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Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA, MERCED

From a Dyad to a Flock – Complexity Matching to Loose Coupling

A dissertation submitted in partial satisfaction of the requirements  
for the degree Doctor of Philosophy

in

Cognitive and Information Sciences

by

Daniel Sean Schloesser

Committee in charge:

Professor Christopher Kello, Chair

Professor Ramesh Balasubramaniam

Professor Paul Smaldino

2021

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The Dissertation of Daniel S. Schloesser is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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University of California, Merced

2021

*To my family,  
whose love, kindness, and support helped shape the person I grew to be.  
You all mean the world to me, and I love you all.*

*To Eli, Leo, and Hlin,  
thank you for knowing when I needed comfort.  
Your love helped me more than you could ever know.*

*To Wrigley,  
the best buddy I could have asked for.  
Miss you always.*

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---

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Croker, S., Jordan, J. S., **Schloesser, D. S.**, Cialdella, V., & Dayer, A. (2016). Contextual Events and Their Role in a Two-Choice Joint Simon Task. Papafragou, A., Grodner, D., Mirman, D., & Trueswell, J.C. (Eds.) (2016). *Proceedings of the 38th Annual Conference of the Cognitive Science Society (pp. 1913-1918)*. Austin, TX: Cognitive Science Society.

Jordan, J. S., Bai, J., Cialdella, V., & **Schloesser, D. S.** (2015). Foregrounding the Background: Cognitive science as the study of embodied context. *Contextuality from Quantum Physics to Psychology*, 6, 209-227.

Croker, S., Jordan, J. S., **Schloesser, D.**, & Cialdella, V. (2015). The effects of racial similarity and dissimilarity on the joint Simon task. In D. C. Noelle, R. Dale, A. S. Warlaumont, J. Yoshimi, T. Matlock, C. D. Jennings, & P. P. Maglio, P. P. (Eds.) *Proceedings of the 37th Annual Meeting of the Cognitive Science Society* (pp. 489- 494). Austin, TX: Cognitive Science Society.

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From a Dyad to a Flock – Complexity Matching to Loose Coupling  
Daniel Sean Schloesser  
Doctor of Philosophy in Cognitive and Information Sciences  
University of California, Merced – 2021  
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**Abstract**

Ranging over a wide array of interactions, coordination comprises the simple to complex interactions that occur within our daily lives. Many events we encounter ask us to work alone or with a group to achieve a common goal. These goals frequently set the stage for how we find a deeper understanding of underlying principles of coordination. Here, began by focusing on the interaction between two individuals cooperating, and how coupling strength could modulate the connection shared between them. In these initial studies we found that principles and measures of complexity matching applied similarly within and between individuals, and perceptual-motor performance can be facilitated by loose response coupling. We concluded that complexity matching observed between individuals can similarly occur within one individual, suggesting a general principle of interaction at work. When response coupling was absent in the dyadic condition, the degree of complexity matching was significantly reduced. The connection shared between the coupled cooperative agents influenced their overall shared success. Expanding upon this research, we asked investigated coordination within larger groups. To do this, we need to find a situation that fit within coordination but allowed for larger group sizes.

A situation that fit these criteria existed in collective foraging. Collective foragers can coordinate and cooperate flexibly over time despite changes to task demands, connectedness, and environmental conditions. The coupling strength linking foragers together often shapes their collective movements. Based on this, we created a scenario where varying degrees of coupling strength bound cooperative agents together as they collectively coordinated their actions in search of hidden targets. We found that loose and flexible coupling among search agents improved collective performance, and that human players improved performance partly by subtle, indirect effects on group interactions. Loose coupling emerged among agents when the rules of interaction were weak enough for agents to act independently or interdependently, while still being strong enough to help hold them together. Movement patterns showed loose coupling enabled collections of agents to self-organize and reorganize into a greater diversity of ad hoc groupings. We continued this work by investigating the link between cooperative interactions among larger groups of agents, coupling strength, and group member effectiveness. By manipulating group member effectiveness, group members performed the search task better than before, but without human intervention, the individual movements of the more-optimal agents continued to lag humans. Based on these results, we successfully instilled a unique agent with a form of memory which helped them to act in more ‘human-like’ ways.

Taken together, this dissertation supports a broader narrative where coordination depends on the loose, and flexible alignment of available actions (Glassman, 1973; Kloos & Van Orden, 2009). This adaptive reorganization of behaviors is supported by an exchange of information, dependent upon the connections linking complex networks together (Nordham, Tognoli, Fuchs, & Kelso, 2018; Rigoli, Holman, Spivey, & Kello, 2014; Schloesser, Kello, & Marmelat, 2019; West, Geneston, & Grigolini, 2008). Future work may continue to uncover the underpinnings of interpersonal coordination – with humans, engineered agents, or both.

## Chapter 1

### 1.1. Introduction

Cooperative tasks bring people together to coordinate their actions to achieve shared goals. Some cooperative tasks can be simple, such as lifting and moving a table, while other tasks can be quite complex. For instance, group activities, such as multiplayer online video games, and team sports, such as soccer, typically require perceptual-motor coordination to occur both within and between individuals. In this way, the coupling of coordinated behaviors, which may range from an individual responding to a stimulus as quickly as possible to a group of subjects searching for hidden targets, unites people into a higher-order system to accomplish collective goals.

What makes human coordination “work” is our ability to anticipate the actions of others. Perceiving another person’s actions allows for behavioral adjustments to occur within others, thereby bringing about more successful coordination during cooperative tasks (Garrod & Pickering, 2009; Marsh, Richardson, & Schmidt, 2009; Valdesolo, Ouyang, & DeSteno, 2010). When acting alone, an individual already knows what to expect next, because, self-evidently, they are the only actor in the system. However, coordinated tasks become increasingly more complex when multiple people work together. In some cases, group coordination can often be more difficult because groups coordinate their actions in complicated ways (e.g., well-strategized soccer) without knowing exactly what will happen next (e.g., specific actions by other players). Frequently, groups rely on their experience acting alongside others, building strategies based on their stored memories and planning to anticipate and adapt during cooperative tasks. The primary goal of this dissertation was to investigate the nature of the connections binding individuals together, and how these connections may relate to underlying fundamental principles of coordination.

#### 1.1.1. Body Movement Dynamics Inform Us about the Other

A significant body of research has investigated the dynamics of body movements during joint activities. This research has been oriented toward understanding how people spontaneously and reciprocally influence each other during cooperative tasks (Nordham, Tognoli, Fuchs, & Kelso, 2018; Schmidt & O’Brien, 1997; Schmidt & Richardson, 2008). Often, researchers vary the extent to which partners can perceive the actions of the other, comparing these actions against responses made with no perceptual restrictions (Marmelat & Delignières, 2012a; Tolston, Shockley, Riley, & Richardson, 2014; Varlet, Coey, Schmidt, & Richardson, 2012). For example, research by Vesper and Richardson (2014) attempted to create an account for dyadic coupling where participants acted as a Leader or a Follower in a joint response “location” task. Leaders were cued by a light signal to respond at the indicated locations. Followers had to respond at the same location as the Leader, but Followers could not see the light cues. Followers attempted to do this under “Full” and “Partial” vision conditions. In the Full vision condition, Followers could see all the Leader’s movements. Conversely, in the Partial vision condition, Followers could only see the starting and finishing points of the movements performed by the Leader.

As expected, the coordination between Leaders and Followers depended on the coupling strength connecting their respective actions together (Vesper & Richardson, 2014). These findings suggest that with greater coupling strength, people are better able to coordinate with others (Newman-Norlund, Noordzij, Meulenbroek, & Bekkering, 2007; Sebanz, Knoblich, Prinz, & Wascher, 2006; Tomasello, Carpenter, Call, Behne, & Moll, 2005; Vesper & Richardson, 2014). Interestingly, when actions were partially occluded, the actions of Leaders became slower and more exaggerated, suggesting the cooperative strategies developed based on the coupling strength connecting the group together (Vesper & Richardson, 2014), i.e., changing their own behaviors to accommodate reaching a shared goal. This fascinating result is related to the concept of relational coordination, also known as metastability, soft-assembly, or loose coupling (Holden, 2005; Kello, Beltz, Holden, & Van Orden, 2007; Kello & Van Orden, 2009; Kloos & Van Orden, 2010, 2009). These concepts are striving to understand a similar construct: how emergent performance strategies depend on a complex system's ability to organize itself within the current context, while remaining open to changing if conditions change. Whether it is locomoting from one location to the next (Harrison & Richardson, 2009; von Holst, 1954) or coordinating actions within or between individuals (Coey, Kallen, Chemero, & Richardson, 2018; Coey, Varlet, & Richardson, 2012; Coey, Varlet, Schmidt, & Richardson, 2011; Fine, Likens, Amazeen, & Amazeen, 2015; Marmelat & Delignières, 2012; Scott Jordan, Schloesser, Bai, & Abney, 2018; Van der Wel, Knoblich, & Sebanz, 2011; Vesper & Richardson, 2014), behaviors are dependent on the context from which they originate. Vesper and Richardson (2014) showed how Leaders tend to slow their actions to match Followers' actions, because task constraints prevented the group from going faster while remaining successful. When allowed full access to see each other's movements, no such slowing was necessary, so a higher-order strategy emerged instead. In both scenarios, groups utilized all available degrees of freedom to organize their behaviors to perform the shared task successfully.

### **1.1.2. Task Constraints Shape Joint Action**

Task constraints can have a broad and significant influence on cooperative behaviors, driving behaviors to change to fit the current context. Task constraints shape emergent behaviors for both individuals and groups (Skewes, Skewes, Michael, & Konvalinka, 2014; Vesper, Van Der Wel, Knoblich, & Sebanz, 2011). conjoined partners were simply instructed to move from one location to another. Being conjoined by a foam appendage, the partners moved together with a distinct gait when visually and mechanically coupled. Developing an emergent gait depended on the connection linking both individuals together as they cooperatively moved from one place to another.

These task constraints resulted in the emergence of a new performance strategy based on the type of coupling binding individuals together (Coey et al., 2011; Harrison & Richardson, 2009; Washburn, Kallen, Coey, & Shockley, 2015). Emergent strategies develop out of groups taking advantage of as many available degrees of freedom as possible. When the coupling strength connecting individuals together changes, so too do their behaviors (Vesper et al., 2011).

### 1.1.3. Complexity Matching in Cooperative Actions

When an individual moves an object by themselves, they know what to expect next because they are the only one doing the moving. By contrast, groups of people collectively moving an object together experience the effects of a partner's actions transferred through the object (Ganesh et al., 2014; Masumoto & Inui, 2014; Reed et al., 2006; Van der Wel et al., 2011). Coordination studies typically employ measures like timing and movement accuracy (Rosenbaum, Dawson, & Challis, 2006; Wel, Knoblich, & Sebanz, 2011), phase relations (Coey, Varlet, Schmidt, & Richardson, 2011), and movement coordination (Schmidt, Morr, Fitzpatrick, & Richardson, 2012; Schmidt & O'Brien, 1997; Stephen et al., 2008) to measure individual and cooperative behaviors in situations like moving an object. Based on such measures, studies have shown how simply perceiving the actions of others can cause actions to become coupled across individuals (Marsh et al., 2009; Valdesolo et al., 2010; Van der Wel et al., 2011; Varlet et al., 2012).

This coupling can also be measured across timescales in terms of *complexity matching*, i.e., a convergence in temporal correlations that are relevant to the variations of each degree of freedom (Abney, Paxton, Dale, & Kello, 2014; Marmelat & Delignières, 2012; West et al., 2008). Complexity matching is measured as a convergence in the long-range temporal correlations produced by two interacting systems. Typically, the long-range dynamics of each system are quantified using spectral or detrended fluctuation analysis, and then the resulting estimated exponents are correlated across a paired population of interacting systems. Generally, complexity matching measures coupling across sequences of behaviors and how they become stitched together, rather than direct dependencies in the timing of successive behaviors. Often, complexity matching research focuses on the strength and modality of the coupling necessary to exhibit higher degrees of complexity matching.

Marmelat and Delignières (2012) were the first to investigate the relationship between coupling strength and complexity matching. Participants attempted to swing separate pendula in synchronous, in-phase movements. Across three trials, the coupling strength shared between the two people was varied by changing which perceptual channels were available to help link their actions together. Each trial consisted of a different coupling strength condition: weak, intermediate, and strong. The weak-coupling condition only allowed for peripheral visual information. The intermediate-coupling condition allowed visual and auditory information, and the strong-coupling condition allowed visual, auditory, and haptic information. Haptic information was made available by instructing participants to cross and link their free arms together.

Marmelat and Delignières (2012) found no significant difference between the intermediate and strong-coupling conditions in terms of the degree of complexity matching, but, interestingly, there was significantly less matching in the weak-coupling condition. This decreased complexity matching indicated that coupling strength affected the extent to which people reciprocally influenced each other's actions, i.e., showing that the presence of perceivable information about the actions of others changed the coupling strength connecting them together. However, the influence and nature of the connections binding individuals together likely differs for groups larger than two.

Frequently, cooperative shared tasks are studied on small groups of interacting agents, but oftentimes tasks require multiple agents to complete the task successfully and effectively. One such task includes foraging. Foraging is frequently studied as an activity performed by individual organisms (Ceia & Ramos, 2015; Patrick et al., 2014; Patrick & Weimerskirch, 2014). For instance, a single bird may fly over an area in search of food, as a tiger roams the jungle, or a person scans their nearby terrain for resources. In other instances, foraging is studied as a collective activity that groups of organisms engage in (Aplin, Farine, Mann, & Sheldon, 2014; Palacios-Romo, Castellanos, & Ramos-Fernandez, 2019), such as schools of fish or colonies of ants seeking food. Collective foraging occurs when groups of organisms interact and move together while searching for resources, and it is more often associated with organisms that have limited cognitive capacities for planning and decision-making (Davidson & Gordon, 2017; Jackson & Ratnieks, 2006; Tereshko & Loengarov, 2005).

Organisms with greater cognitive capacities may also engage in collective foraging, but they are more likely to exhibit flexibility in switching between different foraging modes that are dependent on various factors (Aplin et al., 2014; Harel, Spiegel, Getz, & Nathan, 2017; Nathan et al., 2012). For example, a lion may choose to hunt alone or team up with other lions to locate and take down prey (Lamprecht, 1981). A person may choose to help others harvest a large patch of berries, or alternatively, head off alone in search of unfound berry patches. In general, foragers can communicate information about resources and conditions to each other, and thereby help individuals make decisions regarding where and with whom to forage (Jackson & Ratnieks, 2006; Tereshko & Loengarov, 2005). For these reasons, collective foraging serves as a useful scenario to understand principles of coordination within larger cooperative groups.

Often, foraging can benefit from an agent's ability to vary between searching alone and searching in a group as a means of improving collective performance (Beauchamp, 2005; Lihoreau et al., 2017). Whether it is "better" to search alone or in a group at any given time often depends on various contextual factors (Biesmeijer & De Vries, 2001; Seeley, 1983, 2019). Group cooperation can outperform individual or independent foraging strategies by exploiting food resources more quickly (Beauchamp, 2005), as well as providing security from predation among other social benefits (Lamprecht, 1981; Vicsek & Zafeiris, 2012). However, these benefits may not always be available or sufficiently salient, and further, they may be outweighed when foraging becomes overly competitive (Packer & Ruttan, 1988). This dependence on certain conditions suggests the importance of adaptive flexibility that enables switching between independent and collective modes of foraging.

The benefits of collective foraging have been shown for various birds of prey (Cortés-Avizanda, Jovani, Donázar, & Grimm, 2014; Harel et al., 2017; Jackson, Ruxton, & Houston, 2008; López-López, Benavent-Corai, García-Ripollés, & Urios, 2013), and the apparent prevalence of collective foraging in nature has led researchers to develop and test formal models of collective foraging to investigate the underlying principles and processes. Liu and Passino (2004) created a collective foraging model based on balancing forces of attraction and repulsion, such that agents tended to position themselves relatively near their neighbors while still maintaining some distance. The goal was for agents to find food

resources by following gradients to their locations. Coordinating movements with nearby cooperative agents allowed them to collectively follow otherwise unreliable gradients toward resources (Falcón-Cortés, Boyer, & Ramos-Fernández, 2019; Liu & Passino, 2004; Sellers, Hill, & Logan, 2007). In more recent work, a similar function for balancing attraction and repulsion based on agent separation distance was developed, called the *Lennard-Jones potential* (Copenhagen, Quint, & Gopinathan, 2016; Spears, Anderson-Sprecher, Kletsov, & Rebguns, 2011). The balancing of attraction and repulsion between agents yields loose coupling effects which coordinates the behaviors of the agents as a group, similar to what we have seen emerge within cooperative tasks involving people (Kello & Van Orden, 2009; Kloos & Van Orden, 2009; Van Orden, Holden, & Turvey, 2003). Our flexibility and adaptiveness to changes leaves us ready to meet the demands of the task at hand.

#### **1.1.4. Loose Coupling of Coordinated Systems**

A general feature of living systems is their relative independence from momentary environmental change. This independence shows their stability is achieved across different levels of complexity and organization. For our purpose, it is important to understand how, and to what extent the dynamics of interacting components within a given system influence each other. Such that the degree of coupling among components, subsystems, and systems are tied together through their shared connections.

Here, coupling refers to the strength of the dynamical relations between components of a given system. The degree of coupling between components of a given system depends upon then extent components within a system mutually perturbing and constraining each other. Therefore, the degree of coupling is a continuum where components can range from uncoupled, having no influence or relationship to each other, to tightly coupled, where the dynamics are strongly linked together such that they become entrenched into one dynamical relationship.

The more reliant each component is upon the dynamics of other components within the system, the stronger the coupling between the connected components. Loose coupling stands as a balance between these two extremes along the same continuum of varying coupling strength. Loose coupling implies a form of flexible stability, where components have some degree of influence on each other, while retaining a relative independence of dynamics. These weaker dynamical relationships allow for a loosely coupled system to change its dynamics in response to external events. In this way, the components of loosely coupled systems can be expected to exhibit a range of collective dynamics that emerge over time because they are both sensitive to internal and external constraints and perturbations. This flexible stability is a signature feature of loosely coupled systems because of their susceptible to change, making them unlike uncoupled or tightly coupled systems based on their component dynamics.

As it relates to coordination, we define coordination as the dynamical relations among components that results in a system with some collective function. The coupling strength of a given system allows for systems to mutually constrain and perturbate the dynamics of other components. Loose coupling within a coordinated system supports coordination

because component dynamics are sensitive to constraints and perturbations, allowing for adaption in response to changing conditions, thereby making the dynamical relation functional in nature. By balancing the dependence and independence of components, loosely coupled systems exhibit emergent and functional behaviors based on changing conditions because of the system's susceptibility to change. Based on this notion, when loosely coupled, the actions of an individual, dyad, or flock will all naturally differ in coordinated actions based on their respective component dynamics and external constraints. In this way, loose coupling may support coordination by allowing for an adaptive, flexible stability to emerge between the dynamical relations of limbs, partners, or collective searchers across varying conditions.

## 1.2. Outline of the Dissertation

Everyday people engage in flexible, loosely coupled behaviors while coordinating their actions within themselves and with other people. This flexibility to adapt our behaviors is often the key to our collective success because of how generalizable we can be. Based on humans' general adaptiveness and ingenuity for actions, we began our investigation by testing whether performance *depends* on the coupling strength in a bimanual Fitts' task. Fine and Amazeen (2011) showed how cooperative performance was affected by task constraints in an interpersonal hand-eye coordination task. This flexibility of coordination is reflected in the variability of measured degrees of freedom. Human coordination in tasks like juggling are *soft-assembled*—degrees of freedom are recruited flexibly and temporarily to accomplish the task at hand, while also remaining available to reorganize into other coordinated configurations as the tasks change over time (Kloos & Van Orden, 2009). Specifically, flexible coordination of complex systems requires a coupling of their dynamics at multiple timescales. Marmelat and Delignières (2012) demonstrated how coupling strength can be quantified in terms of complexity matching. Complexity matching measures the degree of coupling arising from such cooperative interactions, and thereby gauging how soft-assembly, or “loose coupling” influences cooperative coordination.

In Chapter 2, we examine complexity matching in a double, coordinated Fitts' perceptual-motor task with comparable individual and dyadic conditions. Participants alternated touching targets with their left and right hands in the individual condition, or analogously with the left hand of one partner and the right hand of the other in the dyadic condition. In Experiment 1, response coupling was manipulated by making targets drift either randomly or contingently based on prior responses. Here, “drift” refers to the variability in the target movements between consecutive response locations. Long-range correlations in time series of inter-response intervals exhibited higher degrees of complexity matching between the left and right hands of dyads and individuals when responses were contingently linked together. Response coupling was necessary for complexity matching in dyads but not individuals. When response coupling was absent in the dyadic condition, the degree of complexity matching was significantly reduced. Experiment 2 showed that the effect of coupling was due to interactions between left and right responses. Results also showed a weak, negative relationship between complexity matching and performance as measured by total response time. Concluding that principles of coordination and complexity matching apply similarly within and between individuals, and perceptual-motor performance can be facilitated by loose response coupling.



Similarly, collective foragers are influenced by the coupling shared between foragers which affects emergent and varying foraging strategies. Social cues serve as at least one connection, helping to bind foragers together (Harel et al., 2017; Jackson et al., 2008; Seeley, 1983). As agents emit social cues, these cues affect the decisions other collective foragers make, causing searchers to flexibly reorganize between individualistic and collective foraging strategies (Dreller, 1998; Harel et al., 2017; Nathan et al., 2012; Seeley, 1983). For instance, when a vulture shows signs of having recently visited a carcass, that vulture is more likely to be followed the next time it leaves the roost (Harel et al., 2017). The flexibility of agents to switch between individual and collective strategies indicates that foragers can reorganize their degrees of freedom and adapt to the task at hand, resulting in individuals and groups having greater success overall. By testing the connections that bind groups together or separate them, we stand to better our understanding of any underlying principles of coordination related to larger groups.

In Chapters 3–5, we investigate how intelligent agents coordinate and cooperate flexibly when rules and dynamics of interaction can change over time and across different tasks and environmental conditions. Loose coupling emerges among agents when the rules of interaction are weak enough for agents to act independently or interdependently, and patterns of interaction vary as a function of conditions. In Chapter 3, we examine collective foraging among simulated agents with and without human intervention. We found that loose coupling among search agents improved group foraging success, and that human players improved performance partly by subtle, indirect effects on group interactions. Analyses of movement patterns showed that loose coupling enabled collections of agents to self-organize and reorganize into a greater diversity of ad-hoc groupings. Building on these promising results, in Chapter 4, we conduct a series of simulations to develop a more-optimal configuration of loose coupling, one that we then compared to human searching behaviors. We found that the searching behaviors of the more-optimal loose coupling agents increased collective performance, but these improved searching agents continued to search the space less effectively than the human player based on individual measures of performance. Considering these findings, in Chapter 5, we continue our investigation by instilling a single autonomous simulated agent with a more ‘human-like’ quality. Specifically, we instilled this new agent with a form of memory that would direct them to favor moving towards yet unsearched areas of the space rather than where they have already been. Surprisingly, we found that this new memory parameter directed this new memory agent to search in more ‘human-like’ ways.

## Chapter 2

### Interpersonal Coordination and Complexity Matching as a function of Dependency

#### 2.1. Preface

In this chapter, I present an analysis of a published study providing evidence for loose coupling, both within and between individuals, as measured via complexity matching. The present study examined complexity matching in a double, coordinated Fitts' perceptual-motor task with comparable individual and dyadic conditions. Participants alternated touching targets with their left and right hands as an individual or as dyads, cooperating as pairs of subjects in the dyadic condition, to repeating patterns of moving targets. In Experiment 1, response coupling was manipulated by making targets drift either randomly or contingently based on prior responses – target drift varied target movements between response locations. Long-range correlations in time series of inter-response intervals showed response coupling was necessary for developing higher degrees of complexity matching in dyads but not for individuals. Individuals were able to develop high degrees of complexity matching regardless of response coupling – due to the individual controlling the timing of all responses.

When response coupling was absent in the dyadic condition, the degree of complexity matching was significantly reduced. These findings demonstrated that the degree of complexity matching within collaborative pairs differed as a function of coupling strength. Additionally, these results support individuals and dyads can become increasingly “coupled” over time when coupling effects are dependently linked to corresponding actions. Adding to the mounting evidence of loose coupling effects emerging during human interactions.

#### 2.2. Introduction

To accomplish a task, e.g., either an “individual” task or a common collaborative goal, people must often coordinate a plurality of discrete actions. For instance, a single person can coordinate discrete actions performed by each of the person’s two hands to juggle a set of objects. Similarly, two people juggling together can mutually coordinate actions by all four of their collective hands. In both instances, bimanual coordination is required to complete the respective task—what differs is whether such coordination is implemented by a single person or between two distinct individuals.

Human coordination in tasks like juggling is *soft-assembled*, meaning the available degrees of freedom for actions are flexibly and temporarily recruited within the present context. At the same time, the available degrees of freedom retain the ability to reorganize based on changing task demands into other coordinated configurations, reflected in the variability of measured degrees of freedom (Kloos & Van Orden, 2009). Coordination of complex systems requires a coupling of their dynamics at multiple timescales. Complexity matching is one way to measure the degree of coordination at multiple timescales, serving as an effective measurement for studying soft-assembly, or loose coupling and its influence on coordination.

*Complexity matching* is based on a theory of information exchange between complex networks (West et al., 2008), measured as convergence in the long-range temporal correlations produced by two interacting systems (Abney et al., 2014; Marmelat & Delignières, 2012). Typically, the long-range dynamics of each system are quantified using spectral or detrended fluctuation analysis. The resulting estimated exponents are correlated across a sampled population of pairs of interacting systems. The same measure of convergence was simultaneously introduced as *strong anticipation* (Stephen, Stepp, Dixon, & Turvey, 2008). For our purposes, these two terms and concepts are interchangeable, and one can interpret our study of complexity matching as also applying to strong anticipation.

