.346***
			(0.145)	(0.136)	(0.159)	(0.127)	(0.160)	(0.125)
			[0.000]	[0.000]	[0.037]	[0.000]	[0.000]	[0.000]
Coordinated Repeated Actions					-2.985***	0.950*	-3.477***	0.324
					(0.185)	(0.482)	(0.240)	(0.388)
					[0.000]	[0.049]	[0.000]	[0.405]
Repeated Actions * Sequential Search							0.989**	1.337*
							(0.302)	(0.533)
							[0.001]	[0.012]
Constant	0.957***	4.290***	1.215***	4.619***	2.599***	4.608***	2.727***	4.601***
	(0.204)	(0.191)	(0.218)	(0.183)	(0.254)	(0.185)	(0.261)	(0.179)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	2,784	2,784	2,784	2,784	2,784	2,784	2,784	2,784
Pseudo-Likelihood		-5252.9349		-5131.2496		-4562.6744		-4534.6244
χ^2		254.69		338.68		497.08		660.75
		[p < 0.000]		[p < 0.000]		[p < 0.000]		[p < 0.000]

Robust standard errors in parentheses, p values in brackets. The scale predictors are standardized (by subtracting the mean and dividing by two standard deviations). All models include a random intercept for each dyad and robust standard errors clustered by dyads. *** p<0.001, ** p<0.01, * p<0.05

Table 3. RE Linear Models on Performance

	Low Interdependence Between Modules		High Interdependence Between Modules	
	(1)	(2)	(3)	(4)
	Maximum Performance	Average performance	Maximum Performance	Average Performance
Lateral Communication	0.015**	-0.001	0.011*	-0.001
	(0.005)	(0.004)	(0.006)	(0.004)
	[0.003]	[0.782]	[0.043]	[0.848]
Global Incentives	0.022***	0.013	-0.005	0.004
	(0.004)	(0.008)	(0.014)	(0.010)
	[0.000]	[0.117]	[0.708]	[0.649]
Global Inc. * Trial	-0.016	0.000	-0.007	0.020*
	(0.014)	(0.010)	(0.015)	(0.010)
	[0.255]	[0.966]	[0.642]	[0.039]
Sequential Search	0.012**	0.007**	0.016***	0.011**
	(0.005)	(0.002)	(0.005)	(0.004)
	[0.009]	[0.003]	[0.001]	[0.002]
Sequential Search * Trial	0.015	-0.001	0.005	-0.002
	(0.011)	(0.007)	(0.011)	(0.008)
	[0.203]	[0.871]	[0.681]	[0.756]
Coordinated Repeated Actions	0.007	0.020**	0.015	0.022***
	(0.008)	(0.006)	(0.008)	(0.006)
	[0.410]	[0.001]	[0.061]	[0.000]
Repeated Actions * Trial	-0.081***	-0.036***	-0.092***	-0.045***
	(0.011)	(0.007)	(0.012)	(0.008)
	[0.000]	[0.000]	[0.000]	[0.000]
Repeated Actions * Sequential Search	-0.003	-0.009	-0.023	-0.011
	(0.010)	(0.007)	(0.013)	(0.008)
	[0.745]	[0.250]	[0.066]	[0.189]
Trial	0.125***	0.112***	0.128***	0.110***
	(0.010)	(0.008)	(0.013)	(0.009)
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.803***	0.656***	0.843***	0.665***
	(0.005)	(0.007)	(0.012)	(0.008)
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1,416	1,416	1,368	1,368
	0.015**	-0.001	0.011*	-0.001
Pseudo-Likelihood	2114.2139	2733.2927	1967.4903	2590.1068
χ^2	272.84	727.33	191.33	810.16
	[p < 0.000]	[p < 0.000]	[p < 0.000]	[p < 0.000]

Robust standard errors in parentheses, p values in brackets. The scale predictors are standardized (by subtracting the mean and dividing by two standard deviations). All models include a random intercept for each dyad and robust standard errors clustered by dyads. *** p<0.001, ** p<0.01, * p<0.05