Complexity matching has been used in many areas involving coordination. From studies in dyadic conversations (Abney et al., 2014; Fusaroli, Raczaszek-Leonardi, & Tylén, 2014), dyadic perceptual-motor coordination (Coey et al., 2016; Den Hartigh et al., 2017; Fine et al., 2015; Marmelat & Delignières, 2012), perceptual-motor coordination with a metronome (Delignières et al., 2016; Stephen, Stepp, Dixon, & Turvey, 2008; Torre et al., 2013), to neural networks and brain connectivity (Mafahim, Lambert, Zare, & Grigolini, 2015).

The pursuit of developing principles of coordination has led researchers to focus on coordination within a person or between multiple people coordinating with a device like a metronome (see Rigoli, Holman, Spivey, & Kello, 2014). Here, we examine complexity matching in a perceptual-motor task that has comparable conditions of individual and dyadic coordination. We test whether complexity matching generalizes across collaborative behaviors, and whether the role of response coupling operates similarly within and across individuals.

Our study is motivated by the hypothesis that loose coupling may be a general principle of coordination akin to models of coupled oscillators. For instance, Haken, Kelso, and Bunz (1985) introduced a model of coupled oscillators that has proven to describe the dynamics observed in many studies of perceptual-motor coordination within and between individuals (Black, Riley, & McCord, 2007; Issartel, Marin, & Cadopi, 2007; Riley, Richardson, Shockley, & Ramenzoni, 2011; Schmidt & Richardson, 2008), in movement activity as well as neural activity (Bressler & Kelso, 2001; Fink, Foo, Jirsa, & Kelso, 2000; Swinnen, 2002). Loose coupling may be a similarly general principle for complex networks of interacting components with heterogeneous dynamics.

### **2.2.1. Bimanual and Interpersonal Coordination**

We start with a review of previous studies of coordination within and between individuals to provide context for complexity matching. Coordination studies typically employ measures like timing and movement accuracy (Rosenbaum, Dawson, & Challis, 2006; Wel, Knoblich, & Sebanz, 2011), phase relations (Coey, Varlet, Schmidt, & Richardson, 2011), and movement dynamics (Schmidt, Morr, Fitzpatrick, & Richardson, 2012; Schmidt & O'Brien, 1997; Stephen et al., 2008). These measures can often be applied similarly within and between individuals. For example, Wel et al. (2011) asked participants to swing a pendulum between two markers by pulling a rope alone or with another person at different amplitudes and frequencies. Individual subjects had control over

both ends of the rope and dyads worked together by only controlling one end each. Results showed that dyads cooperated by pulling their respective end simultaneously with the other to produce perceivable and predictable effects each person could recognize. By contrast, individuals pulled the ends simultaneously only half as often.

Tasks like swinging pendula force participants to time their movements relative to each other, but timing relations are not required to perform these tasks—if oscillations fall out of phase with each other, the task continues without penalty or disruption. Other coordinative tasks require certain timing relations to be performed. Fine and Amazeen (2011) extended the individual Fitts' task to investigate whether the Fitts' law tradeoff between speed and accuracy holds when two people cooperate to perform the task. Participants alternately aimed at targets using their left and right hands. This alternation served as a built-in timing relation necessary to perform the task across three different conditions: unimanual, intrapersonal, and interpersonal. “Unimanual” meant that the participants used either their left or right hands across separate trials; “intrapersonal” participants used both hands; and “interpersonal” participants used their dominant hands while standing alongside another participant.

Results showed interactions between paired individuals emerged implicitly, and arose from perceptual-motor coupling through peripheral vision (Amazeen, DaSilva, & Amazeen, 2008; Mechsner, Kerzel, Knoblich, & Prinz, 2001). Results also showed, in both the intrapersonal and interpersonal conditions, and when task difficulty varied across hands, that movement times for the easy targets slowed down to maintain an in-phase relation with the other hand responding to harder targets. Similar results have been recorded in other shared coordination tasks (Fine et al., 2015; Harrison & Richardson, 2009; Lumsden, Miles, Richardson, Smith, & Macrae, 2012; Vesper & Richardson, 2014). This result is contrary to the Fitts' law assumption of independence between limbs which can be interpreted as evidence against a centralized control of target aiming and reaching (Marteniuk, Mackenzie, & Baba, 1984).

Fine and Amazeen (2011) encouraged alternation to perform the task, whereas other studies have induced more varied forms of coordination necessary to perform a collaborative task (Harrison & Richardson, 2009; Jordan, Schloesser, Bai, & Abney, 2018; Knoblich & Jordan, 2003; Wel et al., 2011). For instance, Jordan et al. (2018) instructed participants to contain a drifting dot within a narrow rectangular box displayed on a computer screen. The dot moved constantly and was controlled with two keys to determine the direction of movement. Individuals controlled both keys, whereas dyads controlled only one key each. This made the timing relations between keypresses necessary to control the moving dot.

In Jordan et al. (2018), individual subjects performed better than dyads, presumably because the individuals had enough control to time precise key presses to control movement effects (Jordan et al., 2018). Such precision of coordination was less feasible for dyads, so a different coordination pattern emerged where people pressed the keys rapidly (i.e., a reorganization of available degrees of freedom). Through movement feedback, players adjusted the phase and frequency of their keypresses to stabilize and hold the dot in the middle of the goal box. Although dyads were less successful than individuals

at performing the task, this study indicated that dyad players were able to utilize the available degrees of freedom to loosely couple with each other.

### 2.2.2. Complexity Matching

Each of the studies reviewed thus far used measures of phase relations in behavior, including methods like recurrence-quantification analysis (Coey, Washburn, & Richardson, 2014; Fusaroli, Konvalinka, & Wallot, 2014; Riley, Richardson, Shockley, & Ramenzoni, 2011). In the current study, we measured the degree to which coordination was in-phase, i.e. *phase matching*, and compared this measure with complexity matching, which was introduced as another measure of coordination dynamics (Abney et al., 2014; Marmelat & Delignières, 2012), to evaluate the viability of complexity matching as an alternative, distributional measure of coordination.

Among the first empirical studies of complexity matching, Marmelat and Delignières (2012) instructed dyads to swing separate pendula back and forth using either their left or right hand. All people started by completing one trial alone, followed by a practice period of about five minutes, and then as a group using the same hand as they did in the individual condition. Afterwards, participants were asked to complete a series of three trials. In each trial, they were asked to consistently swing the pendula in synchronized, in-phase movements. Coupling strength was manipulated through the amount of perceivable information about the other's swinging. There were three different levels of coupling strength: weak, intermediate, and strong coupling. The weak coupling condition allowed for only peripheral visual information about the partners' swinging movements. Intermediate coupling allowed for both visual and auditory information, whereas strong coupling provided the participants with visual, auditory, and haptic information. The haptic information was made available by allowing the participants to lock their free arms together.

Marmelat and Delignières (2012) measured fluctuations in the inter-peak intervals of oscillatory movements, whose temporal autocorrelations were found to follow an inverse-power-law relation. The relation was quantified for each time series by estimating the power law exponent, and complexity matching was measured by correlating the estimated exponents across dyads. Results showed higher degrees of complexity matching for intermediate and strong coupling, and weaker complexity matching for weak coupling. Thus, the strength of complexity matching differed as a function of the amount of perceivable information (i.e., coupling strength).

More recently, some studies have investigated whether complexity matching might relate to measures of collective performance (Abney, Paxton, Dale, & Kello, 2015; Zapata-Fonseca, Dotov, Fossion, & Froese, 2016). For example, Zapata-Fonseca et al. (2016) created a task in which paired individuals interacted with one another by moving virtual "avatars" (points) around an invisible ring. Players received haptic feedback about their avatar positions only when the positions overlapped. The goal of the task was to align both avatars. This effort was made more challenging by the presence of three decoys which were placed on the same ring as the avatars. One decoy was a static point, and the other two would move in ways that shadowed each avatar's movements. Results found higher

complexity matching in the fluctuations of avatar movements, and increased complexity matching was correlated with higher degrees of avatar alignment. These results suggest that complexity matching reflects collective performance in terms of the degree to which common ground is established.

### 2.2.3. Current Study

For the present study, we modified the classic Fitts' task to compare perceptual-motor coordination and performance of individuals to that of dyads. Participants were instructed to reach out and touch targets as the targets appeared on touchscreens. For both individuals and dyads, targets appeared alternatively on opposite (left and right) sides of the touchscreen. For individuals, the participants responded by reaching for all the displayed targets, alternating between using left and right hands to touch targets on the corresponding side. For dyads, the targets were displayed on two touchscreens in two separate rooms. One person in the first room reached for left-side targets with their left hand, and the other person in the second room reached for right-side targets with their right hand.

Both conditions required participants to time their responses between both hands to successfully complete the task. Each hand produced timing fluctuations in a series of *inter-response intervals* (IRIs). We quantified temporal autocorrelations by estimating a spectral exponent for each time series, and we measured complexity matching by correlating the exponent estimates across participants. We evaluated the use of complexity matching as a more diffuse, distributional measure of correlations in timing fluctuations, as compared with phase matching serving as a more local, direct measure of such fluctuations.

Individuals' responses were inherently coupled because responses were controlled by a single brain with two hemispheres connected by a corpus callosum (among other physiological and functional pathways). This inherent, internal coupling in the individual condition initially led us to expect higher complexity matching within individuals. However, we had different sets of expectations for the dyadic conditions. We manipulated coupling strength by causing the targets to appear in positions on the touchscreen according to either a dependent or a random drift. The *dependent drift* condition positioned each target depending on the location of the previous touch by the participant. With a *random drift*, the position of the next target was chosen randomly from within the target area. For dyads, response coupling only existed through the appearance of targets on the screen. As a result, a dependent drift enabled response coupling through bimanual interactions, while a random drift prohibited such interactions.

Our Fitts-like task was designed to address three main research inquiries. First, does complexity matching generalize across both dyadic and individual (e.g., bimanual) perceptual-motor coordination, and if so, how does this phenomenon compare with phase matching? Second, does external response coupling produce similar effects on complexity matching in both coordination conditions? And third, how do complexity matching and phase matching in an "aiming" task relate to overall performance, as measured by total response time?

Previous studies suggest a relationship between coordination and performance, but both the degree and the direction of this relationship are unclear. Matching of movement

dynamics has been shown to correlate with both better task performance (Abney et al., 2014; Zapata-Fonseca et al., 2016), but also worse performance (Abney et al., 2015). In the latter case, dyads worked together to build a tower, and the results indicated that complementary movements that varied in their phase relations over time supported a loose or “flexible” form of coordination.

It was initially unclear whether performance in our Fitts-like task should improve with increased matching in response timing, or whether the participants’ hands can coordinate more effectively when they maintain some independence from each other. Given that prior studies have found differing relationships between performance and coordination, we considered this issue for exploration in the present study. Examining this relationship furthers our understanding of coordination as revealed in the temporal correlations of performance fluctuations.

## **2.3. Methods: Experiment 1**

### **2.3.1. Participants**

Ninety students participated from University of California, Merced for course credit. Each participant signed a consent form explaining that participation was voluntary, and that the participant could end the experiment at any time without penalty. Of the 90 participants who volunteered for this experiment, 62 (69%) were female and 28 (31%) were male. 59 of the 62 females (i.e., 95%), and all 28 of the males (i.e., 100), were right-handed as determined by which hand they use for writing. Given the uneven distributions of genders and handedness (i.e., the negligible proportions of both males and left-handed individuals), we did not analyze potential effects of these parameters any further.

### **2.3.2. Apparatus**

For each dyad, each participant sat roughly 30 cm (11.81 in) in front of their own 22-inch Planar PCT2235 touchscreen monitor at approximately a 65° angle, in a separate room from their partner. The height of each chair relative to the table was set to a comfortable level for each participant. Both rooms were 7 feet by 9 feet in size. Individuals were separated across rooms, each with a monitor present. A single computer sent the same graphical display to one or both monitors, and collected user input (i.e., touchscreen responses) from one or both monitors via a program written in Python using the Pygame module.

### **2.3.3. Procedure**

The experiment began with verbal instructions to the participants regarding the overall nature of the task, which was to reach out and touch targets, in the form of red circles, as they appeared on the touchscreen monitors. Targets appeared on the screens, one-at-a-time, and players were asked to touch them as quickly as possible with the corresponding hand. Each target was 2.3 cm (0.9 in) in diameter, and the targets appeared in certain positions on the screen according to a repeating sequence (see Figure 1). Specifically, the target first appeared in the top-left quadrant of the screen, then in the top-right quadrant, followed by the lower-left quadrant, and finally in the lower-right quadrant. This sequence repeated 300 times in each session block.

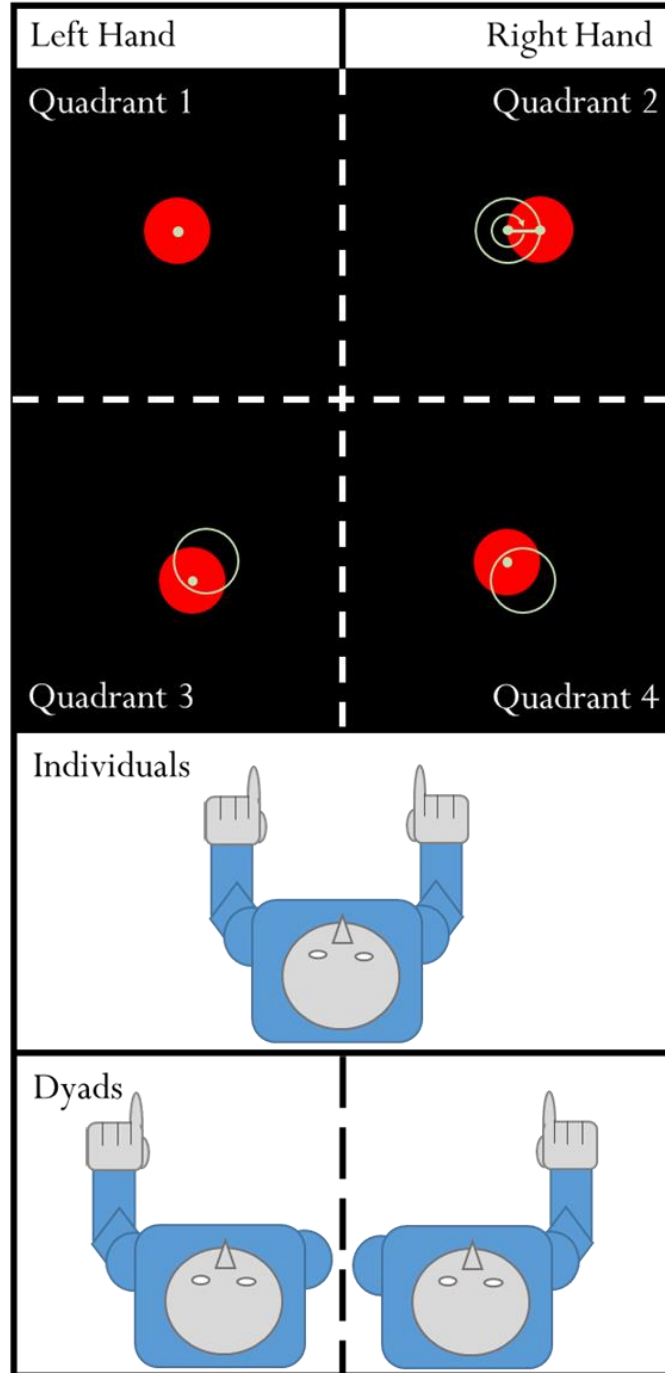
An auditory tone 200 ms in duration followed each target response to indicate the response time. The frequency of the tone was linearly related to the response time within a bounded range. The lower frequency bound was 250 Hz, indicating a user-response time of 1750 ms or longer, and the upper frequency bound was 2000 Hz, indicating a theoretical “perfect” response time of 0 ms. The tone provided an indication of relative performance to participants, with higher pitch meaning faster (better) performance, and lower pitch meaning slower (worse) performance.

A participant’s left hand responded to targets in the left two quadrants, and the right hand responded to targets in the right two quadrants (see Figure 1). Individuals used both hands, whereas dyadic players each responded to only one side (half) of the targets. One dyadic participant responded to left-sided targets with their left hand, and the other participant responded to right-sided targets with their right hand (see Figure 1). All participants observed all the targets in all four quadrants, and dyads were shown an indication of their partner’s touch responses in the form of brief gray concentric rings centered on the response location.

Although confined to a particular quadrant according to the sequence described above, the relative positions of the targets drifted within the quadrants from one response to the next. This positional drift was either dependent on participant responses or randomized. The random drift positioned each target as if it had shifted in any random direction. The distance between consecutive target locations was sampled uniformly from a set of lengths ranging from zero to the radius of the circle that formed the target. This distance was then translated from the corresponding location in the next quadrant to position the subsequent target. In cases in which the randomly selected direction and distance would have caused the target to drift outside the quadrant boundary, the direction was “reflected” to the opposite direction to keep the targets within the set bounds. The dependent drift created a new center for each target determined by an accurate response located within the previous target circle. In both drift conditions, target positions were restricted from drifting off the screen by always keeping at least half the target circle in view.

Overall, the task was identical for both individuals and dyads, except individuals responded to all the targets, whereas each member of a dyad responded to only half. Each block of 1200 targets were preceded by 40 “practice” targets. Each participant completed one “random” drift block and one “dependent” drift block, and the order of these blocks was counterbalanced across participants.





*Figure 2. 1.* (Top) Four initial response locations are depicted in the individual and dyadic conditions (the white dashed lines were not visible in the experiment). (Bottom) Response configurations are depicted for individual and dyadic conditions.

#### 2.3.4. Data Collection/Processing

Responses both inside and outside the target areas were recorded, but only “accurate” responses (i.e., inside the target areas) counted toward response times and any dependent

drift. The primary dependent variable of interest was the duration between consecutive responses, or the *inter-response interval* (IRI). The IRI provides an indication of relative performance, given that the goal was to complete each block of targets as quickly as possible. IRIs above or below 2.5 standard deviations were replaced with the mean IRI for the corresponding block—on average, 2.89% of responses were replaced. The 1200 responses in each block were divided in half to identify the responses produced by the left and right hands. The last 512 responses of each hand were retained and analyzed. Figure 2 shows example IRI time series for the left and right hands from each of the four different conditions.

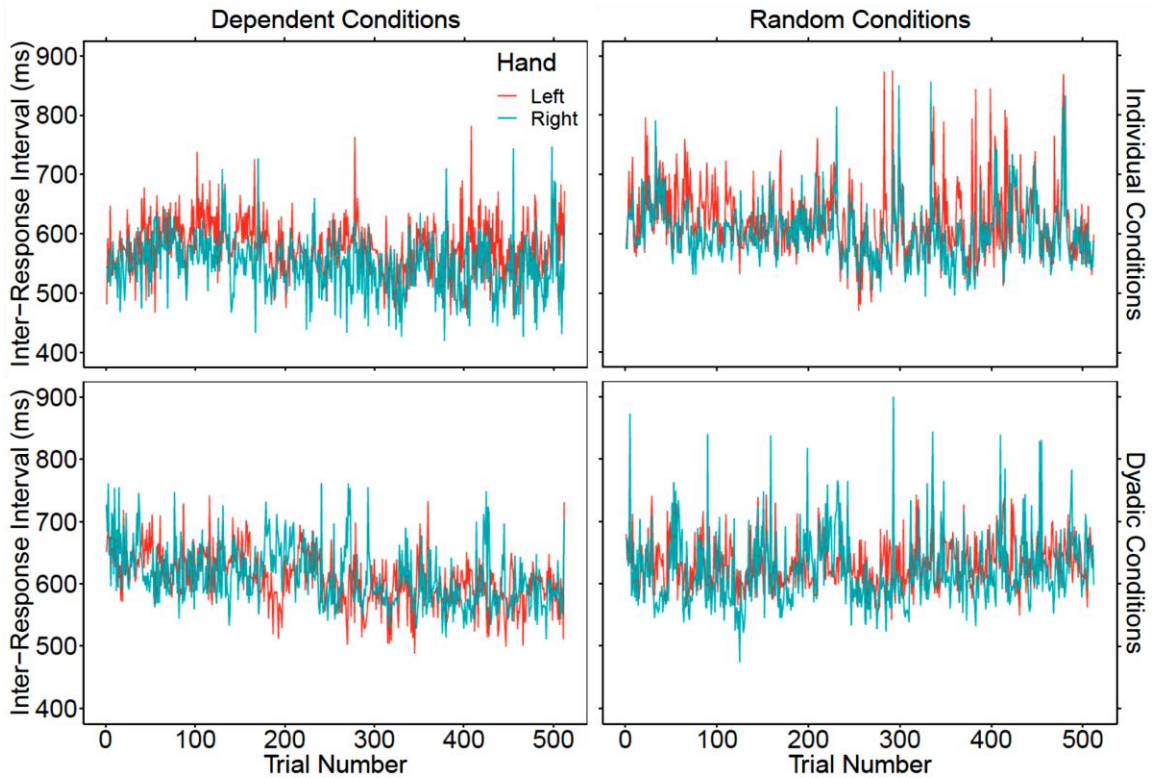


Figure 2. 2. An example time series for the four conditions: Individual dependent (top left), individual random (top right), dyadic dependent (bottom left), and dyadic random (bottom right).

The time series show that IRI fluctuations tend to rise and fall together, indicating visual evidence of phase matching. However, closer examination reveals that fluctuations cover timescales of multiple trials, rather than varying from trial-to-trial. We explored the scale at which to measure phase matching by correlating IRI series after convolving them with a moving-average window of several different widths. Phase matching on longer timescales was measured by correlating series convolved with wider moving-average windows. We tested windows in multiples of four, reflecting one “cycle” of responses over each of the four quadrants. Correlations began to asymptote at a window size of 16 responses, so for the results reported herein, we measured phase matching by correlating IRI series after being smoothed-out by a moving-average window 16 responses wide.

### 2.3.5. Analyses

#### 2.3.5.1. Spectral Analysis

We used spectral analysis to measure temporal autocorrelations in IRI time series for each condition and measured the degree of complexity matching in response time fluctuations. Temporal autocorrelations in response time series are commonly expressed as an inverse relation between frequency and spectral power (Gilden, 2001; Holden, Van Orden, & Turvey, 2009; Kello, Beltz, Holden, & Van Orden, 2007). When temporal correlations extend over many trials (i.e., long-range correlations), the spectral function often resembles a power law as expressed by a linear relation between spectral power and frequency in log-log coordinates. Statistical tests have concluded that, in many cases, power laws provide better fits to the data than short-range correlations (Gilden, Thornton, & Mallon, 1995; Kello, Anderson, Holden, & Van Orden, 2008; Wagenmakers, Farrell, & Ratcliff, 2004). Here, we are only interested in capturing variability in the degree of autocorrelation across timescales, rather than determining the best-fitting statistical function. Therefore, it suffices to estimate degrees of autocorrelation by fitting polynomial functions to spectra in log-log coordinates.

#### 2.3.5.2. Complexity Matching

Complexity matching is commonly measured in terms of correlations in the linear coefficients of fits to log-log spectra (or analogously, for detrended fluctuation functions; (Delignières & Marmelat, 2012; Marmelat & Delignières, 2012). In analyses of speech (Abney et al., 2014), complexity matching has been determined based on fits of the lower frequencies of variation, rather than of all measured timescales. Speakers matched prosodic features of their speech that span longer timescales (e.g., phrases and other large units of language), and the utilized measures of clustering in speech timing are sensitive to prosodic variations (Falk & Kello, 2017). However, the perceptual-motor task employed herein is distinguishable from a conversation. For instance, speakers have relatively few constraints on how they coordinate their utterances because conversational turns, as well as pauses and even periods of overlap in speaking, may vary widely in duration. By contrast, this target-aiming task requires strict timing and sequencing between the left and right hands. It is possible that the hands are too constrained to vary freely and match their correlations over timescales like those observed for speech. Therefore, we tested complexity matching over low, middle, and high ranges of timescales to see which, if any, timescales express greater levels of matching.

Out of eight logarithmically binned estimates of spectral power, we fit a line to the six highest frequencies for the High-Frequency estimate, the six middle frequencies for the Mid-Frequency estimate, and the six lowest frequencies for the Low-Frequency estimate. Complexity matching was computed as an estimate by correlating the corresponding left-and-right-hand slopes. The High-Frequency estimate yielded the strongest mean correlation across conditions,  $r(118) = 0.421$ , followed by Mid Frequency,  $r(118) = .184$ , and then Low Frequency  $r(118) = .118$ . We surmise that the greatest degree of complexity matching occurred in the High-Frequency range because the highly constrained nature of

the Fitts-like task attenuates the adaptation of lower-frequency dynamics. We therefore focus our analyses on spectral slopes in the High-Frequency range.

## 2.4. Results

### 2.4.1. Total Time

We first analyzed overall performance for each condition in terms of the total amount of time it took to complete each block. A two-way analysis of variance was conducted with “Group Type” (i.e., individual versus dyadic) as a between-subjects factor, “Movement Type” (i.e., dependent drift versus random drift) as a within-subjects factor (dependent versus random drift), and participants as a random factor. We found a significant main effect of Group Type,  $F(1, 58) = 17.71, p = .001$ , a main effect of Movement Type,  $F(1, 58) = 66.01, p < .001$ , and a significant interaction,  $F(1, 58) = 4.73, p = .034$  (see Figure 3). Overall, individuals were faster (i.e., performed better) than dyads. Although the dependent drift supported faster responses than the random drift in both cases, the dependent drift benefited individuals more than it benefited dyads. Individuals also committed more errors; however, they were still able to recover from those errors fast enough to complete the blocks faster than dyads, on average. Therefore, in terms of overall performance, some sacrifice of accuracy for the sake of speed appeared to be worthwhile for individuals, given that the only objective was to complete the task as fast as possible (see Figure 3). Anecdotal experience indicates that it takes some tens of milliseconds to recover from each missed (i.e., outside-target) response, so any speed gained beyond the mean recovery time is worth the tradeoff.

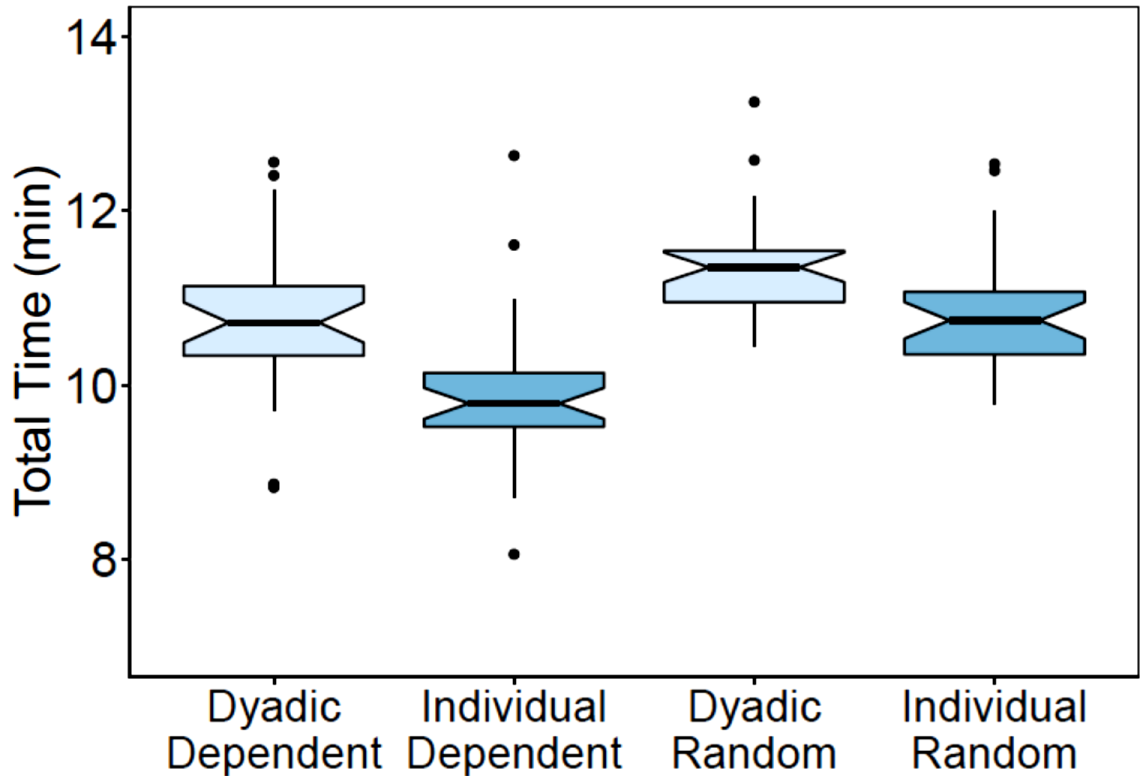


Figure 2. 3. Total time to complete each block as a function of Group Type and Movement Type. Boxes correspond to group means, and individual points correspond to outliers.

#### 2.4.2. Spectral Analysis

Figure 4 shows the mean spectra as a function of condition, with spectral power logarithmically binned as a function of frequency so that each bin is estimated from comparable amounts of data (Gilden et al., 1995). Figure 4 shows spectral power increasing as frequency decreases across all measured timescales, for all four conditions. This inversely proportional relationship also appears to flatten out in the higher frequencies, which is common in behavioral and neurophysiological measures due to measurement and timing errors, among other possible factors. To estimate the degree of autocorrelation while accounting for its flattening, we fit a first-order polynomial to the IRI time series for each hand in each block of trials, and we used the linear coefficient as a dependent measure to estimate the degree of autocorrelation.

We conducted a 2x2x2 (i.e., Group Type—individual or dyad; Movement Type—dependent or random; Hand—right or left hand) mixed ANOVA on the linear coefficients of a first-order polynomial for each IRI spectrum produced by each hand in each block. We found a significant main effect of Group Type,  $M_{ind} = -0.852$ ,  $M_{dyad} = -1.012$ ,  $F(1, 58) = 36.53$ ,  $p < .001$ , Movement Type,  $M_{dependent} = -1.091$ ,  $M_{random} = -0.772$ ,  $F(1, 58) = 31.9$ ,  $p < .001$ , and a non-reliable effect of Hand,  $F(1, 58) = 3.51$ ,  $p = .072$  (more negative coefficients for the right hand). All other main effects and interactions were non-significant,  $p > .05$ . Additionally, spectral slopes did not show a reliable, consistent relationship with performance.

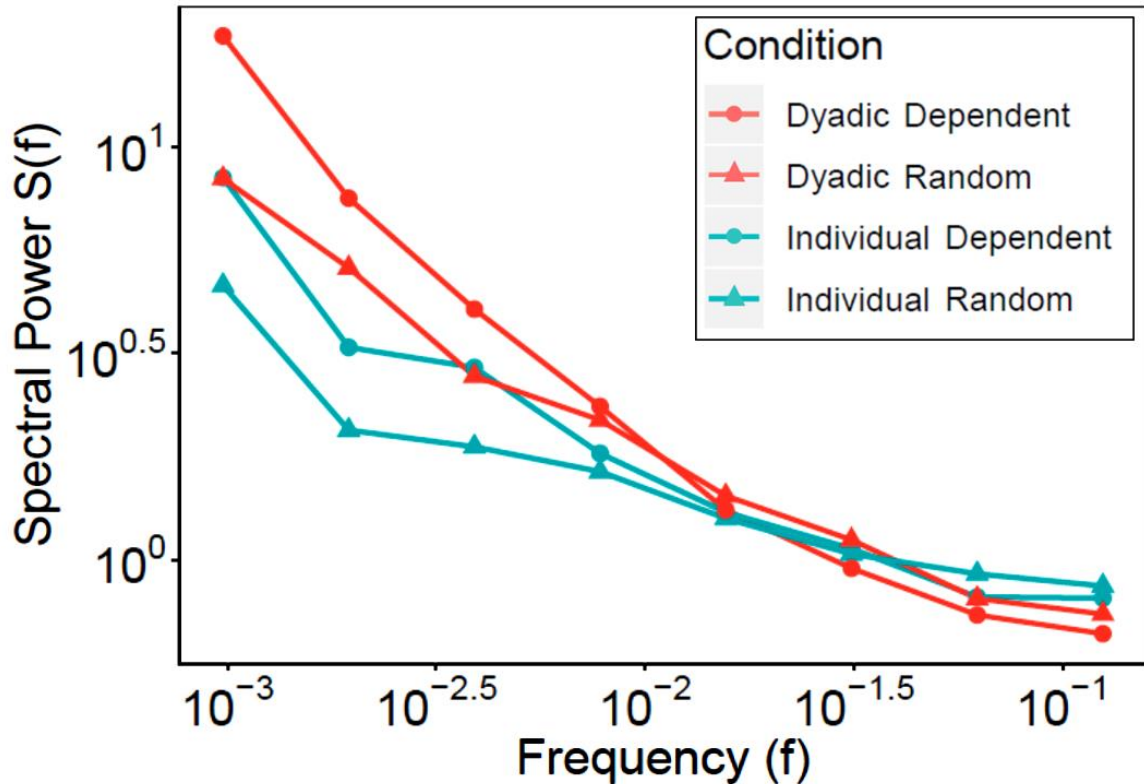


Figure 2. 4. Logarithmically binned, mean spectra as a function of Group Type and Movement Type.

As can be seen in Figure 4, spectral functions were steeper for dyads and dependent drift compared to individuals and random drift, respectively. These effects were not a focal point of our study, but one might expect random perturbations caused by random drift to disrupt temporal autocorrelations relative to non-random drift. Weaker autocorrelations for individuals are harder to interpret, but we note that the faster responses of individuals were much more error prone. Based on the same rationale as random drift, aiming errors disrupted performance because they required monitoring and recovery. Such disruptions may have weakened autocorrelations akin to random-drift perturbations.

### 2.4.3. Complexity Matching

We found significant positive correlations of spectral slopes for individuals in both movement conditions and the dyadic dependent-drift condition, but not for the dyadic random drift condition (see Figure 5). This pattern of slope correlations indicates that complexity matching occurred when the hands were coordinated *either* within an individual or through dependencies in the positioning of targets across separated hands. When neither of these two channels of coupling were available, complexity matching was inhibited.

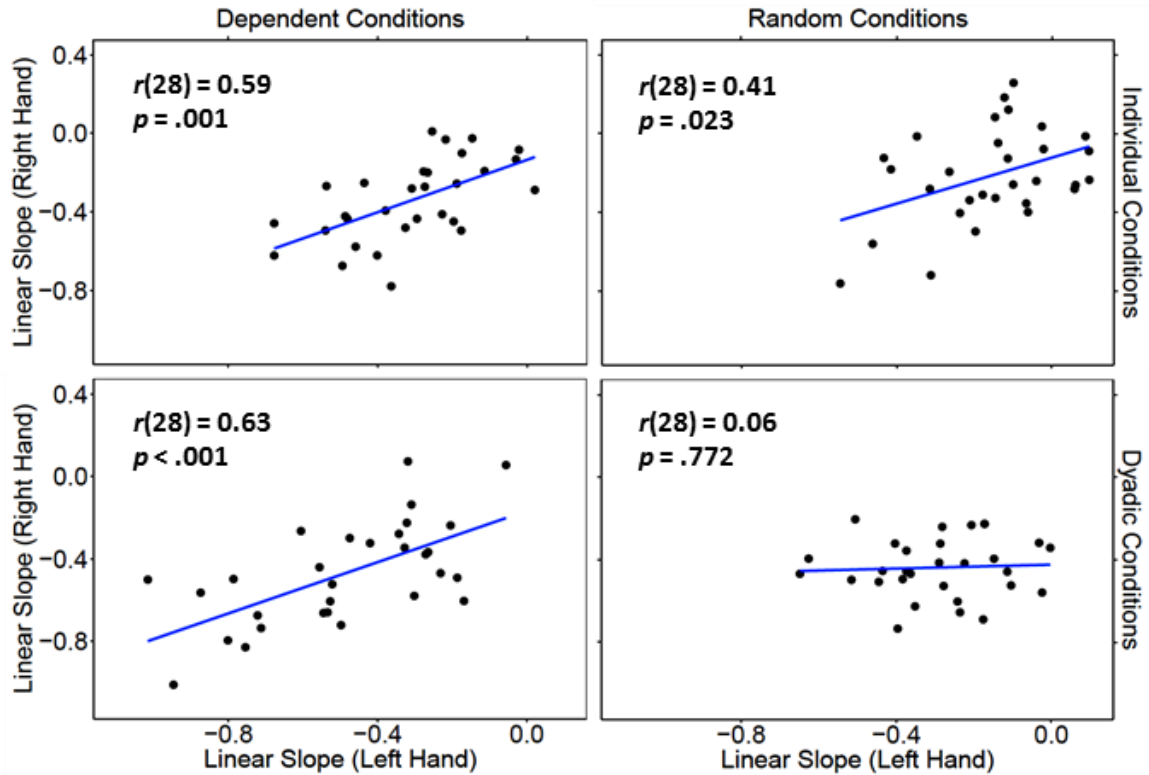


Figure 2. 5. Left-hand slope plotted against right-hand slope per block, separated by Group Type and Movement Type.

#### 2.4.4. Phase Matching

We measured phased matching per response series by correlating the left and right hand IRI series, after convolving each one with a moving-average window 16 responses wide. The mean and variance of Pearson's  $r$  values are shown in Figure 6 below, separated by condition. Figure 6 shows that nearly all correlations were above-zero across conditions, indicating that phase matching was a general feature of performance in our Fitts-like coordination task, even when coupling was inhibited in the dyadic random-drift condition.

To test whether phase matching varied by condition, we conducted a two-way analysis of variance with Group Type as a between-subjects factor (individual versus dyadic), Movement Type as a within-subjects factor (dependent versus random drift), and participants as a random factor. We found a significant main effect of Group Type,  $F(1, 58) = 8.13$ ,  $p < .01$ , and a main effect of Movement Type,  $F(1, 58) = 4.97$ ,  $p < .05$ , but there was no significant interaction between Group Type and Movement Type,  $F(1, 58) = 0.94$ ,  $p = .336$ . Figure 6 shows that phase matching was greater for individuals and for dependent drift, as compared with dyads and random drift, respectively. In summary, these phase-matching results indicate an additive effect of internal coupling and response coupling on phase matching, whereas the complexity matching results indicated a multiplicative effect because the latter occurred equally when either coupling was present, and not at all when neither coupling was present.

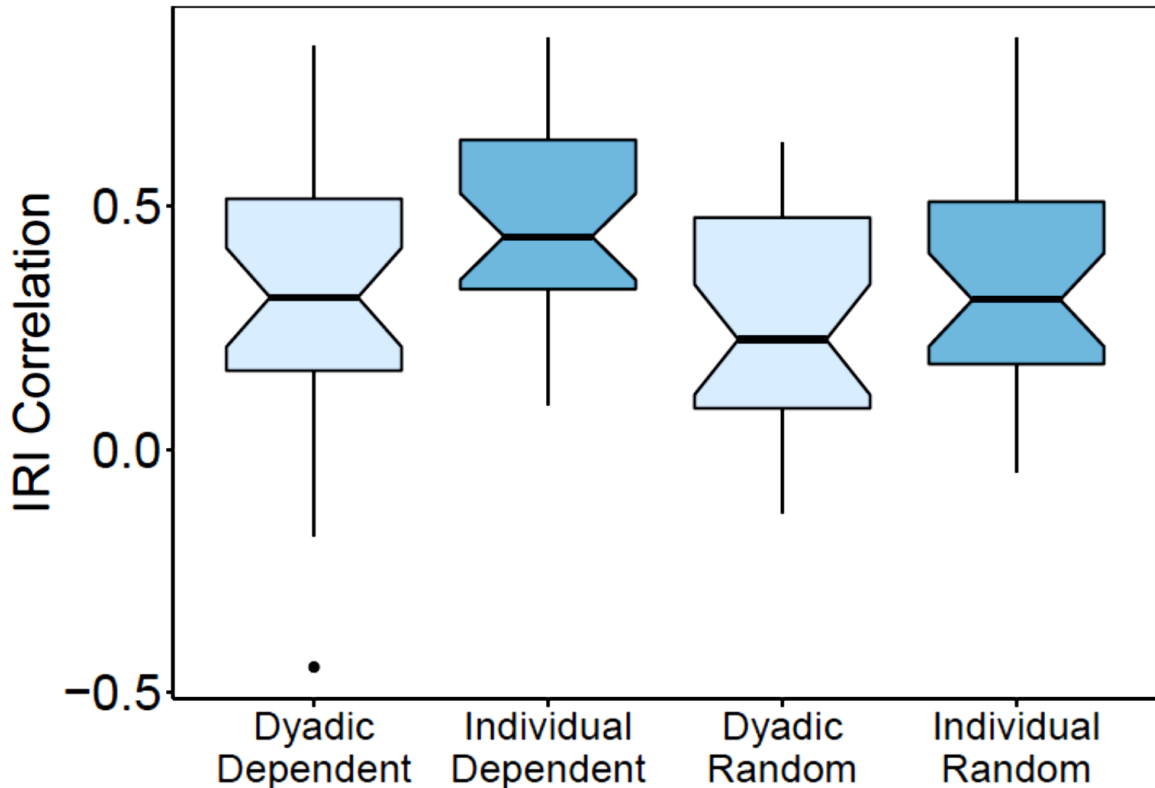


Figure 2. 6. Phase matching of smoothed IRI series in each block as a function of Group Type and Movement Type.

#### 2.4.5. Matching and Performance

Next, we investigate the relationship between complexity matching and performance in terms of total time for each response series in each condition. We followed this analysis with another in which complexity matching was replaced with phase matching. The latter analysis is feasible with our phase-matching measure because it yields a correlation per response series, but we need a similar per-series measure of complexity matching. We formulated a per-series measure of complexity matching as the absolute difference between the left-hand and right-hand slopes, with smaller differences indicating closer matching of slopes for a given response series.

We conducted a 2x2 mixed analysis of variance with Total Time as the dependent variable, and Movement Type and per-series complexity matching as the predictors. We also ran the same analysis with phase matching in place of complexity matching. There was no significant relation between phase matching and performance, but complexity matching exhibited a weak, negative relationship with total time that was marginally reliable,  $F(1,57) = 3.27$ ,  $p = 0.07$ . The weak trend suggests that better performance is, if anything, associated with *less* complexity matching, but the results are not statistically reliable, so we avoid drawing any conclusions based on this experiment alone.



### 2.4.6. Positional and Directional Target Drift

To this point, the drift manipulation employed so far has been framed in terms of response coupling—dependent drift is a channel for left and right responses to affect each other, and random drift eliminates this channel while preserving target movement. The two different drift conditions were designed to be roughly equivalent in terms of drift magnitude, mainly by virtue of bounding them within the same radius. However, random drift steps were drawn from a uniform distribution, without directional bias, whereas dependent drift may be corrective in nature and hence autocorrelated with smaller step sizes. If so, complexity matching may be facilitated by less variability and greater predictability in dependent drift rather than response coupling.

We measured each angular and distance deviation in target position and plotted their histograms aggregated over each response series, as a function of group type and movement type (see in Figure 7). The random-drift conditions showed uniform distributions, as anticipated. The dependent-drift conditions were far from uniform, showing large biases towards smaller steps in corrective directions *opposite* the prior target movement. This anti-persistence in drift direction indicates that participants used their control over the drift to actively stabilize targets toward the middle of each quadrant, occurring somewhat more frequently in individuals than dyads. Individuals responded much faster overall compared with dyads, causing their drift deviations to be larger (as shown in Figure 7), but which the individuals somewhat counteracted through increased negative feedback via the response-tone frequency.

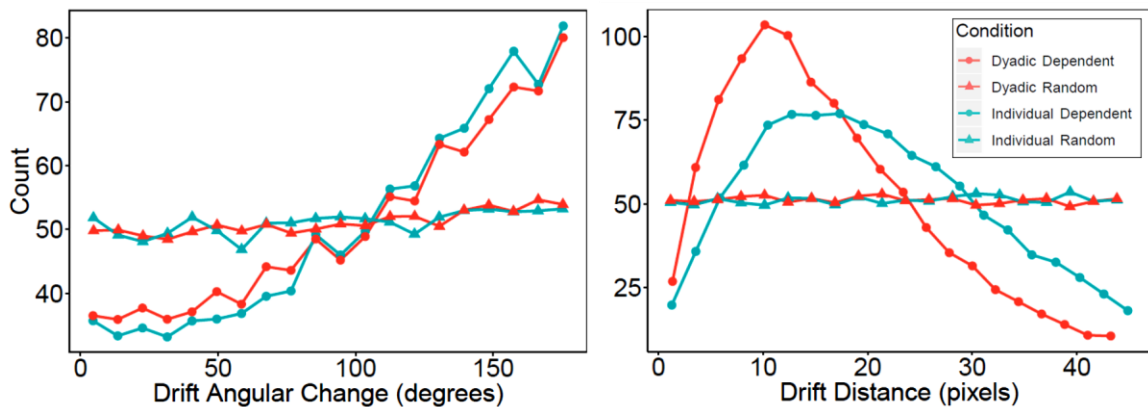


Figure 2. 7. (Left) Direction in degrees ( $0^{\circ}$ – $180^{\circ}$ ) of target movements from one target to the next by Group Type and Movement Type. (Right) Movement distance of the target (measured in pixels) on the x and y-axis from one target to the next by Group Type and Movement Type.

### 2.5. Preliminary Discussion

The directions and sizes of dependent-drift deviations indicate that the effect of dependent drift on complexity matching may have been due to increased predictability in target positions. The other possibility, which we originally hypothesized, is that dependent drift facilitates response coupling between left and right responses. In turn, this coupling

was hypothesized to provide a channel of information exchange that facilitates loose coupling.

In Experiment 2, we tested these competing explanations by dissociating the possible effect of target predictability from response coupling. We created a “playback” condition in which the series of target positions from each block of the dependent condition of Experiment 1 were used to display targets to new participants in Experiment 2. The new participants experienced the same exact target predictability that occurred in Experiment 1, but without the response-to-response interactions across hands. If the effect of dependent drift on matching (complexity or phase) is due to target predictability, then the degree of dyadic matching should be the same for dependent-drift and playback-drift conditions in Experiment 2. By contrast, if matching depended on interactions in Experiment 1, then playback drift should be like random drift, and the playback-drift condition in Experiment 2 should replicate the random-drift condition in Experiment 1.

## **2.6. Methods: Experiment 2**

### **2.6.1. Participants**

To maintain equivalent sample sizes to those of Experiment 1, we collected another 90 students from UC Merced who all participated for course credit. All participants signed a consent form which explained that participation was voluntary, and that the participant could end the experiment at any time. Of the 90 participants (68 female) who volunteered for this experiment, 59 females and 16 males were right-handed, based on which hand they use for writing.

### **2.6.2. Apparatus, Procedure, and Data Collection/Processing**

The experimental setup was the same as Experiment 1, as was the experimental protocol and design. Conditions were also the same, except that random drift was replaced with playback drift. Each series of playback target positions corresponded to one of the series generated by participants in Experiment 1, such that every series was played back once. Data collection and preprocessing procedures were the same as in Experiment 1.

## **2.7. Results**

### **2.7.1. Distance and Angle Variability**

Before reporting the main results, we first verify that dependent drift in Experiment 2 was comparable to playback drift, which was equal to dependent drift in Experiment 1. As shown in Figure 8, variability in drift distance and angular change was highly similar between the Dependent and Playback conditions. This equivalence allows us to ascribe the upcoming effects of dependent drift to response coupling, as opposed to target variability or target predictability.

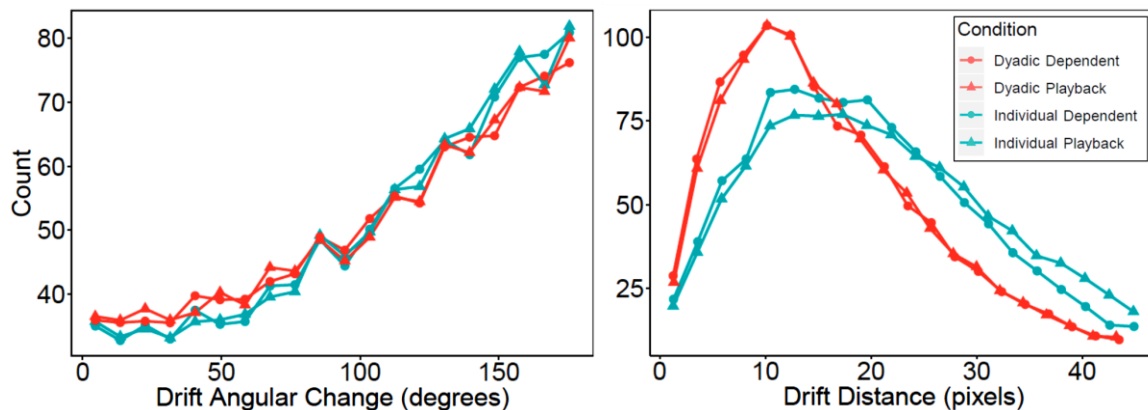


Figure 2. 8. (Left) Direction in degrees ( $0^{\circ}$ – $180^{\circ}$ ) of target movements from one target to the next by Group Type and Movement Type. (Right) Movement distance of the target (measured in pixels) on the x and y-axis from one target to the next by Group Type and Movement Type.

### 2.7.2. Total Time

A 2x2 (i.e., Group Type – Individual or Dyad; Movement Type – Dependent or Playback) two-way ANOVA was conducted with individual or dyad as a random factor. The results indicated a marginally significant main effect of Group Type,  $F(1, 58) = 3.7$ ,  $p = .059$ , and a significant two-way interaction between Group Type and Movement Type,  $F(1, 58) = 6.11$ ,  $p = .016$  (see Figure 9). Individuals were again faster than dyads, especially with dependent drift, but playback drift supported the same overall levels of performance as random drift in Experiment 1. Error rates followed the same pattern as in Experiment 1. These results suggest that target predictability is more relevant to performance than bimanual interactions created by response coupling. Whether it is more relevant for our measures of matching is addressed after we report the spectral analyses.

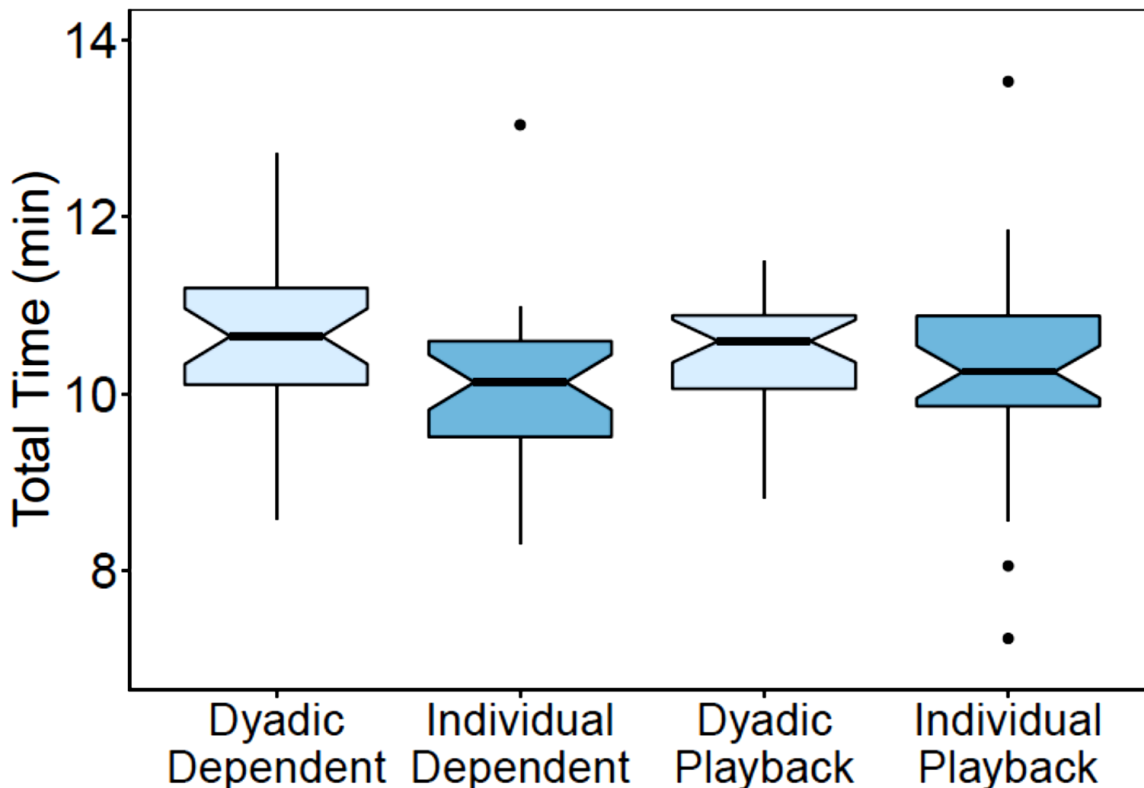


Figure 2. 9. Mean time to complete the task as a function of Group Type and Movement Type.

### 2.7.3. Spectral Analysis

As in Experiment 1, we conducted a 2x2x2 (Group Type by Movement Type by Handedness) mixed ANOVA with linear coefficients of a first-order polynomial as the dependent measure. The results replicated Experiment 1 with reliable or nearly reliable effects of Group Type,  $M_{ind} = -0.704$ ,  $M_{dyad} = -0.928$ ,  $F(1, 58) = 18.87$ ,  $p < .001$ , Movement Type,  $M_{dependent} = -0.9$ ,  $M_{playback} = -0.732$ ,  $F(1, 58) = 3.44$ ,  $p = .069$ , and Hand,  $M_{right\ hand} = -1.614$ ,  $M_{left\ hand} = -1.393$ ,  $F(1, 58) = 5.76$ ,  $p = .02$ . As shown in Figure 10, spectral slopes were steeper for dyads and dependent drift compared with individuals and playback drift, respectively. This pattern replicated Experiment 1, as did steeper slopes for right-hand responses, and no correlations between slopes and performance. The marginal difference between dependent drift and playback drift, compared with a stronger effect of drift type in Experiment 2, suggests that spectral slopes are affected by response coupling as well as target predictability.

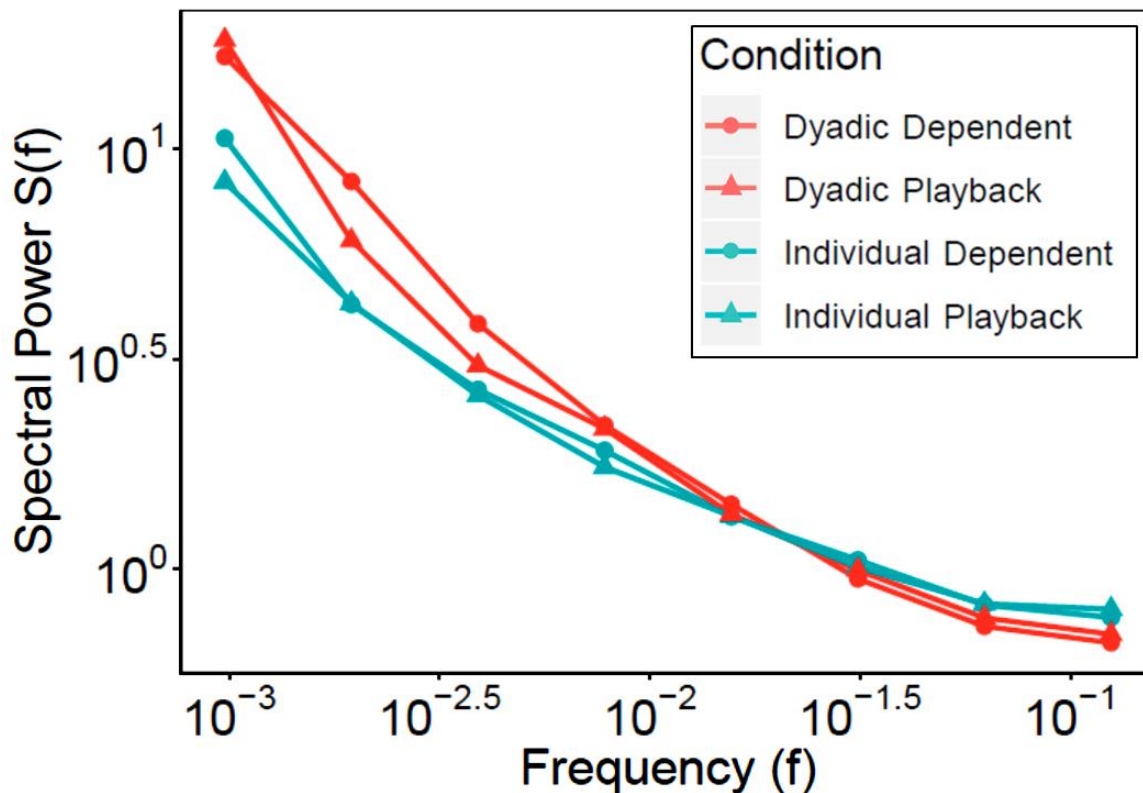


Figure 2. 10. Spectral analysis: Group Type by Movement Type.

#### 2.7.4. Complexity Matching

As in Experiment 1, spectral slopes for left and right responses were correlated within each condition to measure complexity matching. Results again replicated Experiment 1. There were significant positive correlations for both individual conditions and the dyadic dependent-drift condition, but not for the dyadic playback drift (see Figure 11). These results indicate that complexity matching is facilitated by response coupling as afforded by dependent drift, and not by target predictability. If predictability was the operative factor, then we would expect complexity matching in all four conditions since target predictability was equated across them.

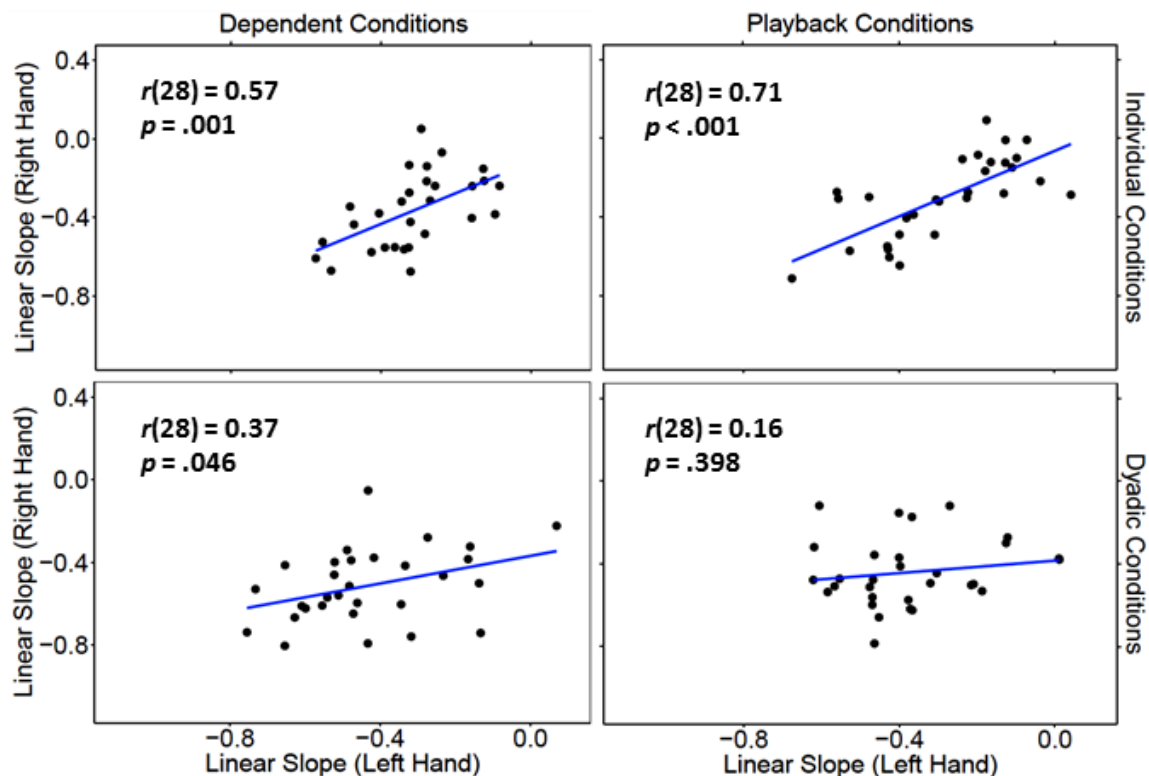


Figure 2. 11. Correlations for Group Type and Movement Type at High Timescales.

### 2.7.5. Phase Matching

As in Experiment 1, we examined the pattern of phase-matching effects by correlating smoothed left-hand and right-hand IRI series, and then analyzing Pearson's  $r$  values as a dependent measure in a 2x2 (Group Type by Movement Type) analysis of variance. The means and variability of  $r$  values are shown in Figure 12. As in Experiment 1, nearly all correlations were positive in all four conditions, indicative of pervasive phase matching. The analysis of variance yielded a significant main effect of Group Type,  $F(1, 58) = 35.84$ ,  $p < .001$ , but no significant main effect of Movement Type,  $F(1, 58) = 1.58$ ,  $p = .213$ , and no significant interaction,  $F(1, 58) = 0.48$ ,  $p = .492$  (see Figure 12). Unlike complexity matching, playback drift facilitated phase matching to the same degree as dependent drift. Therefore, it appears that phase matching was affected by target predictability in Experiment 1, and *not* the lack of response coupling in Experiment 2.

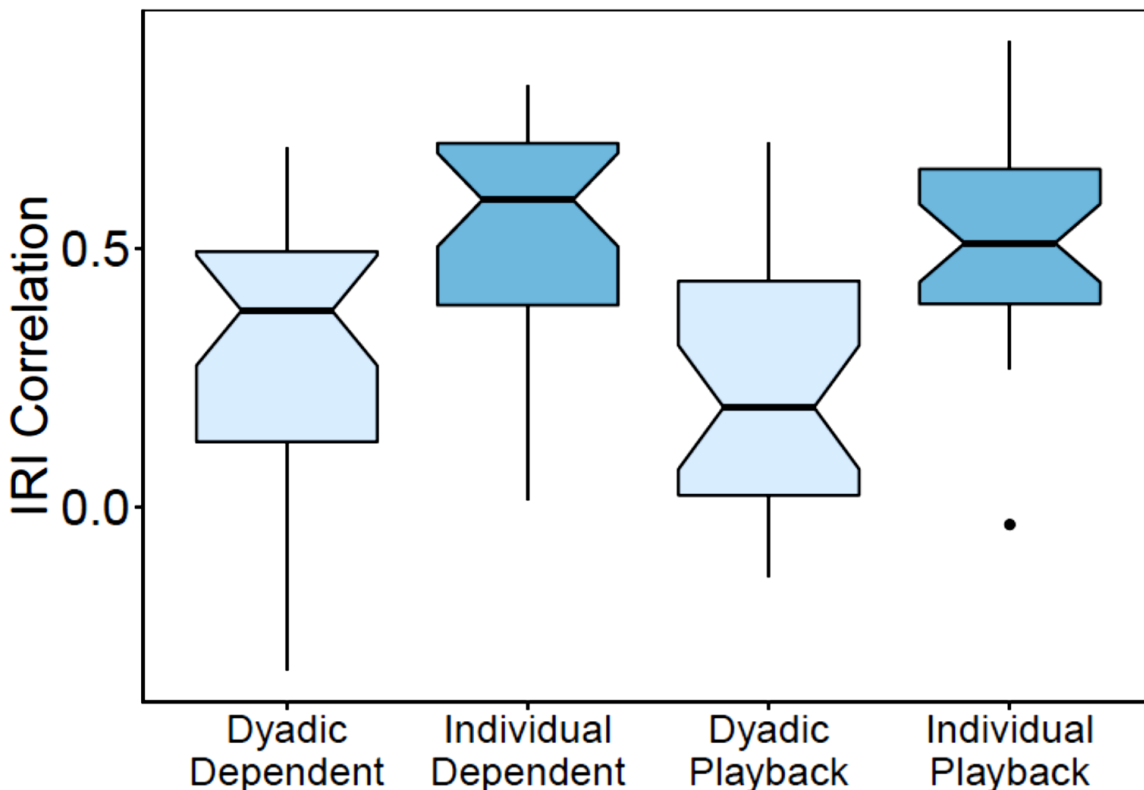


Figure 2. 12. Regular matching of IRI correlations in each block as a function of Group Type and Movement Type.

### 2.7.6. Matching and Performance

As in Experiment 1, the relationship between total time and matching was subtle for both measures, but also consistent enough with Experiment 1 that we combined the data from the two experiments into a single analysis. We combined Random and Playback Drift into a single “Uncoupled” condition, which we then compared to Dependent Drift. We conducted an ANOVA with Total Time as the dependent variable, and Drift Type and either complexity matching or phase matching as the independent measures. Results showed that phase matching was not reliably related to performance,  $F(1, 117) = 2.13, p = 0.147$ , but that complexity matching was marginally related to performance in the dependent drift condition:  $F(1, 117) = 3.49, p = 0.064$  (see Figure 13). This analysis clarifies the weak effect found in Experiment 1 (as seen in Section 2.4.5), by showing that response coupling is helpful to reveal the subtle, inverse effect of complexity matching on performance. The analysis also corroborates other results suggesting that complexity matching, and phase matching reflect distinct processes and principles of coordination (Coey et al., 2016; Delignières et al., 2016).

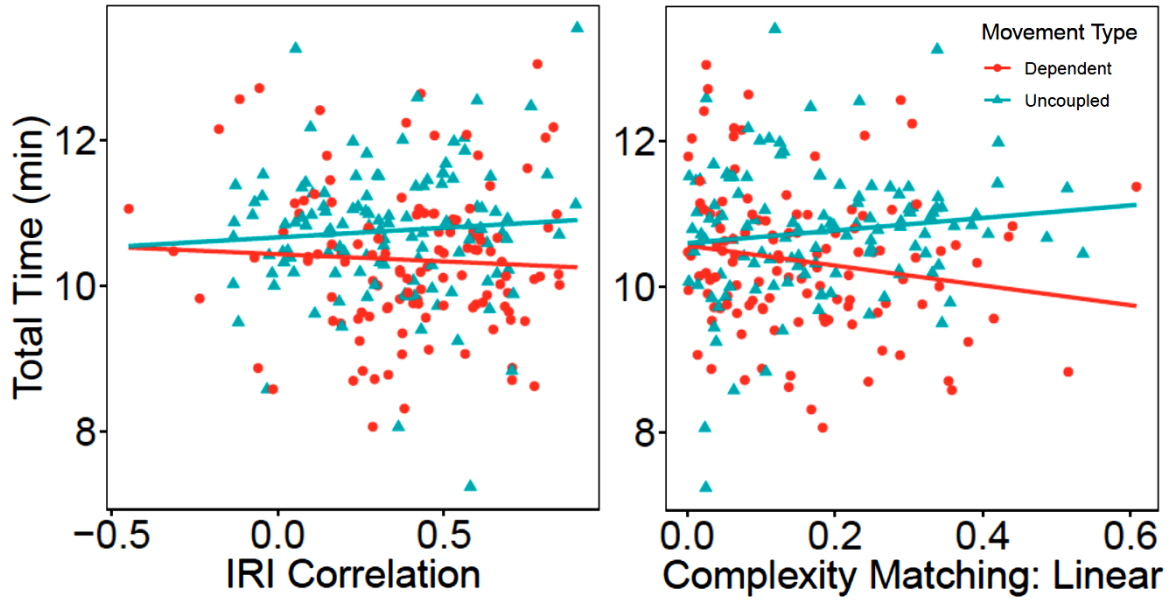


Figure 2. 13. Phase Matching (left) and Complexity Matching (right) by Movement Type: Dependent and Uncoupled (Random and Playback Drift combined).

## 2.8. Discussion

The main goal of our study was to examine complexity matching as it may generalize across dyadic and individual modes of coordination. We also compared complexity matching with phase matching, and we tested whether either measure was related to coordinative performance in a Fitts-like aiming task. We found that complexity matching and phase matching both occur for individuals and dyads, but that the two measures reflect different aspects of coordination. Specifically, complexity matching required response coupling when internal coupling was unavailable (for dyads), whereas phase matching occurred under all conditions. Thus, complexity matching appears to be more sensitive to response coupling, whereas phase matching was more sensitive to target predictability, as evidenced by Experiment 2.

The divergence of complexity matching, and phase matching was also observed in another study that compared complexity matching and phase matching within individuals. Rigoli and colleagues (2014) asked participants to tap in concert with a visual metronome, and they measured long-range correlations in two fluctuations of tapping responses (keypress times and durations) and two fluctuations of the autonomic nervous system (pupil dilation and heart rate). They found complexity matching between the two keypress measures and between the two autonomic measures, but no reliable phase matching among any measured time series. They concluded that complexity matching reflected the interacting networks of activity that produce keypress responses, and likewise within the autonomic nervous system, but that these two sets of networks do not exchange information during a simple, relaxed task of tapping along with a metronome.

Results of the current study, taken together with those of Rigoli et al. (2014), support the theory of complexity matching as a general principle of information exchange between



complex networks. We now have evidence that the principle holds equally for interactions both within and between individuals. We also have additional evidence that complexity matching requires coupling between networks to facilitate information exchange, whereas phase matching does not. These results encourage future investigations into models of information exchange between complex networks that may further illuminate principles of intrapersonal and interpersonal coordination.

We also found that individuals performed better overall compared with dyads, which indicates an advantage when one hand can “anticipate” the response of the other—that is, when the left hand “knows” what the right hand is doing, so to speak. Also, performance was better overall when there was dependent drift, and this advantage appeared to derive from response coupling as well as target predictability. Finally, there was no relationship between performance and phase matching, and only a weak relationship between performance and complexity matching. Complexity matching was related to performance only when responses were coupled via dependent drift, yet better performance was associated with *less* complexity matching.

This relationship with performance was relatively weak and only marginally reliable, so we do not draw any strong conclusions from it. That said, it appears that response coupling enabled response dynamics to *diverge* somewhat between the hands, and that this mode of complementary interaction resulted in faster responses to some extent. Keep in mind that there was a strong overall complexity-matching effect with dependent drift, so apparently, it was advantageous to diverge from complexity matching, at least to some degree. At least two other studies have shown negative relationships between performance and matching (Abney et al., 2015; Wiltshire, Steffensen, & Fiore, 2018). Taken together with several other studies showing positive relationships (Abney et al., 2015; Fine et al., 2015; Zapata-Fonseca et al., 2016), the evidence suggests that a complex relationship between matching and performance may depend on specific characteristics of the coordination task.

Future studies of coordination may advance our methods for measuring coordination and its relationship to performance. For instance, recent advances in studies of human dynamics have introduced multifractal measures of time series (Delignieres & Marmelat, 2012; Ihlen & Vereijken, 2010). Multifractal analyses provide more in-depth measures of long-range temporal dependencies in behavioral dynamics, and recent studies generalized complexity matching to correlate functions of estimated multifractal exponents (Coey et al., 2016; Delignières et al., 2016). Multifractal analyses of IRI series in the present study did not shed any new light on complexity matching and its relation to performance (results not reported here), but future studies may formulate new measures of coordination that further our understanding of the principles underlying its many forms.

## Chapter 3

### Individual and Collective Foraging in Autonomous Search Agents with Human Intervention

#### 3.1. Preface

In this chapter, we departed from Chapter 2 in both the type of interactions that occurred, as well as the measurements we used to evaluate performance across conditions. Here, we transitioned away from dyads to groups, and perceptual-motor coordination to collective search. Importantly, Chapters 3–5 are all related based on the methodology and analytics that are developed within this first set of experiments and simulations. Despite this transition away from more traditional scenarios designed to investigate the dynamics of cooperative interactions, we posit that collective search serves as a useful and rich area for studying coordination, and the influence loose coupling may have within groups larger than two. Typically, loose coupling has been studied within or between individuals (Kello, Anderson, Holden, & Van Orden, 2008; Kello & Van Orden, 2009; Kloos & Van Orden, 2009). Here, we seek to expand this area of knowledge by examining effects of loose coupling in larger group sizes.

Often the context collective searchers find themselves in dictate the strategies that help improve collective outcomes. Here, we investigate whether social foragers can benefit from the ability to vary the degree of individual and collective search modes as a means of improving group foraging performance. Searching strategies may be more-or-less advantageous based on various foraging factors and conditions. For instance, group cooperation can outperform individual foraging strategies by exploiting food resources more quickly (Beauchamp, 2005), in addition to providing security from predation, among other social benefits (Lamprecht, 1981; Vicsek & Zafeiris, 2012). However, these benefits may not always be available or salient. For instance, these benefits are outweighed when foraging becomes sufficiently competitive (Packer & Ruttan, 1988). This dependence on conditions suggests the importance of adaptive and flexible loose coupling that enables switching between independent and collective modes of foraging.

We were inspired by Harel and colleagues (2017), who showed how griffon vultures (*Gyps fulvus*) switch between independent and cooperative foraging strategies in response to certain social cues (Dechaume-Moncharmont et al., 2005; Harel et al., 2017). They found that individual vultures who share visible signs of having recently discovered food were more frequently followed back to the same carcass location at a subsequent point in time. Uninformed vultures used these visible cues, such as blood stains on the head and body, to flexibly choose when and with whom to collectively forage. Flexibly switching between these two strategies increased group foraging success by helping uninformed vultures find new carcasses more quickly, and together, they were able to consume carcasses more quickly, thereby leaving less chance for other scavengers to share in the meal.

In the present study, we developed an agent-based simulation in which both individual and collective foraging strategies provide distinct advantages, such that the ability to vary between them should be advantageous to the group. We created a social foraging

simulation in which we could test collections of autonomous agents with movement rules that varied between more and less flexible modes of interaction. We were also able to test how humans move and interact with autonomous foraging agents by including a condition in which a human player controlled one of the search agents. Our aims were to 1) understand how coupling strength in the movements of autonomous agents plays a role in foraging performance by diversifying their collective movement patterns, and 2) test whether human agents with memory and more-complex strategies engage in loose coupling with autonomous agents in the service of collective foraging.

We manipulated the degree of coupling strength using the Lennard-Jones potential (Spears & Spears, 2012) plus a flocking term that correlated the direction of movement among nearby search agents. We expected the intervention of a human player to improve group performance. We also tested whether the degree of loose coupling, in terms of distancing and flocking among autonomous agents, influenced human search performance. By comparing agent-based simulations with and without human intervention, we tested the benefits of human memory and decision-making while managing a balance between independent and collective foraging behaviors.

### **3.2. Introduction**

Foraging is often studied as an activity performed by individual organisms. A single bird may fly over an area in search of food, as a tiger would roam the jungle, or a person might scan their terrain for resources. In other instances, foraging is studied as a collective activity that groups of organisms engage in, such as schools of fish or colonies of ants seeking food. Often, groups of organisms interacting and moving together while searching for resources are associated with limited cognitive capacities for planning and decision-making. Organisms with greater cognitive capacities may also engage in collective foraging, but they are more likely to exhibit a flexibility or adaptiveness by switching between different foraging modes, like how a lion may choose to hunt in a pride or alone (Lamprecht, 1981). Similarly, a person may choose to help others harvest a large patch of berries or head off alone in search of unfound patches. In general, foragers communicate information about resources and conditions to each other, and thereby help individuals make decisions about where and with whom to forage (Jackson & Ratnieks, 2006; Tereshko & Loengarov, 2005). This sharing of information with others predicates efficient foraging.

More generally, efficient foraging needs to result in both finding and consuming enough food for everyone in the group to survive (Dechaume-Moncharmont et al., 2005; Dreller, 1998; Lihoreau et al., 2017; Seeley, 1983, 2019). One such example by Beauchamp (2005) demonstrated this principle of efficient foraging when simulated agents consumed food at a faster rate than individuals, at the expense of consuming less food per forager. However, there was also reduced variability in the frequency of food consumption, indicating that social foraging may provide protection against long periods of famine.

The apparent prevalence of collective foraging in nature has led researchers to develop and test formal models of collective foraging, to investigate the underlying principles and processes. Liu and Passino (2004) created a collective foraging model based on balancing

forces of attraction and repulsion. Agents tended to position themselves near adjacent neighbors while keeping others distant. The agents were designed to locate resources by following a gradient to their location. By coordinating movements with nearby agents, groups were better able to follow otherwise-unreliable gradients toward resource locations (Falcón-Cortés et al., 2019; Liu & Passino, 2004; Sellers et al., 2007).

The balancing of attraction and repulsion produced *loose coupling* effects that helped coordinate the behaviors of the foraging agents as a group. Larger group sizes helped because the random variability inherent within everyone was averaged out by being loosely coupled. More recently, similar effects were created using the so-called *Lennard-Jones potential* (Copenhagen et al., 2016; Spears et al., 2011) to govern the degree to which agents are attracted or repelled from each other, as a function of the distance between them. As detailed below, we used the Lennard-Jones potential along with two other control parameters to manipulate the coupling strength shared between cooperative foraging agents.

### 3.3. Methods

#### 3.3.1. Simulation Setup and Parameters

Our agent-based foraging model was implemented in NetLogo with a 200x200 grid of pixels with periodic boundary conditions and based on a previous social foraging model (Vicsek & Zafeiris, 2012). The grid was empty except for one target at a time, positioned randomly within the grid. The goal was for ten agents to search the task space for a gold-star target, and to find as many of these targets as possible within a set amount of time. While searching for targets, all agents moved at a constant velocity of 1 pixel per timestep. Agents could not “see” anything until they came within a  $dv = 22.5$  pixel radius of their position, which meant the visible area for each agent was 4% of the total game space. With ten agents searching together, it did not take long to find each next target, which helped to find multiple targets (and hence variability in performance) within short amounts of time.

When an agent detected the target, its status changed such that other agents within view could “see” that the first agent detected a target, even if the second agent could not see the target directly. Specifically, once a simulated agent detected the target, the agent would turn red. When an autonomous agent detected the target either directly, or indirectly via another agent who detected the target, it automatically headed straight for the target or agent, respectively. Agents immediately started consuming the target upon arrival, at a rate of one unit of consumption per time unit, wherein each target initially consisted of 500 consumption units. Therefore, it required 500 timesteps for a single agent to fully consume a target. Less time was required to consume the target as more agents arrived at its location and consumed it simultaneously. Each target “disappeared” once it had been completely consumed, and a new target subsequently repopulated at a random location within the grid.

Each simulation session was defined by the rules applied to all ten autonomous agents that generated search movements to find each target or other agents who found the target (i.e., “visual chaining,” see Cortés-Avizanda et al., 2014). The default rule present in all conditions was a correlated random walk (CRW), which caused each agent to randomly wander through space with some tendency to maintain their current heading. Next was a

“flocking” rule that added a tendency for movement in the average direction of nearby agents. Third and finally was a “distancing” rule based on a generalization of the Lennard-Jones potential (Copenhagen et al., 2016; Spears & Spears, 2012), that drove agents to maintain a given distance from each other. The governing equations for the CRW, flocking, and distancing forces on the  $i$ -th agent (given  $i \neq j$ ) at time  $t$  are as follows:

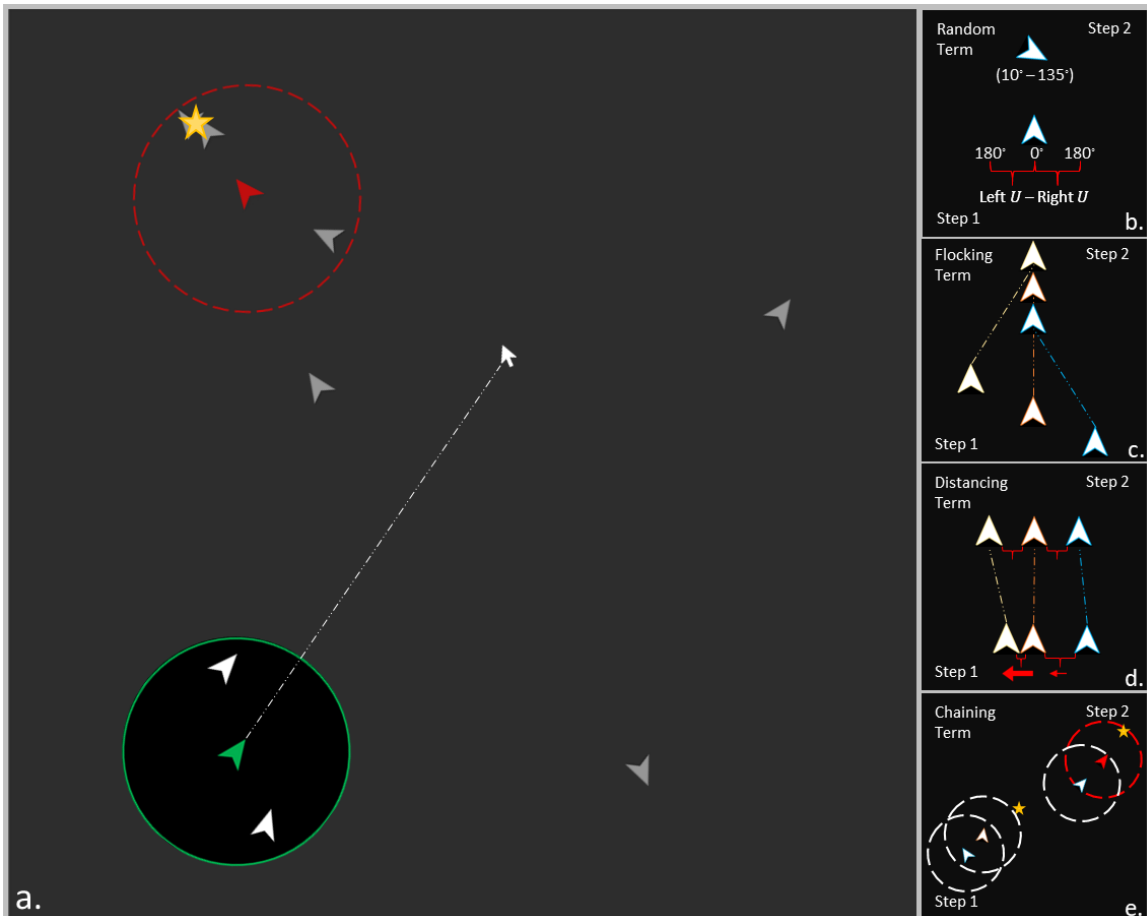
$$\text{CRW } (\vec{d}_N): \quad \vec{d}_{i,N} = [\cos(\theta_i(t - \delta t) + \theta_N), \sin(\theta_i(t - \delta t) + \theta_N)],$$

$$\text{Flocking } (\vec{d}_A): \quad \vec{d}_{i,A} = \sum_{j=1}^{\Omega} \vec{d}_j(t - \delta t),$$

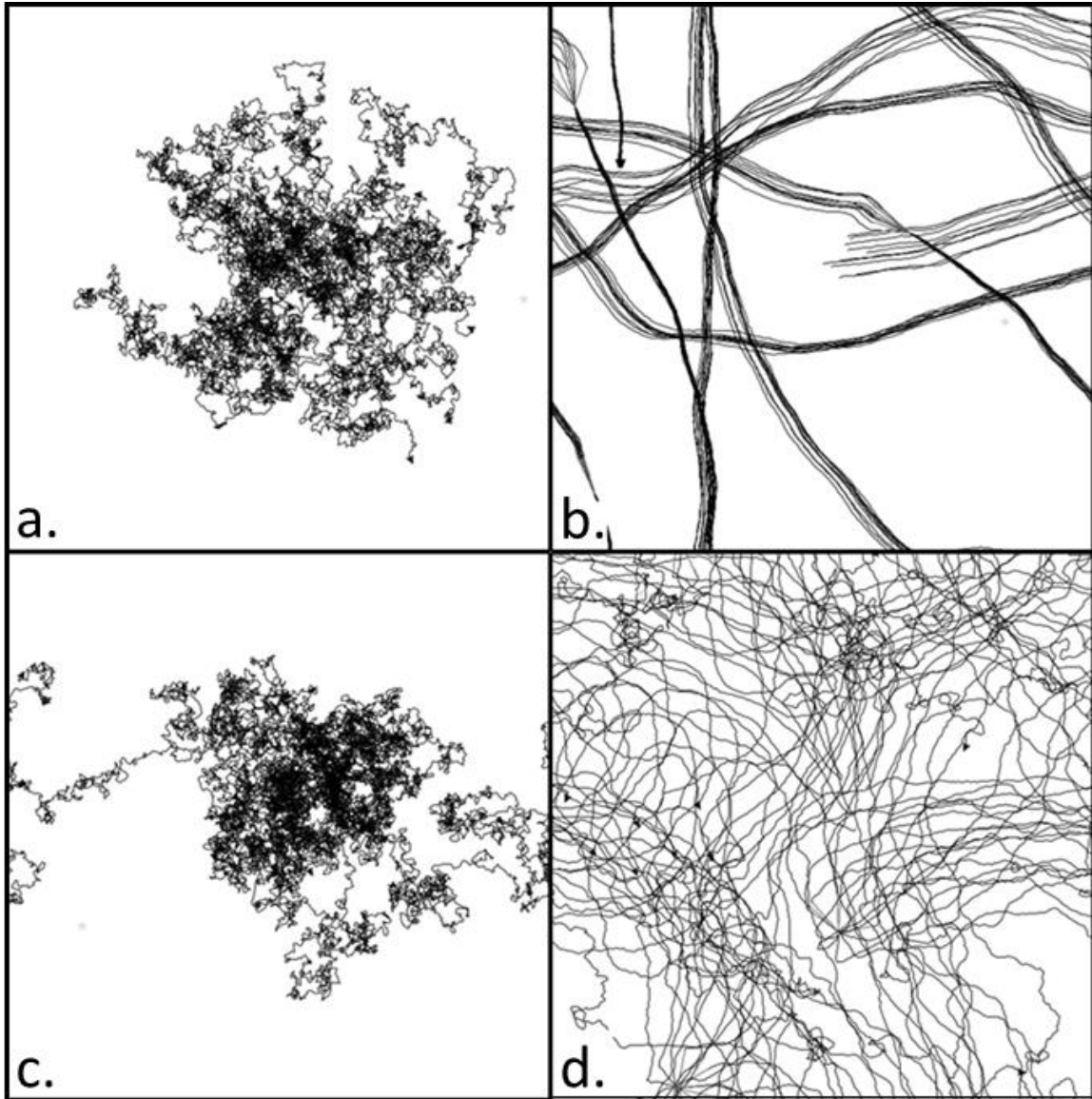
$$\text{Distancing } (\vec{d}_{LJ}): \quad \vec{d}_{i,LJ} = -\sum_{j=1}^{\Delta} \left[ \left( \frac{s}{\|\vec{d}_{ij}\|} \right)^4 - \left( \frac{s}{\|\vec{d}_{ij}\|} \right)^3 \right] \frac{\vec{d}_{ij}}{\|\vec{d}_{ij}\|}.$$

For the CRW,  $\theta_i$  represents the current heading of the  $i$ -th agent and  $\theta_N$  is a correlated random angle given by  $\theta_N = \theta_R - \theta_L$ , where  $\theta_R \sim U(0,180)$  and  $\theta_L \sim U(0,180)$  are independent random turning angles between 0 and 180 degrees. The difference between these random uniform turning angles produces a symmetric probability distribution from  $-180$  to  $180$ , linearly weighted toward zero. For flocking, the vector  $\vec{d}_j$  represents the directional heading of the  $j$ -th agent at time  $t - \delta t$ , where  $\delta t$  represents the timestep. The flocking direction  $\vec{d}_A$  is calculated as the sum of the set of all the agents within the vision distance  $d_v$  denoted as  $\Omega = \{ \vec{d}_j \mid \|\vec{d}_{ij}\| < d_v \}$ . The vector  $\vec{d}_{ij}$  represents the distance in pixels from the  $i$ -th and  $j$ -th agents. The distancing  $\vec{d}_{LJ}$  is calculated from the separation parameter  $s$  (the desired distance between agents), and the distance  $\vec{d}_{ij}$  between pairs of agents belonging to the set  $\Delta = \{ \vec{d}_{ij} \mid \|\vec{d}_{ij}\| < 1.5d_v \}$ . To avoid losing sight of the agents, the separation distance  $s$  was set to  $s = 15$  pixels, which is inside the vision distance  $d_v$ . This distance  $s$  also set the field of view agents could see targets. The exponents 4 and 3 in the distancing rule  $\vec{d}_{LJ}$  represent the repulsion and attraction terms, respectively. The original exponent values for the Lennard-Jones potential are 12 and 6, respectively. These values were chosen arbitrarily, through trial and error, to reflect the loose coupling between agents. The result is a mostly repulsive force with a weak attractive component that fades away as the agents separate by a distance greater than  $s$ .

The governing equation for the  $i$ -th agent at time  $t$  is found by combining additively,  $\vec{d}_i = \vec{d}_{i,N} + \vec{d}_{i,A} + \vec{d}_{i,LJ}$ . Simulation conditions were defined by turning off or on the flocking and distancing rules such that the CRW rule was always in effect, resulting in four different movement conditions: Random (CRW only), Flocking (and CRW), Distancing (and CRW), and Loose Coupling (all three rules combined). See Figure 1 for visual illustrations of the movement rules and see Figure 2 for general trajectory examples of each movement condition.



*Figure 3. 1.* a) Illustrative view of the task space (not shown to players). The green agent and circle represent the human's agent and their field of view (detailed more below). Area outside their field of view was occluded (greyed out area). The dotted line represents that the human agent moved toward the mouse-pointer position, so the human could control movement direction by moving the mouse. b) Random movement shown to be random angular deviations of movement from each previous heading. c) Flocking term directed agents to converge toward a similar shared movement trajectory. d) Distancing term prompted agents to separate from one another when close and move toward each other when farther away. e) Visual Chaining prompted agents to move directly toward an agent flagged as detecting the target.



*Figure 3. 2.* Example movement trajectories for 2000-time steps for each movement condition: a) Random; b) Flocking; c) Distancing; and d) Loose Coupling.

Each simulation session lasted 13,500 timesteps long, which corresponded to about eight minutes in real time when simulated through the NetLogo interface. Performance was measured in terms of the number of targets found and consumed, which in turn was based on the number of timesteps needed to find and consume targets. Each movement condition was tested in 60 sessions to match the number of sessions with data collected from participants in the human intervention experiment, described next.

### **3.3.2. Participants, Materials, and Experimental Setup**

The simulated collective foraging sessions described in the previous section consisted of autonomous agents only, with no human intervention. Matching sessions with human

players, where each session included one human controlling one of the ten agents, were conducted as follows.

Sixty participants from the University of California, Merced were recruited for course credit. After being instructed about the game and filling out the consent form, each participant controlled one of the ten search agents and engaged in collective foraging with the goal of finding and consuming as many targets as possible in the allotted time. Each participant controlled their on-screen avatar by using a computer mouse to place a pointer at the desired location, causing their avatar to move in the direction of the pointer. If the avatar reached the desired location, it kept moving in the same direction until the human player moved the mouse to change course. Participants had the same visual radius as autonomous agents, and their avatar affected autonomous search agent movements according to the rules described above. Alternatively, autonomous agents did not affect movement of the human avatar except for the chaining rule—the human avatar went straight to another agent if the agent was tracking towards the target.

The foraging game was designed to give human players the same operational information and latitude as automated agents so that the only difference from human players was their memory and decision-making about prior states of the environment and foraging outcomes developed through experience. The simulation ran at about 35 msec per update, and each human player ran through one session for each of the four movement conditions, in counterbalanced order across participants. The number of timesteps was chosen to be long enough to elicit variability in performance, but short enough to complete each session in about eight minutes.

### **3.3.3. Measures and Analyses**

The overall measure of performance for each game session was the total number of targets found (session duration was constant), which was determined by the time needed to find and then consume each target. These two components of performance were measured by search time and consumption time, which were computed on a per-target basis, and then averaged for each session. Overall performance was also measured by the average total trial time, i.e., the sum of search and consumption time, where lower times corresponded with better performance.

Two factors were manipulated to test the efficacy of loose coupling and the role of memory and strategy in collective foraging. The efficacy of loose coupling was tested by comparing different movement rules for autonomous search agents across different sessions, where all agents in each session were governed by the same set of rules. The role of memory and strategy was tested by comparing sessions with and without human intervention, and because simulations are not statistically comparable to humans in terms of their variability, we ran separate analyses with and without human intervention.

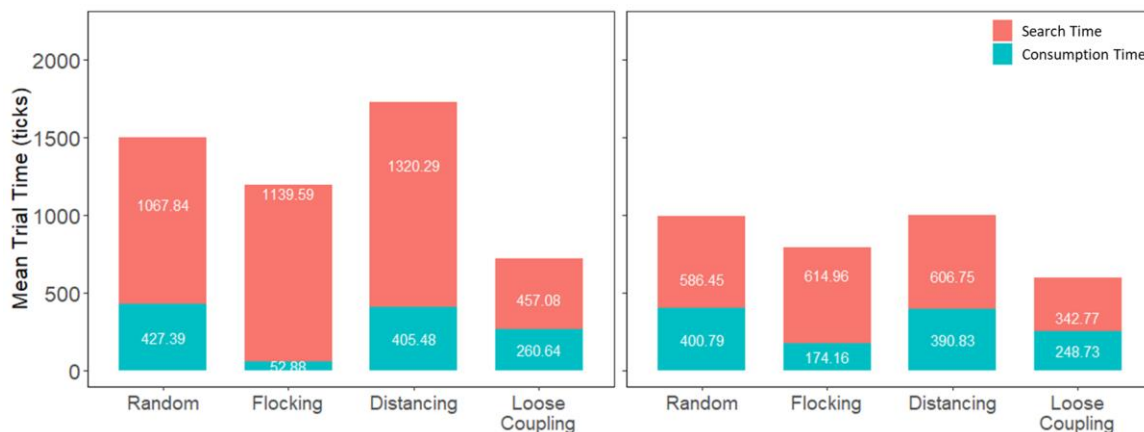
## **3.4. Results**

### **3.4.1. Loose Coupling and Human Intervention Promote Collective Foraging Success**

We first determined group search performance by assessing the metrics of average search time, consumption time, and total targets found in each movement condition with



and without intervention. To test the outcomes of these measures independently, we conducted separate within-subject analyses of variance (ANOVA) with each metric as the dependent measure, and two independent variables: human intervention (present or absent) and movement type (random, flocking, distancing, and loose coupling).



*Figure 3.* 3. Mean trial time per session as a function of movement type without human intervention (left) and with human intervention (right). Mean trial times are divided into their composite search times (red) and consumption times (teal).

Results showed that search performance as measured by mean trial time was better with loose coupling and human intervention, as seen in the lowest average trial times in Figure 3. Movement type had a reliable effect on performance without human intervention,  $F(1,59) = 27.65$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.319$ , and with human intervention,  $F(1,59) = 20.85$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.261$ . The specific direction of effect was supported by post-hoc Tukey HSD comparison tests showing that loose coupling was significantly better than other movement types both with and without human intervention (each  $p < 0.001$ ). By necessity, the same pattern of results was found when performance was measured by the number of targets found per session.

On average, more targets were found with human intervention ( $M = 16.94$ ) than without ( $M = 5.89$ ), and more targets were found with loose coupling ( $M = 16.26$ ), compared with other movement types ( $M = 9.8$ ). Human intervention did not interact with movement type,  $F(1,59) = 2.55$ ,  $p = 0.116$ ,  $\eta_p^2 = 0.141$ , which indicates that more targets were found on average per session for all movement conditions ( $M = 11.04$ ) with human intervention (see Figure 4 below).

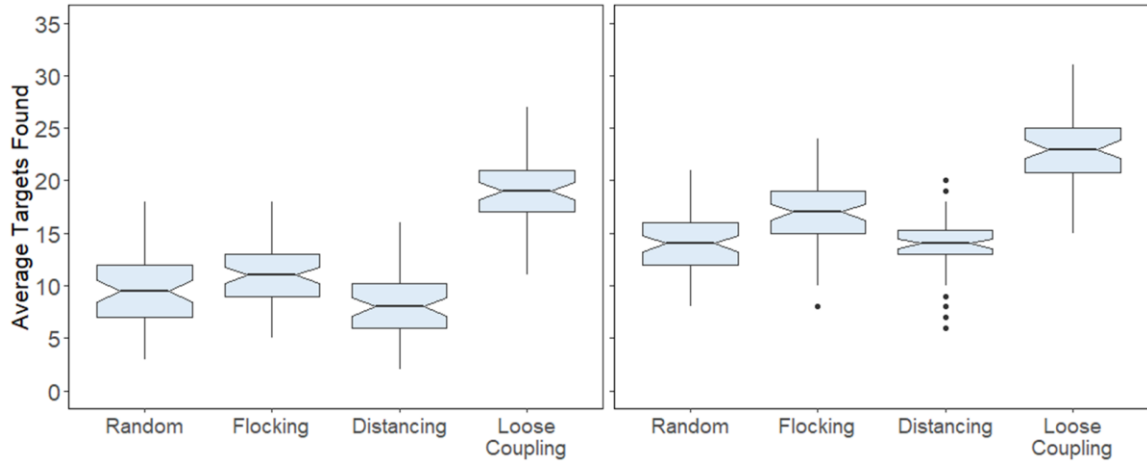


Figure 3. 4. Mean targets found per session as a function of movement type without human intervention (left) and with human intervention (right).

To look further at overall performance, we broke the performance measure of mean trial time into its two component parts: Search Time (i.e., the time from the start of a trial to when any of the agents spotted the target) and Consumption Time (the time from the first agent landing on the target to completely consuming it, which decreased as additional agents arrived to share in consumption). Mirroring mean trial times, search times were fastest in the loose coupling condition regardless of human intervention: without,  $F(1,59) = 48.17$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.449$ , and with intervention,  $F(1,59) = 41.24$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.411$ . Based on Tukey HSD results, both loose coupling conditions were significantly faster than all other respective movement conditions,  $p < 0.001$ . By contrast, consumption times were fastest in the flocking condition: without,  $F(1,59) = 542.2$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.902$ , and with intervention,  $F(1,59) = 56.79$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.49$ . All Tukey HSD flocking condition comparisons were significant,  $p < 0.001$ . Flocking produced faster consumption times because agents were uniformly clumped together when they found a target, so they all landed at one time to consume it together. This effect of flocking was predicted to occur, and we also predicted that the distancing condition would produce the fastest search times by means of a divide-and-conquer strategy. Results were not consistent with this latter prediction, because adding flocking to distancing improved search times by way of loose coupling. We return to this unexpected result later when we present analyses of the rate at which agents collectively covered the search area.

Analyses of search times and consumption times as a function of human intervention found that, again mirroring mean trial times, human intervention improved search times substantially across all four movement conditions, albeit less reliably for loose coupling because of an apparent ceiling effect (loose coupling without human intervention already produced fast search times):  $F(1,59) = 22.24$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.086$ . By contrast, human intervention improved consumption times in most conditions,  $F(1,59) = 80.00$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.253$ , but surprisingly, humans caused slower consumption times in the flocking condition; for comparison, Tukey HSD  $p < 0.001$ . The apparent detriment of human intervention on flocking consumption times can be explained by humans finding targets on

their own, without the benefit of other agents nearby to join in consumption. This explanation is further addressed in the next section.

### 3.4.2. Loose Coupling Diversifies Groupings of Search Agents

Collective foraging performance was best with loose coupling, which was predicted based on the hypothesis that loose coupling balances the benefit of flocking versus distancing. This balance should result in more flexibility in agent groups as they merge, reorganize, and split over time—the agents only partially affect each other’s movements, thereby allowing interactions between search agents to vary as they come in and out of view of each other. To quantify flexibility in grouping, we examined the distribution of numbers of agents in view for each given tick, trial, and agent. If groupings do not change much within each trial, then there should be little variation in the numbers of agents in view, and the distribution should have a sharp peak. By contrast, if groupings vary during a trial, then the numbers of agents in view should vary, and hence their distribution should be more spread out.

We used information entropy to quantify flexibility via the diversity of each distribution over the number of search agents in view. *Grouping entropy* was calculated as  $-\sum[p(x_i) \log(p(x_i))]$  where  $x_i$  is the number of agents viewed by agent  $i$  over time, and  $p$  is the associated proportion of time that  $x_i$  agents were in view. To focus on grouping entropy from the perspective of autonomous agents, we removed the human player from entropy calculations, and to make analyses comparable, we removed a simulated agent at random in sessions without intervention so that entropy was computed over zero to eight possible agents in view in both conditions. The first 14 timesteps at the start of each new trial (when each new target was generated) was removed to avoid initial transients due to agents starting together from the previous target location. Entropy was computed over the subsequent timesteps for each trial, up to the timestep when the next target is detected by one of the agents. We also computed grouping entropy with respect to the human agent, and again we removed one autonomous agent at random so that entropy was computed over zero to eight possible agents in view.

Figures 5 and 6 show distributions of agents in view aggregated over trials and individuals for each movement condition with respect to autonomous agents in the simulation (Figure 5) and with respect to human agents in the experiment (Figure 6). These histograms show that the rules governing agent movements and interactions had large effects on agent groupings. The random and distancing conditions were similar in that agents traveled solo much of the time, with another agent in view sometimes, and two or three more on occasion. Adding the flocking rule to each of these two conditions resulted in opposite effects on the entropy of the distributions. Flocking plus correlated noise (the random condition) resulted in all agents converging and moving together such that variability caused by noise was not enough to disperse the single grouping once it was formed. By contrast, adding the distancing term to flocking (along with the correlated noise) was sufficient to counteract flocking and disperse agents such that their flight configurations varied over time. Variations in loose coupling effects resulted in more varied group sizes and hence more variability and greater entropy in the number of agents in view.

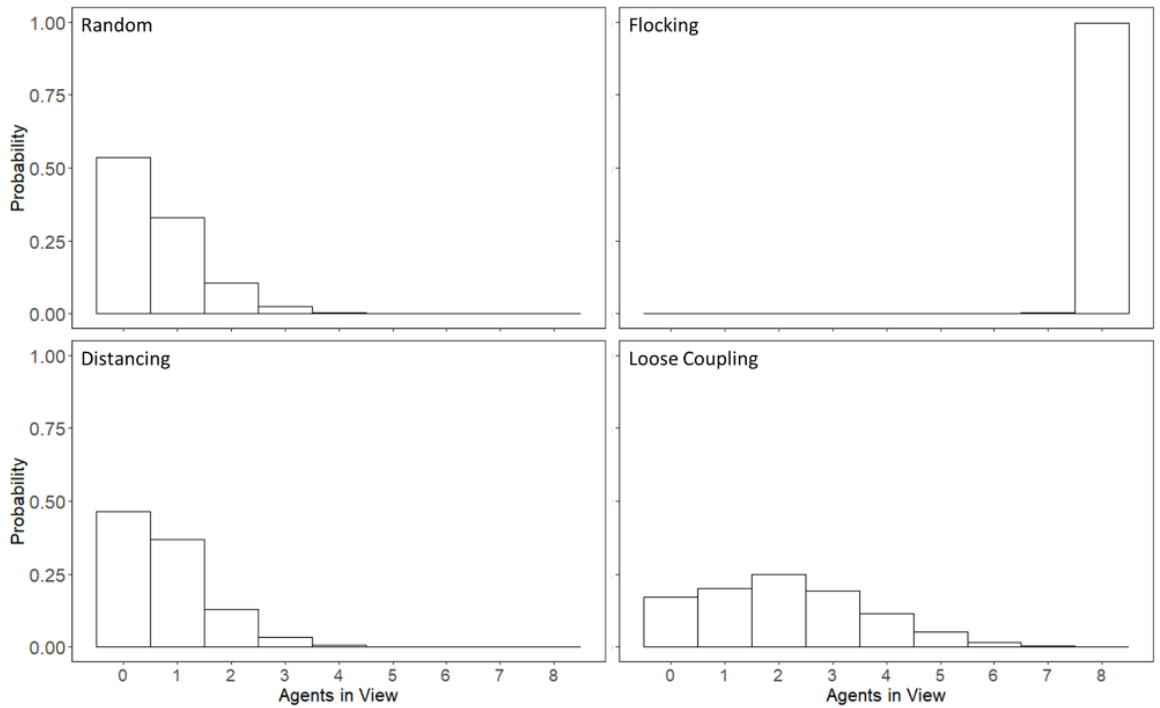


Figure 3. 5. Normalized histogram of the number of agents in view during the search time period respective to one autonomous agent without intervention.

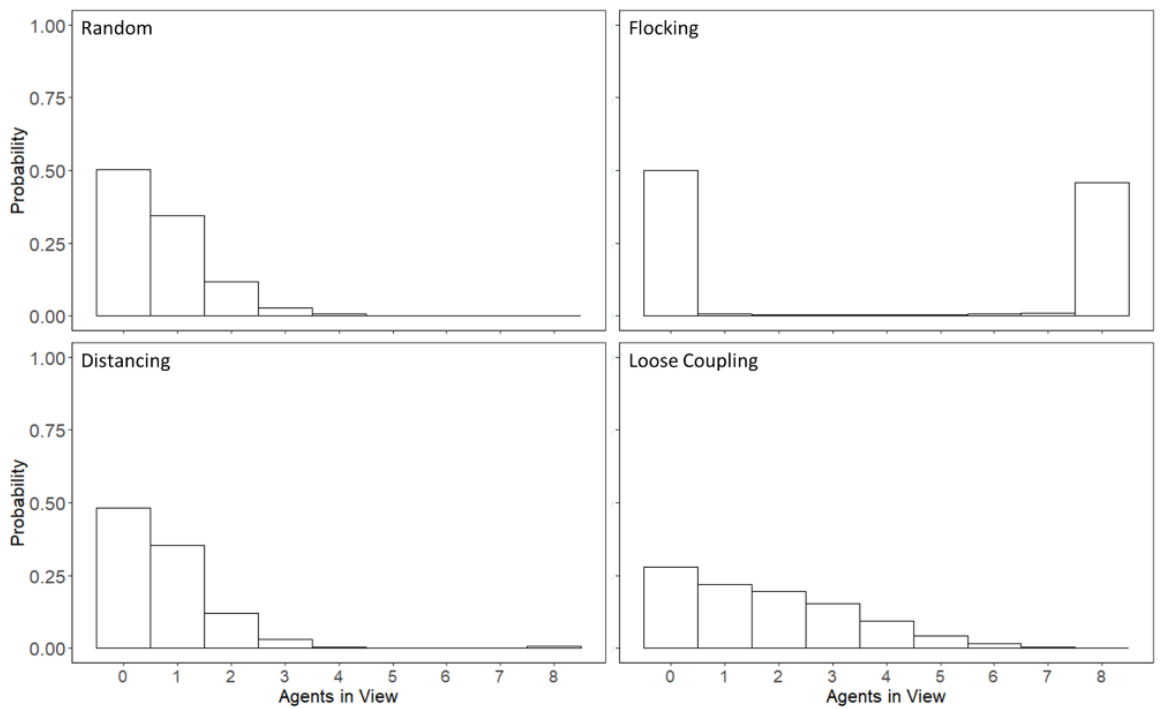


Figure 3. 6. Normalized histogram of the number of agents in view during the search time period respective to only human agents.

We tested the effects of movement type and human intervention on grouping entropy using two different statistical analyses. First, we tested entropy values for individual simulated agents with and without human intervention, as a function of movement type, as shown in Figure 7. By conducting these analyses on individual agents within each movement condition we avoid unequally inflating the frequency count of some grouping sizes over others. Entropy values were minimal in the flocking condition because agents were always in a unified group, so we removed this condition from statistical analyses. We also removed trials with human intervention when the human player was first to find the target, so that entropy values are not directly affected by human intervention. Therefore, differences can be ascribed to the effect of human intervention on the movements of autonomous agents.

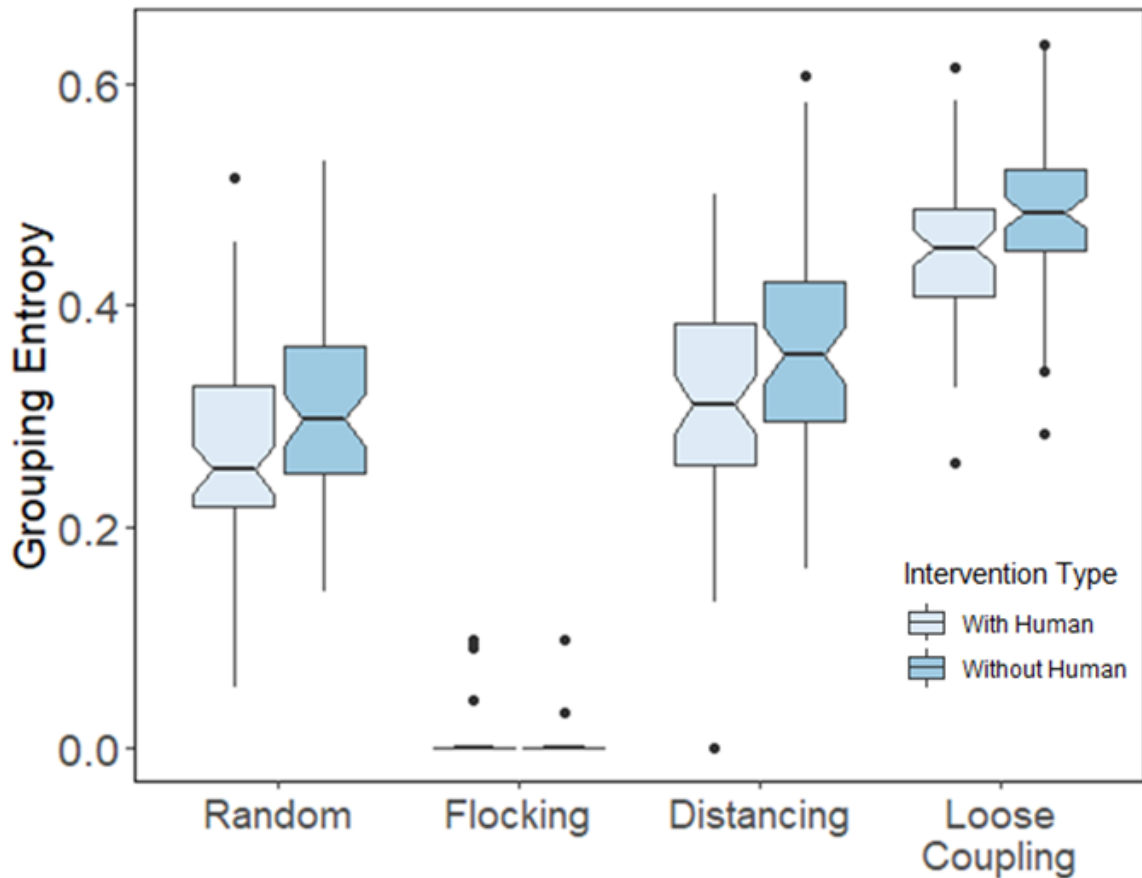


Figure 3. 7. Entropy values for simulated agents as a function of movement type (Random, Flocking, Distancing, and Loose Coupling) in the experiment (With Human) versus the simulation (Without Human).

We conducted a mixed-effects ANOVA with movement condition as a within-subjects factor, human intervention as a between-subjects factor, and entropy as the dependent variable. First there was a significant main effect of human intervention whereby human players caused autonomous agents to exhibit less entropy in their distributions over agents in view,  $F(1,59) = 21.43$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.058$ ; and a marginally significant main effect of movement type,  $F(2,59) = 2.41$ ,  $p = 0.091$ ,  $\eta_p^2 = 0.014$ . The interaction was non-

significant,  $F(2,59) = 0.49$ ,  $p = 0.613$ ,  $\eta_p^2 = 0.003$ . Individual post-hoc tests confirmed that grouping entropy was highest with loose coupling compared with the distancing and random conditions,  $p < .001$ . Human intervention appeared to decrease grouping entropy for autonomous agents by giving them less time to group by converging on targets. This decrease in grouping entropy was evident even in the random condition when humans had no direct effect on agent movements—instead, humans had indirect effects because they helped find and consume targets more quickly, thereby decreasing the time available for agents to converge on targets, leaving them less grouped and more dispersed in general.

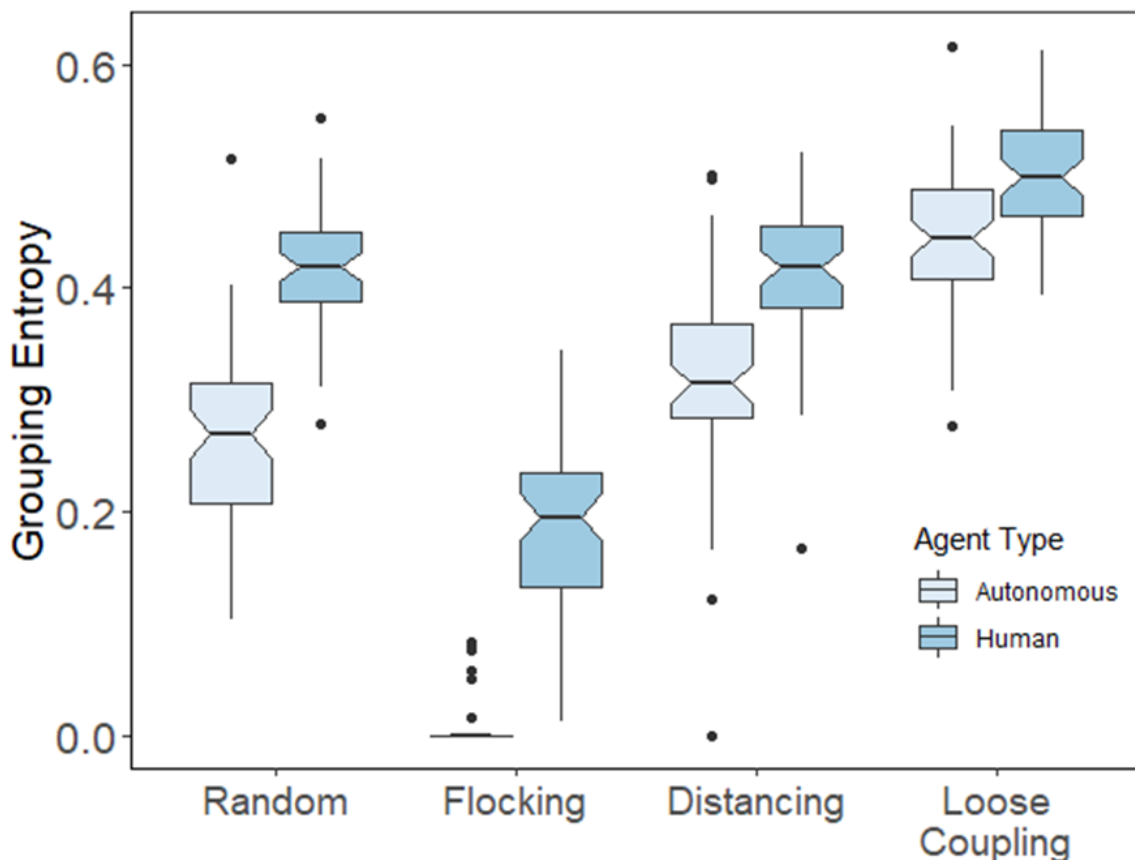


Figure 3. 8. Entropy values by movement condition (Random, Flocking, Distancing, and Loose Coupling) for human players (Human) versus simulated agents (Autonomous) in the experiment.

In our second analysis, we compared grouping entropy for human players against grouping entropy for individual simulated agents in the experiment with human intervention (Figure 8). We ran another ANOVA like the previous analysis, but with “intervention type” replaced by “agent type” (human or autonomous) as a between-subjects factor, again excluding the flocking condition from movement type. We found that grouping entropy was greater for humans compared with autonomous agents,  $F(1,59) = 213.85$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.379$ , and grouping entropy was again influenced by the movement condition,  $F(2,59) = 8.11$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.044$ , and post-hoc tests showed it was greatest with loose coupling,  $p < 0.001$ . There was also an interaction such that

grouping entropy for human players was more like autonomous agents when the latter were loosely coupled compared with other movement types,  $F(2,59) = 16.9$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.088$ . Moreover, human movements exhibited the most grouping entropy when coordinating with loosely coupled agents,  $p < 0.001$ . Overall, given that grouping entropy was higher, and performance was better, with loose coupling and with human intervention, we can infer that collective foraging in our simulation benefits from loose coupling between autonomous agents as well as for mixtures of agents and humans.

### 3.4.3. Human Intervention Benefits Search Performance for Non-Random Agents

Entropy analyses in the previous section showed that human intervention decreased the grouping entropy of autonomous agents, even though performance was generally better with human intervention and with increased grouping entropy. Therefore, it is unclear whether human intervention improved the way that autonomous agents searched, or if humans are simply better searchers and therefore find and consume more targets than autonomous agents.

To test the search performance of autonomous agents themselves, we measured how fast they covered the game space when searching for each next target, and we compared their rates of search-area coverage with and without human intervention as a function of movement type. Specifically, *area search rate* was computed as the number of unique pixels searched on each trial, divided by the time spent searching prior to finding the target, and converted into a percentage of total pixels ( $200 \times 200 = 40,000$  pixels).

To test more specifically how human intervention affected autonomous agents, we measured area search rate at both the individual and collective levels for autonomous search agents. Human movements may perturb autonomous agents such that they individually reduce the number of returns to areas already searched, and human movements may also perturb agents to reduce overlap among their collective search areas. Figure 9 shows area search rates for autonomous agents with and without human intervention for individual search and collective search. As before, the human was removed from rate calculations, and trials were excluded when search was terminated by the human player finding the target first. We used ANOVA models as in the previous results for grouping entropy, but with area search rate as the dependent measure instead, and flocking was brought back into the statistical model.

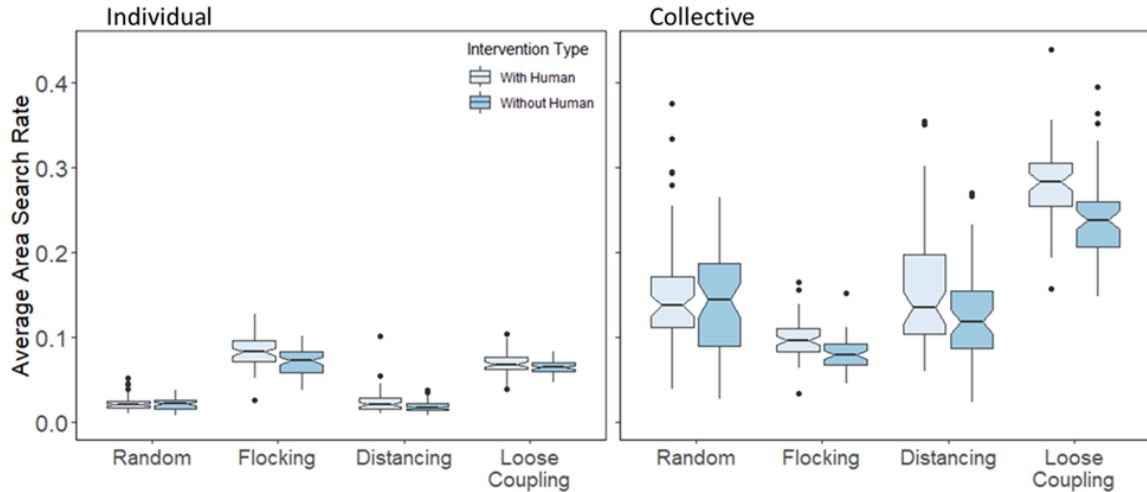


Figure 3. 9. Area search rate for autonomous agents, averaged for each session, and plotted as a function of movement type and human intervention for agents individually (left) and collectively (right).

We found that human intervention improved both individual search rates and collective search rates,  $F(3,59) = 43.09$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.044$ , but had no effect on random movement conditions because humans had no direct effect on random agent search movements, all  $p > 0.95$ . The benefit of intervention was greater for collective versus individual area search rates,  $F(3,59) = 17.28$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.018$ , indicating that human intervention reduced overlap in autonomous agent search areas, as well as reduced the degree to which individual agents returned to previously covered areas. We also found individual area search rates were not reliably different between the flocking and loose coupling conditions, all  $p > 0.7$ , but collective search rates were greater with loose coupling compared with flocking, all  $p < 0.001$ . These results indicate that loose coupling preserved the individual diffusivity of flocking agents, but the addition of distancing helped to reduce their overlap and thereby improve collective search effectiveness.

#### 3.4.4. Human Search Benefits from Coordinating with Loosely Coupled Agents

The previous section focused on the beneficial effect of human intervention on the individual and collective search performance of autonomous agents as a function of different movement rules. We can also test whether different movement rules have different effects on human search performance. In theory, human players could search on their own, unresponsive to the movements of other agents. However, to the extent players try to guide or otherwise coordinate with autonomous agents, the efficacy of human search movements may be affected by the way agents move and coordinate. Results presented earlier showed human intervention affected autonomous agents via their grouping entropy, and agents affected human players in kind. Given that human players showed the greatest grouping entropy when agents themselves showed the greatest grouping entropy in the loose coupling condition, we can hypothesize human search performance may benefit from coordination with loosely coupled agents.



To test the effect of movement rules on human search performance, we computed area search rates for the human players individually. Not surprisingly, as shown in Figure 10, humans covered the search space at a faster rate than the individual agents they foraged with,  $F(1,59) = 536.04$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.534$ . For each given target, humans can use memory and strategy to avoid inefficiently returning to previously searched areas. More interestingly, human players outperformed themselves in the Random and Distancing conditions when coordinating alongside loosely coupled agents, both  $p < 0.001$ . The human players performed similarly across the Flocking and Loose Coupling conditions,  $p = 0.535$ , but the human player searched equally as well alongside Flocking, Distancing, and Random agents, all  $p > 0.1$ . What this analysis shows is that, not only can human players search effectively across all movement conditions, but also that the humans' searching performance can improve even further when working alongside loosely coupled agents. Exceeding their own effectiveness when coordinating with loosely coupled agents by expressing their intelligence and cooperativeness.

Taken together with results from the previous section, we can conclude that human players and loosely coupled agents benefitted from each other to improve search performance by virtue of flexibly coordinated movement patterns, as evidenced by higher values of grouping entropy.

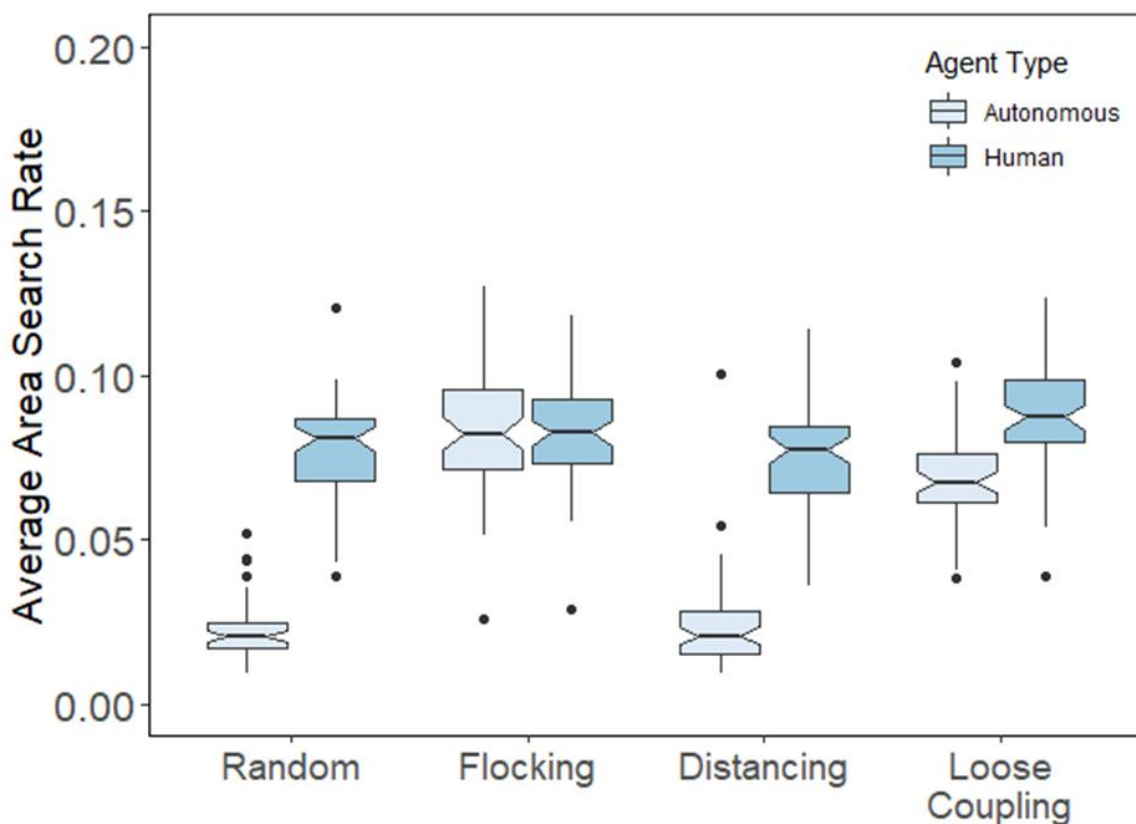


Figure 3. 10. Area search rate averaged for each session and plotted as a function of movement type and agent type for human players and individual agents with intervention.

### 3.4.5. Human Players Adapt their Foraging Strategies to Agent Behaviors

At this point, we have seen how human players improve collective foraging by means of memory and strategy, however, the evidence has not been direct. It is difficult to infer specific strategies from gameplay data alone, but one apparent choice players can make in collective foraging is the emphasis on finding versus consuming targets. Players may try to find targets with other agents following or not, or they may instead seek out other agents to collectively consume each target so the next one comes faster. Human players may improve collective foraging in part by adapting their emphasis on finding versus consuming targets based on the rules governing the movements of the other agents.

To measure the emphasis on finding versus consuming targets, we analyzed the proportion of targets found versus consumed by human players as a function of movement type. As a baseline, assuming that humans are no better than their autonomous counterparts, they should find targets 10% of the time (0.1 proportion of times) and consume 10% of the target units (recall that each target consisted of 500 consumption units), given that the human player is one of ten foraging agents. The difference between finding and consuming proportions is a measure of the emphasis that human players placed on one versus the other component of collective foraging.

Regarding adaptations in strategy, we can see the differential between proportions varied as a function of movement type, for finding targets,  $F(3,59) = 36.07$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.187$ , and consuming targets,  $F(3,59) = 30.8$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.164$ . Specifically, players emphasized finding targets and consuming targets when agents were not loosely coupled, all  $p < 0.001$ . This contrast of emphasis across loose and non-loose coupling conditions is evidence players adapted their strategy to the movement rules for agents—emphasizing independent detection and consumption when agent search was directed by non-loose coupling rules, and more equitable detection and consumption rates with loosely coupled agents. This equity in emphasis indicates the human player sharing more equally to off-load responsibility for the overall performance of the group when loosely coupled – i.e., acting as a member of the group rather than as a lone searcher.

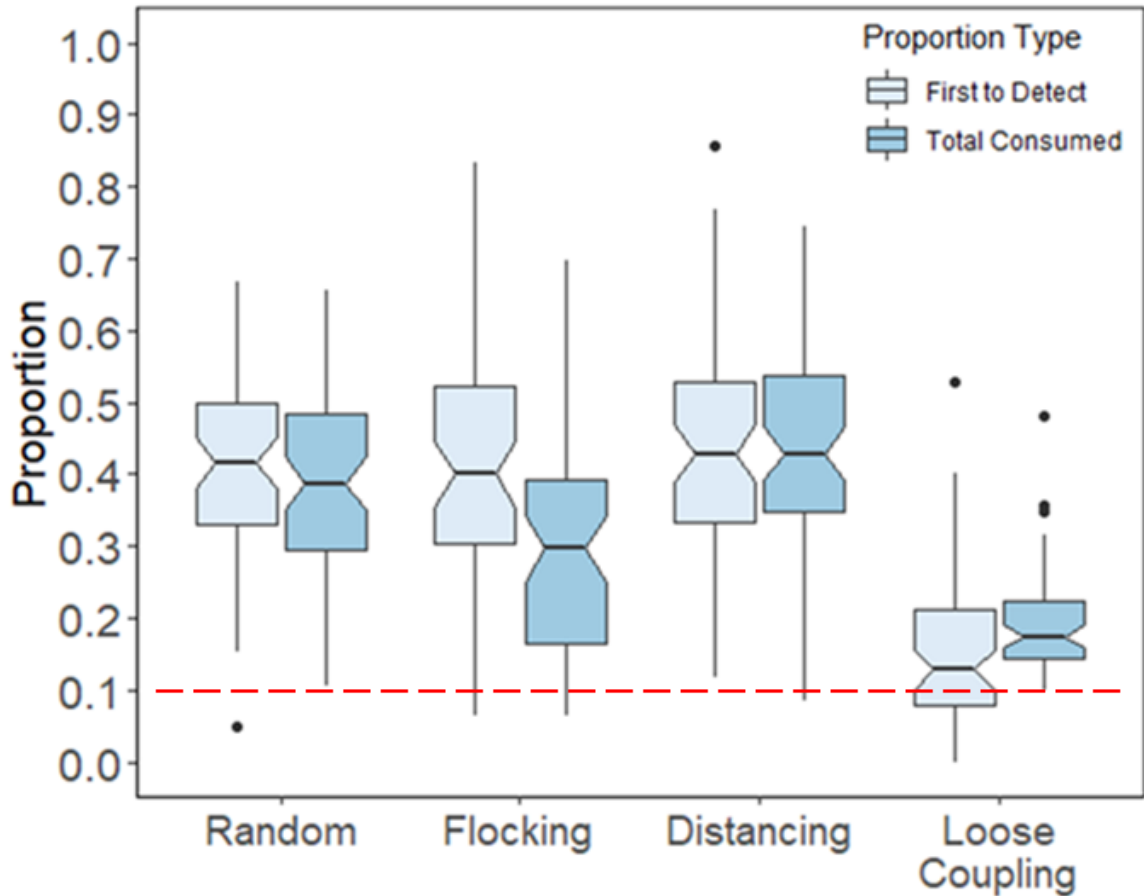


Figure 3. 11. Finding and consuming proportions for human players as a function of movement type. The red line indicates the expected proportion to be found and consumed if human performance was no better than that of simulated agents. Proportions above the expected baseline indicate the degree to which humans outperformed simulated agents.

First one can see that both proportions were significantly above 0.1 in all movement conditions, all post-hoc tests  $p < 0.001$ . Greater-than-chance proportions support that at least some of the benefit human intervention provides comes from the superiority of human players, although this benefit was lowest when agents were loosely coupled, all  $p < 0.001$ , because loose coupling was the most-effective movement rule.

### 3.5. General Discussion

Our principal goal here was to investigate the benefits of balancing individual and collective modes of interaction in loosely coupled systems. We designed an agent-based model in which finding targets benefitted from individual agents diffusing across the search space, whereas consuming targets benefitted from convergence of agents on target locations. We formulated movement rules that balanced a tendency toward distancing with a tendency towards flocking, and simulations showed that the resulting loose coupling among agents was beneficial to overall group performance. Analyses of grouping entropy

showed loose coupling diversified the range of more-individual to more-collective search configurations, because flocks of various sizes formed and dissolved as time unfolded.

Our simulation showed how loose coupling is beneficial even when agents are memoryless and unable to learn, adapt, or develop strategies through experience. The diversity of search patterns did not come from decision-making of any kind—it was instead driven primarily by injecting noise with the CRW movement component, plus additional randomness from positioning of targets. Our simple model of loosely coupled foraging agents is useful in its economy of mechanism and may be appropriate for collections of simple organisms and artificial agents with minimal capacity for computation. However, foraging is necessary for the survival of all mobile species, including for humans and other social animals with extensive capacities of memory, learning, and strategy to drive decision-making over time. To test how decision-making capacities might interact with simple rules of loose coupling, we compared simulations of autonomous agents with and without human intervention.

Human players exhibited an even greater diversity of search configurations than loosely coupled agents, and both humans and autonomous agents covered the search area at faster rates in the loose coupling condition compared with too much distancing or too much flocking. These results provide evidence that abilities like learning and memory may complement simpler rules of loose coupling to support social foraging, rather than supplant them. It is difficult to determine movements were controlled based on strategies learned through experience, but we did find evidence that players adapted their strategies to coordinate with agents differently depending on the agent search behaviors. Specifically, we found human players emphasized finding and consuming targets individually when agents distanced too much or flocked too much, whereas they shared more equally when agents were loosely coupled. This finding suggests intelligent agents can learn to leverage other agents for the good of the group, depending on their abilities.

Our agent-based model proved useful for demonstrating the benefits of loose coupling and adaptive foraging strategies, but future studies could undertake more thorough analyses of the model and its parameters to understand which aspects are most important for loose coupling in social foraging. Also, while the distancing and flocking rules combined to produce loose coupling, they were not quite complementary on their own. Flocking had the desired effect of longer search times offset by shorter consumption times relative to random search, but distancing did not have the reverse effect—instead, distancing did not have an appreciable effect beyond noise from the CRW rule, although it synergized strongly with the flocking rule. Future studies may consider a different form of distancing that has the opposite effect of flocking, i.e., shorter search times offset by longer consumption times.

Finally, it would be informative to study how groups of human foragers coordinate to play our social foraging game. The most salient question is whether players would still exhibit signs of loose coupling in terms of flexibly diverse groupings, and whether group performance would still benefit from loose coupling. Theories of self-organization suggest that loose coupling may be generally useful for adapting coordinated behavior to respond to changes in conditions as they unfold (Van Orden et al., 2003). For instance, it may be

useful to follow one or more agents when they are first encountered in the hopes of finding targets and consuming them together, but it may become more beneficial to break from the group and seek new search opportunities as time goes by instead of following the group with no success. In this way, loose coupling may enable agents to enact a “stay-or-go” decision between exploiting nearby agents or exploring new opportunities, similar to the stay-or-go decision at the heart of optimal foraging theory (Charnov, 1976; Ehinger & Wolfe, 2016; Pleasants, 1989). The agent-based modeling and experimental paradigm introduced herein could be extended to investigate these and other questions about individual and collective foraging.

## Chapter 4

### Optimizing Loosely Coupled Cooperative Agents

#### 4.1. Introduction

Here, we continue our investigation into the effects loose coupling can have on collective performance by refining the rules governing the searching behaviors of cooperative agents. We further optimized loose coupling effects based on collective performance and individual search rates. By refining Lennard-Jones potential exponents and creating a new separation-distance parameter, we increased the positive outcomes resulting from loosely coupled agents working together. By further refining the attraction and repulsion parameters of the Lennard-Jones potential, we expected to see increased collective and individual performance metrics. Specifically, with increased loose coupling effects we expected to see increased numbers of targets found, grouping entropy, and area-search-rates.

An important part of loose coupling that made agents successful in Chapter 3 was their ability to diversify the size of their groupings. We predicted that refining the Lennard-Jones potential would increase diversification of group sizes, resulting in higher grouping entropy. Similarly, increased performance in Chapter 3 resulted in part from agents covering the space more effectively and efficiently. For this reason, we predicted that search efficiency and area-search-rate measures would both improve as well when loose coupling effects are enhanced.

Both search efficiency and area-search-rate measures are related, but each tap into differing aspects of searching behavior. Search efficiency as we defined it related to the rate agents collectively found and consumed targets. This balance was imperative to performance in Chapter 3. Movement configurations needed to balance both finding and consuming targets quickly to improve collective performance. We hypothesized that enhanced loose coupling effects would lower collective searching and consuming times across the more-optimal loose coupling agents. Relatedly, area-search-rate gauges an individual's ability to effectively search the space, benefitting significantly from covering areas that have yet to be searched by that individual. Anticipating more-optimal configurations of the Lennard-Jones potential would allow agents to move more efficiently, we expected these improvements to prompt agents to search the space more effectively as well. Adding further evidence that loose coupling, or soft-assembly benefits collective performance.

To test our hypotheses, we first swept across the Lennard-Jones potential exponents to vary the strength of loose coupling shared across agents. Varying the strength of loose coupling effects resulted in definitive improvements in collective performance for some configurations, while others saw a drastic decrease in performance. As agents become more loosely coupled and flexible, we saw them search more effectively.

Additionally, we added a control parameter varying the separation distance between agents after a target repopulated. This added feature simulated the emergent distance separating agents as time went on. Originally, in Chapter 3, agents would continuously

search the space for targets, and following the repopulation of a target, agents would continue searching from their present location. Here, we simulated this separation distance by recentering all agents back, within a set radius, to the center following a target being fully consumed. We varied this radius to observe its effect on collective performance.

Returning all the agents nearer to the middle can benefit performance because agents working together in larger groups consume targets faster. By returning to the middle, agents can more reliably search within larger groups, allowing these groups to quickly consume targets together. Alternatively, at greater radius distances from the center, this separation parameter spread agents out across the search space. By spreading agents out, agents may collectively find targets faster by covering space more quickly than they could in larger groups. Prospectively, this separation-distance parameter simulates the spread of agents as it would otherwise emerge over time, but in a more deliberate and controlled way. Allowing us to better understand its impact on reorganizing group sizes via loose coupling effects.

## 4.2. Methods

### 4.2.1. Simulation Setup and Parameters

Apart from a few key changes, nearly all the parameters used in Chapter 3 are replicated here. Using Netlogo, ten agents would search for a single hidden target within a 200 x 200 pixel space with periodic boundaries. All agents moved at the same constant velocity and would search the space over the same 13,500 timestep duration. All ten agents had the same visual radius size to see other agents and spot targets. As before, agents who spot a target turn red, visually indicating they found the target to others within view and would head directly towards the target location. Upon arrival, agents consume targets at the same rate, with a maximum duration of 500 timesteps if consuming the target alone. If multiple agents found the target, the target would be consumed more quickly, with a minimum of 50 timesteps.

Importantly, the alignment, noise, and Lennard-Jones potential well-depth components functioned the same as before. However, we made a few key changes from our previous model. Based on how loose coupling helped to improve collective performance over other movement conditions, our aim was to further explore its impact on collective performance and grouping variability. To do this, we swept across the two exponents of the Lennard-Jones potential (LJP) in increments of 0.5 units to pursue a more-optimal configuration, enhancing the effects of loose coupling. Additionally, all ten simulated agents had an increased visual radius for spotting targets from  $dv = 15$  pixels to  $dv = 22.5$  pixels, making the radius for viewing other agents and targets equal. This increase also makes their vision equal to the human players from Chapter 3.

In Chapter 3, all agents moved based on the present movement conditions, which frequently caused them to spread out over time. This emergent separation likely contributed to collective performance. To simulate emergent separation distance between agents, we varied the positions of agents by recentering them following a target repopulating. After fully consuming a target, agents would be repositioned within some set radius from the middle of the search space. We varied this radius from zero to 100 in increments of 20. An

initial separation distance of zero put all the agents in the exact middle of the space, while a separation distance of 100 randomly populated them throughout the entire space. Each agent would calculate x and y coordinates ranging positively or negatively from 0 to the set maximum distance (see Figure 1). Coordinates were independently calculated for each agent using the following:

$$\text{Initial Separation Distance (ISD}_{xy}): X_{\text{pos}} = ((-X_1) + X_2); Y_{\text{pos}} = ((-Y_1) + Y_2)$$

where  $X_1$ ,  $X_2$  and  $Y_1$ ,  $Y_2$  were all independent random samples ranging positively from 0 to the set maximum radius distance. The remainder for  $X_{\text{pos}}$  and  $Y_{\text{pos}}$  then formed the respective coordinates for each agent around the origin.

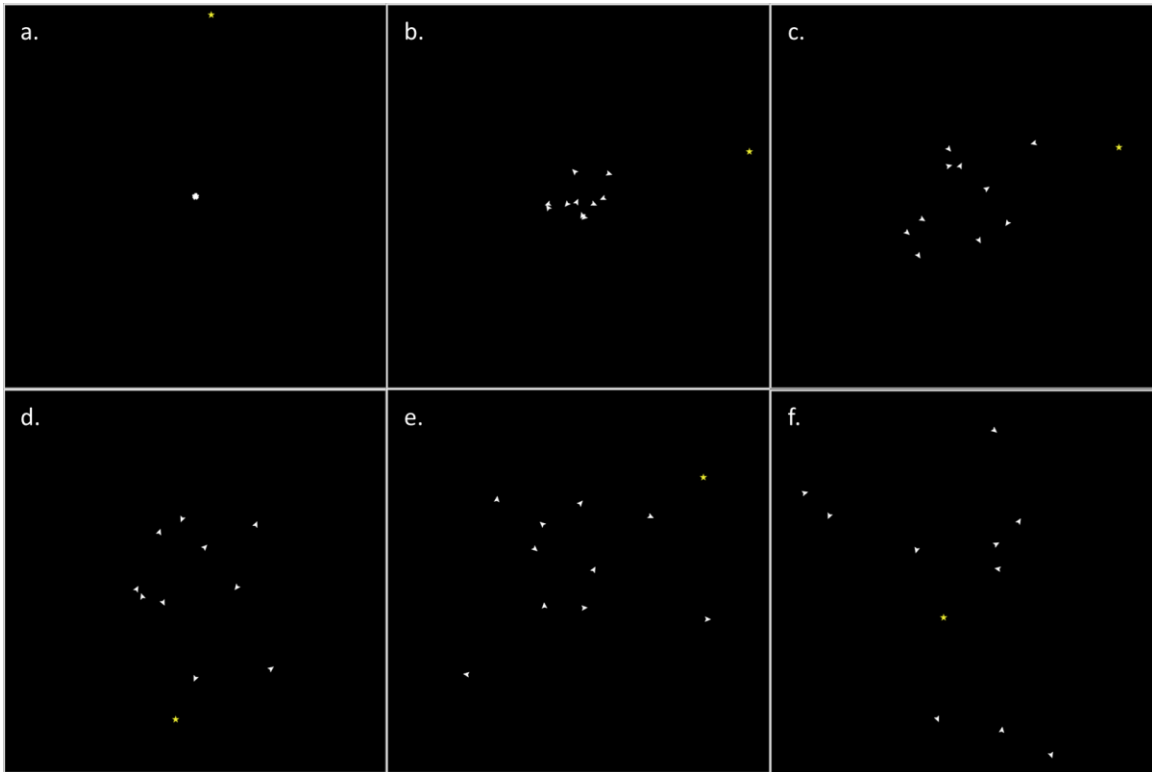


Figure 4. 1. Example initial agent separation distances at zero (a.), 20 (b.), 40 (c.), 60 (d.), 80 (e.), and 100 (f.) maximum patches from the center origin of the search space.

ISD<sub>xy</sub> allowed grouping variability to be more consistently controlled as the task developed over time rather than relying on this variability to emerge spontaneously. All other remaining features of the task space and agents were carried over from the original model configurations in Chapter 3.

### 4.3. Results

#### 4.3.1. Loose Coupling Improves Performance, Relying on Grouping Diversity

First, to determine if there are more-optimal loose coupling configurations, we needed to reduce the number of exponent configurations for the attraction and repulsion



components of the LJP. To do this, we swept across each exponent in 0.5 increments. To recap, see the original distancing equation below:

$$\text{Distancing } (\vec{d}_{LJ}): \quad \vec{d}_{i,LJ} = -\sum_{j=1}^{\Delta} \left[ \left( \frac{s}{\|\vec{d}_{ij}\|} \right)^4 - \left( \frac{s}{\|\vec{d}_{ij}\|} \right)^3 \right] \frac{\vec{d}_{ij}}{\|\vec{d}_{ij}\|}.$$

The exponents 4 (alpha) and 3 (beta) in the distancing rule  $\vec{d}_{LJ}$  represent the repulsion and attraction terms, respectively. These values were originally chosen through trial and error to reflect the loose coupling between agents. Resulting in a mostly repulsive force with a weak attractive component that dissipates when agents separate greater than  $s$ . Here, by sweeping across a range of exponent values, we are deliberately configuring agents to find increasingly more-optimized loose coupling effects. Each configuration was repeated 10 times. See Figure 2 for the average number of targets found for each configuration.

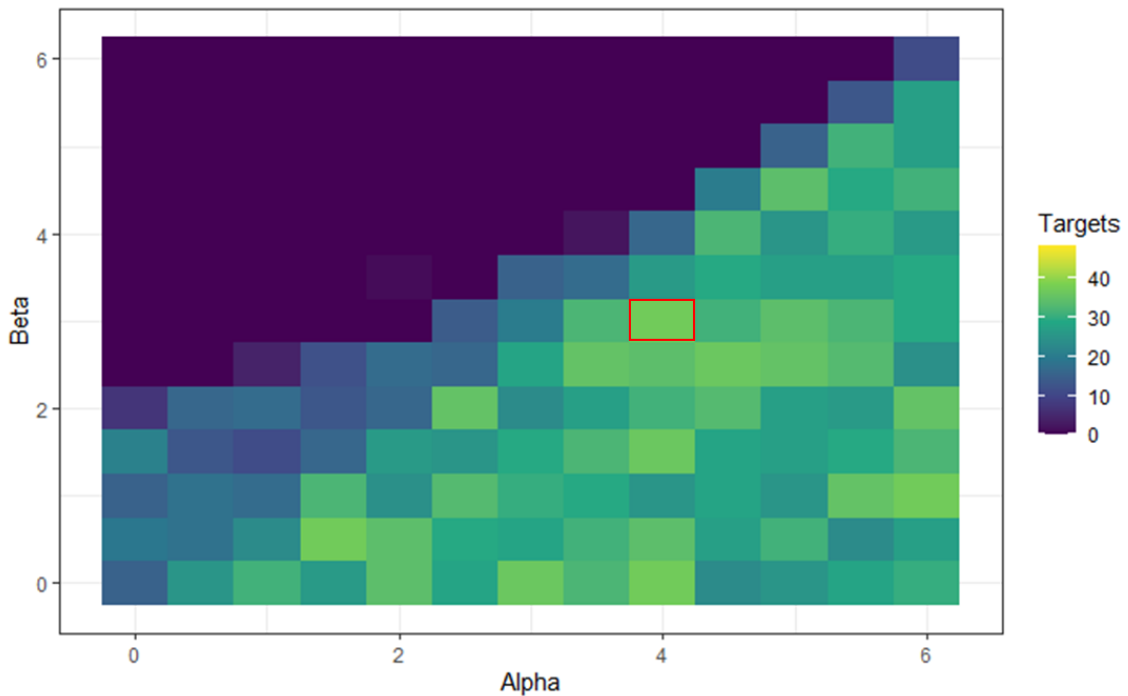
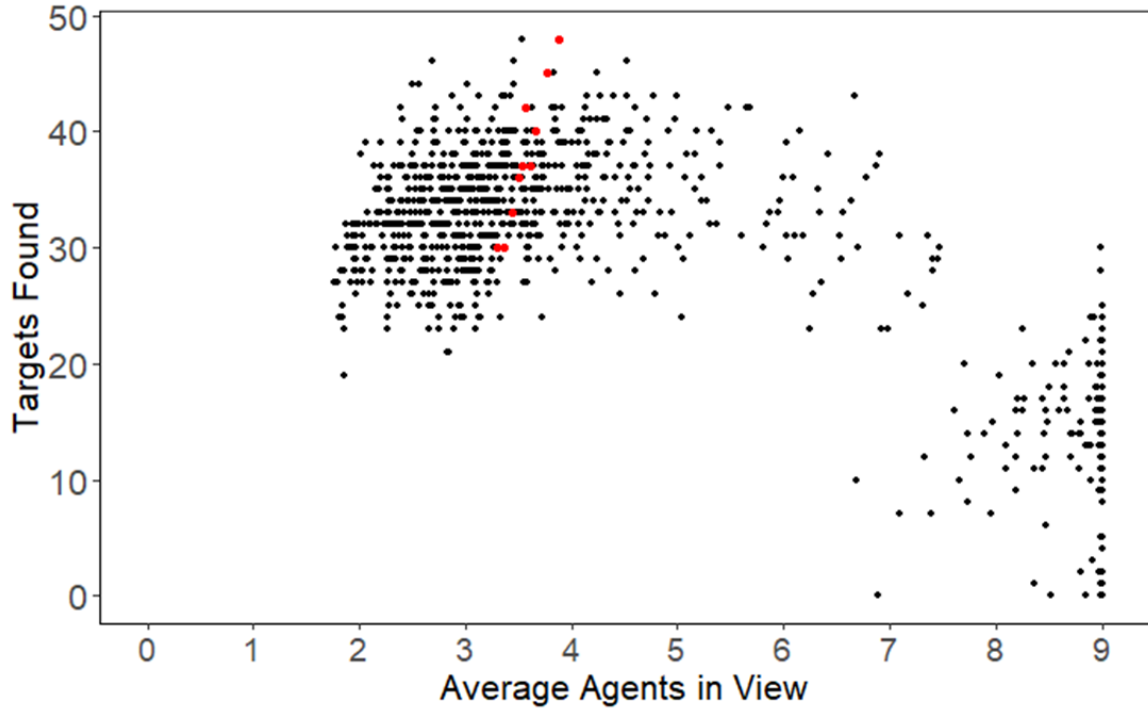


Figure 4. 2. The number of targets found per configuration averaged across 10 repetitions. The tile outlined in red indicates the original configuration of alpha and beta values.

As indicated by the dark colored tiles in the upper-left portion of Figure 2, quite a few setups result in approximately zero targets found. These configurations disproportionately favored attraction resulting in the agents converging towards a single stationary point, completely unable to search the space for targets. Compared to configurations with larger group sizes on average (i.e., an average of seven or more), diversifying the total number of groups helped to improve performance, as seen in Figure 3.



*Figure 4. 3.* The number of targets found as a function of the average agents in view across all agents. Each point indicates an independent alpha and beta configuration. Red points indicate the ten repetitions for the original LJP configuration.

Next, to better differentiate these configurations, we looked at group search efficiency. As used herein, the “search efficiency” refers to the additive sum of the average search and consumption times. This total indicates on average the duration to find as well as consume targets throughout the simulation. For example, if agents were quick to find a target, but slow to consume it, then this value would be higher. Search efficiency scores are only low when targets are both found and consumed quickly, as seen in Figure 4.

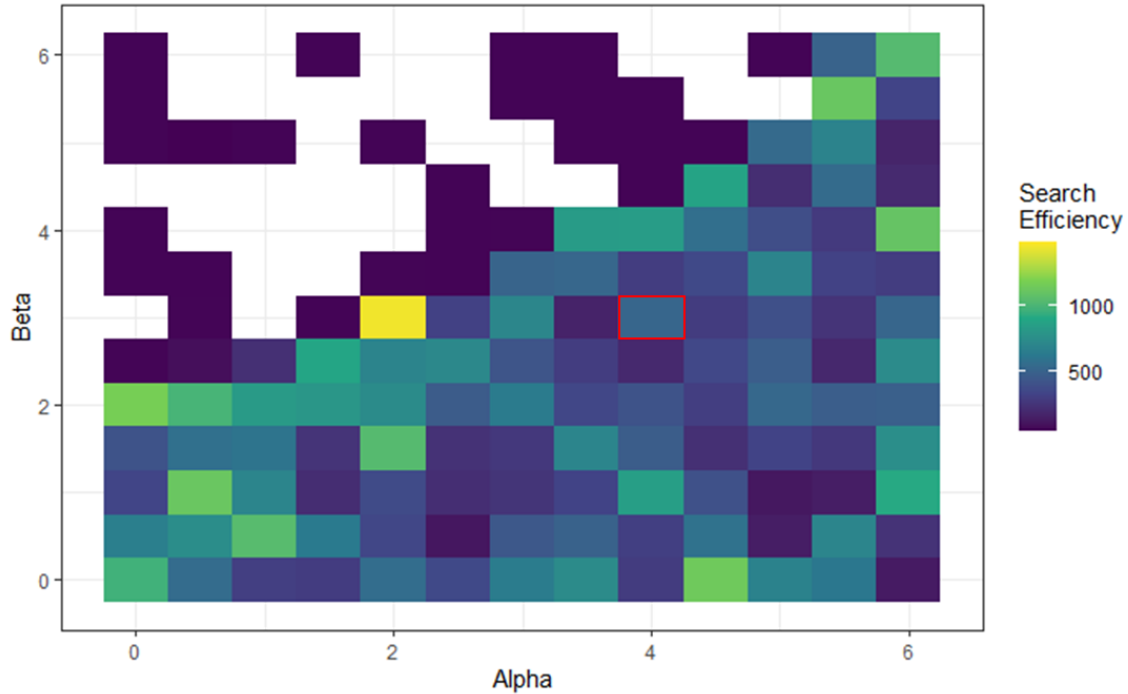


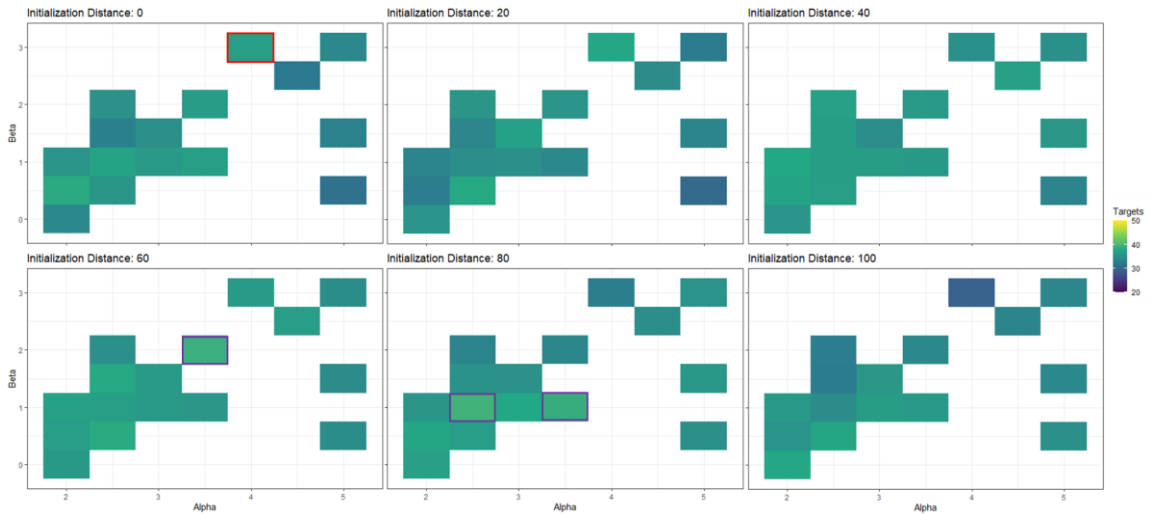
Figure 4. 4. The average search efficiency, i.e., the sum of the average search and consumption times per configuration. The tile outlined in red indicates the original configuration. Configurations above 1500 timesteps were removed due to the number of configurations well below this threshold, in addition to those who only found one target.

On its own, search efficiency is not sufficient to determine the best-performing configurations. It measures the averaged search and consumption times, but it does not necessarily reflect the number of targets found beyond a single target. Rather, this estimate of efficiency becomes less varied with increased targets found. Despite this limitation, optimal loose coupling agents should be able to find and consume many targets quickly. Consistent with this assumption, configurations that found many targets also had better search efficiency. Based on the consistency between these two measurements, we ranked the top 15, plus the original configuration, in order of the average number of total targets found. These 16 configurations were then varied across a range of initial separation distances.

Again, agents were set at varied distances from one another after a target was fully consumed to test how separation between agents affected effects of loose coupling and performance. This separation-distance parameter was designed to emulate the emergent distance agents would create between one another over time. By parameterizing this naturally occurring distance, we can better understand how separation distance influences collective performance in a more controlled manner.

Each initialization distance was repeated 10 times for the remaining 16 configurations to establish a rank based on the number of targets found. Interestingly, the average number of targets found was not highest when the separation distance was at its maximum value. Some of the lowest-scoring configurations were at a distance of 100. This likely resulted

from agents being overly spread out, making it difficult to work together to speed up consumption times. Instead, the more mid-ranged separation distances enhanced performance, as seen in Figure 5.



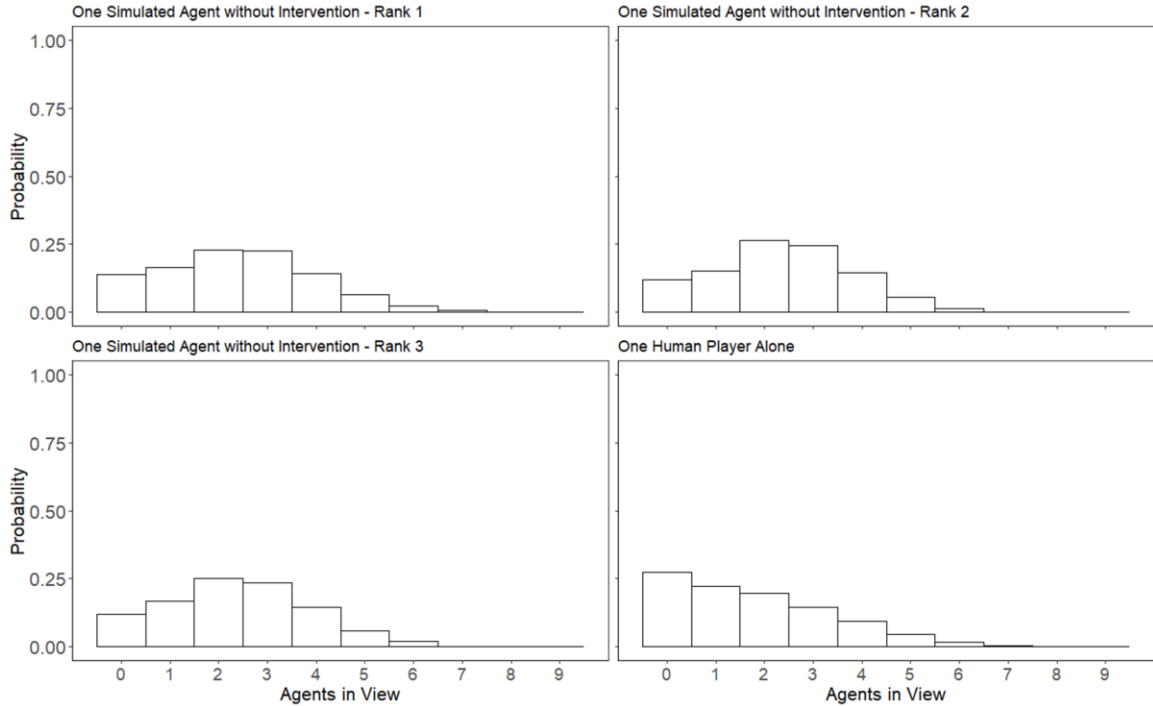
*Figure 4. 5.* The number of targets found per alpha and beta configuration across initial separation distances. The number of targets found was averaged across 10 repetitions. The tile outlined in red indicates the original configuration. Tiles outlined in purple indicate the top-three-performing configurations.

Throughout this section, the original configuration of simulated agents has been outperformed by other configurations, including when it varied across initial separation distances. Thus far, the results indicate that loose coupling effects can be made more effective and efficient within cooperative groups. Next, we compared individuals from the top-three configurations and against human players from the original experiment to measure additional qualities of the new, loosely coupled agents.

#### 4.3.2. Loose Coupling Agents have more varied Group Sizes

Based on the results so far, the human player is the only remaining agent left to be outperformed by the new, loosely coupled agents. For this reason, focusing on individual measurements of loose coupling and performance became our next objective. To do this, we separated individual simulated agents and human players from their respective groups. Based on the sample size from the original experiment, we conducted 60 runs for each simulated configuration to maintain equal sample sizes.

Figure 6 shows the distributions of the number of agents in view, averaged over trials for an individual agent in each configuration, and for the human player alone. These histograms show that human players spent more time searching alone than any simulated agent, from any configuration. Alternatively, the simulated agents tended to search in multiple, smaller groups (i.e., of about 2-3 other agents).



*Figure 4. 6.* Normalized histogram of the number of agents in view during the search time period respective to one agent only, either one simulated or human player.

Using the same measure of grouping variability as before, grouping entropy was calculated as described above in Chapter 3.4.2. A simulated agent and a human player from each configuration were treated as individuals who each had a respective distribution of agents-in-view over time. Using the same entropy calculation (i.e.,  $-\sum [p(x_i) \log(p(x_i))]$ , where  $x_i$  is the number of agents viewed by agent  $i$  over time, and  $p$  is the associated proportion of time that  $x_i$  agents were in view), each agent was given a “grouping entropy” score, which was averaged across configurations, as seen in Figure 7.

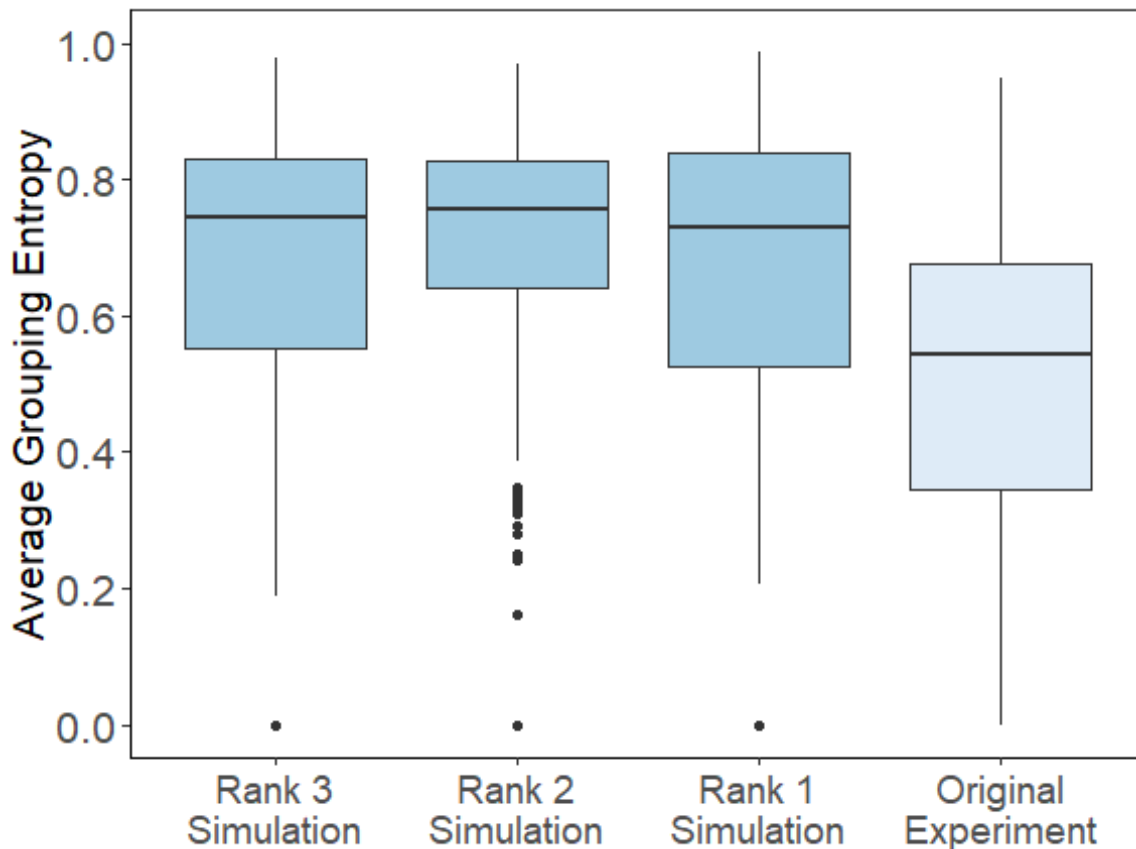


Figure 4. 7. Average Grouping Entropy of the number of Agents-in-View during the search time period of the task for a single autonomous agent and for a human player, respectively.

We tested the effect “Rank” (Rank 1, Rank 2, Rank 3, or Original) had on Grouping Entropy with a one-way ANOVA. The simulated agents displayed higher grouping entropy than the human player,  $F(3,6935) = 86.67, p < 0.001, \eta^2 = 0.04$ . Post-hoc comparison tests showed that simulated agents spent more time in varying group sizes than the human players, all  $p < 0.001$ . This is visually supported by the normalized histograms in Figure 6. Group sizes spanned a wider range of possible groupings for simulated agents than human players. Replicating our previous findings, variation in loose coupling effects affects group sizes, resulting in greater grouping entropy. This measure indicates how collective or individualistic the searching behaviors of a simulated agent or human player was. Next, we see how effective the more-optimal agents are at covering the space while searching for targets, as compared to human players.

#### 4.3.3. Individual “Optimized” Loose Coupling Agents Lag Behind Human Players

To recap, the increasingly optimized, loosely coupled agents outperform the original simulated agents from Chapter 3. These new agents also show higher degrees of grouping diversity than human players, but how effectively these new agents search the space as individuals has yet to be determined. To measure the overall effectiveness of searching behaviors, we utilized the same area-search-rate measure from before, see Chapter 3.4.3.

*Area search rate* was computed as the number of unique patches searched during each trial, divided by the time spent searching prior to finding the target, and converted into a percentage of total patches (e.g.,  $200 \times 200 = 40,000$  patches). Higher averages for this measure indicate a more-efficient coverage of space in the time it took to find the target, see Figure 8.

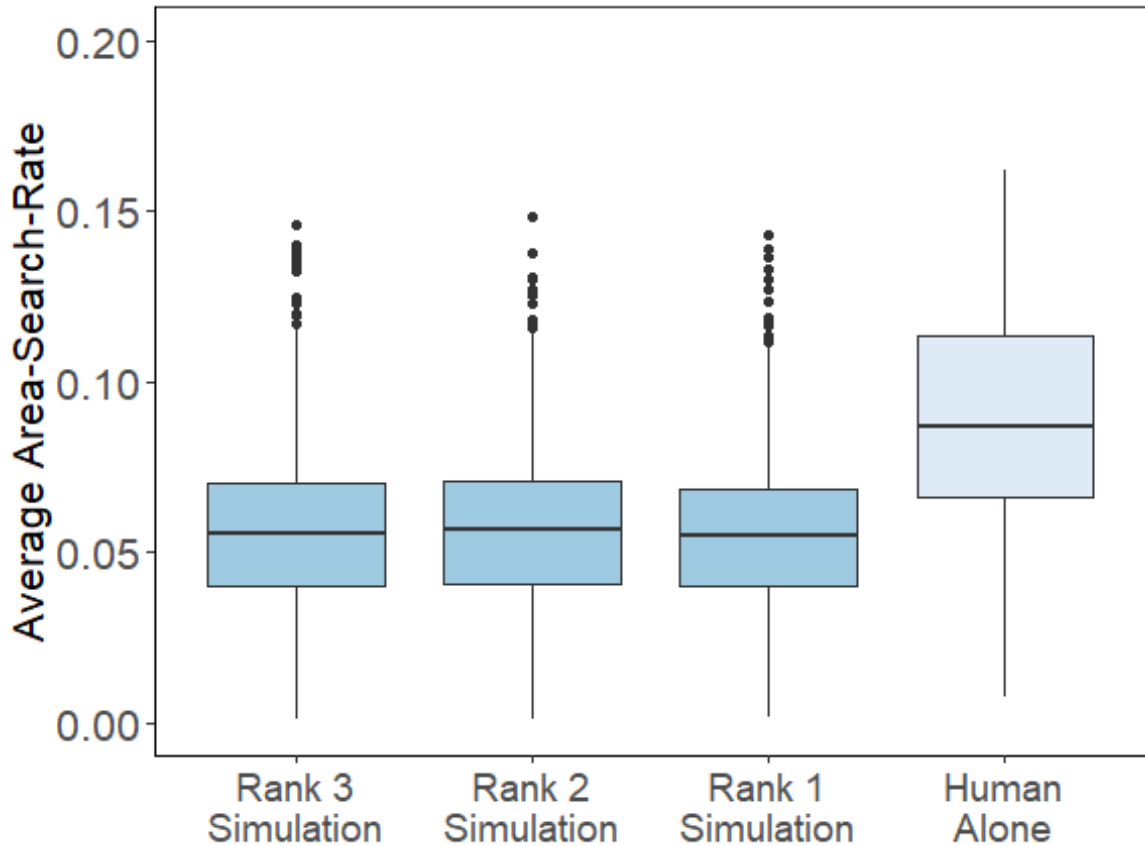


Figure 4. 8. The average area search rate for one simulated agent in the top-three-performing configurations and for the human player alone from the original experiment.

Using the same one-way ANOVA as before, the human player covered the space more effectively than all the new autonomous simulated loosely coupled agents,  $F(3,7771) = 540.2, p < 0.001, \eta^2 = 0.17$ . Despite the simulated agents outperforming the original agents, the human player continued to move more effectively, all  $p < 0.001$ . For this reason, we are motivated to create a more-human-like simulated agent, i.e., one who is better-suited to searching the space effectively and efficiently. This measurement supports the previous finding with the normalized histograms and grouping entropy. The human player searched the space differently from the simulated agents. For instance, they spent more time searching as an individual than any other agent. This is something that we try to instill within a simulated agent in Chapter 5.

#### 4.4. Discussion

Here, we saw some dramatic improvements to collective performance based on maximizing loose coupling effects. Changes to the Lennard-Jones potential could dramatically influence the movement patterns that emerged as the group searched for targets. The most important factor was the balance between the respective attraction and repulsion exponents governing their movement rules. If the configuration even moderately favored attraction, the group could find itself completely trapped as a stationary point or resembling the movement patterns of the Flocking conditions from Chapter 3. This resulted in less successful collective performance. Conversely, if the configuration favored separation, the individual agents would be able to search the space but could struggle to consume targets quickly enough as a group to maximize performance. Balanced configurations resulted in maximal collective performance, where the group both found and consumed many targets quickly.

The maximal loosely coupled agents outperformed the original configuration and further benefited from increases in initial separation distances. Importantly, setting agents to increased separation distances recreated spreading over the space, but interestingly, the maximum initial distance rarely increased performance over other shorter distances. Shorter initial separation distances improved the distribution of agents over the space while maintaining multiple group configurations to consume targets cooperatively.

At the individual level, the maximal loosely coupled agents searched more effectively than their previous counterparts by being even more loosely coupled. The new maximal configurations spent more time searching in a wider range of possible group sizes, favoring to search in smaller groups than alone. Each maximal configuration increased their grouping diversity based on our grouping entropy measurement. Agents preferred to search in smaller group sizes, but the changes made within the Lennard-Jones potential allowed these agents to flexibly shift between collective and independent searching strategies.

Despite the improvements in collective performance for the maximal configurations, simulated agents as individuals continue to lag the human players. Human players likely leverage their memory to learn throughout their experiences while searching alongside the group or individually, which is something the present iterations of the simulated agents lack the capacity to do. These qualities remained uniquely human within the current setup. From here, we ask whether a simulated agent can behave more like the human players.

In Chapter 5, our aim was to create a unique simulated agent to replace the human player, but which behaves more like them. By leveraging a form of memory, we created an agent that adaptively reacts to the area that they have already covered while searching for the current target. For example, human players likely recall memories that prompt them to search some areas over others, thereby favoring areas they have not yet visited. Accordingly, if a simulated agent reacts to previously covered areas in an avoidant way, we may similarly prompt a unique memory agent to search new areas instead of covering old ground.



## Chapter 5

### Loose Coupling with Memory

#### 5.1. Introduction

For humans and other animals, memory and learned strategies aid collective coordinated performance. Typically, coordinated task performance improves when people can perceive the actions of others by allowing co-actors to adjust their own behavior to successfully coordinate during cooperative tasks (Garrod & Pickering, 2009; Marsh et al., 2009; Valdesolo et al., 2010). Individuals avoid such limitations when working alone because they know what to expect next by being the only actor. Tasks become complicated by adding others into the mix. Groups work differently than individuals because they need to anticipate the cooperative behaviors of others, leveraging the skills and knowledge of the whole group to succeed. This allows groups to coordinate their behaviors in often complex ways (e.g., well-strategized soccer).

A modern twist to these typical forms of interaction shared between people has been introduced by adding autonomous agents into the mix. In many ways, humans cooperatively interacting with others and machines has become a nested part of everyday life. By reducing the actions of humans down to their primitive components, we may be able to instill these facets of human behavior back into the cooperative agents we interact with. In this way, we may allow agents to better assist us in a wider range of tasks to the benefit of the individuals involved and the group at large (Auletta, Fiore, Richardson, & di Bernardo, 2020; Lamb et al., 2017; Nalepka et al., 2019; Rigoli et al., 2020; Wiltshire et al., 2018; Wiltshire, Steffensen, & Likens, 2020). For example, instilling an automated agent with more ‘human-like’ qualities helped human players to learn a task quicker and to complete it more successfully (Nalepka et al., 2019). Leveraging the intelligence of automated agents allows humans to learn from their interactions with them. This is especially important, given the propensity for people to adapt their behaviors spontaneously and reciprocally while interacting with others (Nordham, Tognoli, Fuchs, & Kelso, 2018; Schmidt & O’Brien, 1997; Schmidt & Richardson, 2008). Such behaviors emerge as a result of the physical, informational, and task constraints that define a given context (Richardson et al., 2016; Saltzman & Caplan, 2015; Warren, 2006). Based on these ideals, we instilled one agent with the capacity to remember locations where it has already been, in order to be of better service to overall collective performance.

Chapter 4 covered the cultivation of a more-optimal loose coupling configuration that directed agent movements. These improvements resulted in greater collective performance, but human players continued to search the space more effectively than any autonomous agent. To further improve the performance of the autonomous agents, we instilled a single simulated agent with a more ‘human-like’ quality. Based on an assumption of human behavior and learning, we began by including an autonomous agent with a form of spatial memory which would help direct their movements. To do this we created an agent with a locally situated, but globally perfect form of spatial memory at the scale of navigation. Done in such a fashion as to enhance the searching performance of a unique agent by encoding information about searched and unsearched areas into their foraging behaviors

(Kerster, Rhodes, & Kello, 2016). This new and unique agent was sensitive to the pixels they previously covered while searching for the current target. The agent's stored spatial memories of previously covered areas would reset after a target repopulated, thereby creating a situationally based form of spatial memory that is nested within the progress of the group's success. For example, the faster that agents found and consumed targets, the faster the target would repopulate, and the faster the agent's spatial memory would be reset.

When moving across unsearched areas, the memory agent moved according to the same movement configuration as the other agents, however, when faced with a previously searched area, the memory agent would adjust its heading by facing toward the most-unsearched area within view. By adjusting its heading to move toward unsearched areas rather than searched areas, we intended the memory agent to act in a more human-like fashion, i.e., adjusting and adapting its movements in accordance with what it has experienced while searching for the current target. This was intended to tap into an aspect of human behavior that made them previously successful at this task.

The implemented memory parameter relates to the previous work that originally inspired the creation of this project. Specifically, we took reference from the social foraging behaviors in larger birds of prey, because their capacity for remembering carcass locations improved individual and group fitness (Cortés-Avizanda et al., 2014; Harel et al., 2017; Jackson et al., 2008; López-López et al., 2013). Based on an individual's memory, group performance can be improved because an individual can help guide others toward that which the group is collectively searching for. Whether an individual is leading others directly towards a source of food (Harel et al., 2017; Nathan et al., 2012), or whether an individual is informing others about a possible location of a resource (Seeley, 1983, 2019; Visscher & Seeley, 1982; von Frisch, 1969), an individual with some memory about the searchable area helps to improve collective performance. This was a quality we aimed to instill within our new memory agent, i.e., aiding others by being increasingly more flexible and loosely coupled, adapting its movements based on the context to favor new areas over those they know the target is not.

## 5.2. Methods

### 5.2.1. Simulation Setup and Parameters

Like in Chapter 4, many of the parameters here are replicated from the original simulation from Chapter 3. Using Netlogo with a space of 200 x 200 patches with periodic boundaries, ten agents moved at the same velocity while searching for targets over a 13,500 timestep duration. Once an agent discovered a target, it would turn red and move directly toward the target location. Other nearby agents who saw an agent turn red would follow that agent toward the target location. Once an agent reached a target, it began to consume the target at a rate of 1 consumption point per timestep. This rate increased with the number of agents who found the target, with a minimum consumption time of 50 timesteps. Simulated agent movements followed the alpha and beta parameters set from the top-ranked configuration ( $\alpha = 2.5$ ,  $\beta = 1$ ) and included an initial separation distance within 80 pixels from the center following a target repopulating. All remaining original movement condition parameters featured in Chapter 4 were replicated here.

A new parameter added into the simulation was the memory parameter. This memory parameter was added into the movement configuration of one agent. This new agent was provided a form of memory that assisted the agent to head towards new searchable areas. The nature of how it functioned was generally straightforward.

The unique memory agent would react differently to areas it had previously covered while searching for the current target. Once a target repopulated, the memory agent's memory was wiped clean, setting the value of all pixels within the search space to equal 0. Pixels that have yet to be searched for targets assume a value of 0, and pixels that have been searched for the current target assume a value of 1. Pixels change from a value of 0 to 1 by entering and then subsequently leaving the memory agent's field of view. These pixels would remain at a value of 1 until the current target was fully consumed, and repopulated. After a target repopulated, all pixels within the search space were reset to a value of 0 and the memory process would begin anew.

Importantly, the only agent who had any impact on the value of any pixel was the memory agent. No other agent had any effect on, or was influenced by, the value of a given pixel. Additionally, the memory agent remained completely unaware of the area that any other agent had previously covered. The only information the memory agent used to augment its movements were based on its own memory of covered pixels within its visual radius.

As the memory agent searched for targets, and while the value of the pixels in view summed to approximately 0 (i.e., 0.03% of pixels-in-view with a value of 1), the memory agent's movements were governed by the same movement configuration rules as the other nine simulated agents. Alternatively, if the value of the pixels in view exceeded this minimal threshold, then the memory parameter would affect the unique memory agent's heading direction.

When the memory parameter turned on, it would direct the memory agent to face toward a direction determined as the average x and y coordinates of all the pixels in view that were equal to 0, before the agent took its next step forward. This caused the memory agent to face away from the patches of pixels with a value of 1. Therefore, the memory agent was biased toward searching new areas rather than continuing over previously searched spaces. This memory parameter was designed to help capture some of the unique and intelligent behaviors we assumed the human players were implementing while searching for targets. Over time, if a target had yet to be found, the memory agent would have covered a greater area of the search space, creating a larger proportion of patches with a value of 1. As this proportion of patches with a value of 1 increased, the movements of the memory agent would become increasingly directed by the memory parameter, thereby directing the memory agent to favor areas left unsearched. Our intention for these moments would be for the memory agent to be better suited at finding the hidden targets, i.e., finding them more easily than if they simply followed the same movement rules as the other agents.

To compare the effect of the new memory agent on any collective or individual measure of performance, we conducted the same movement and separation configurations with a separate group of 10 non-memory agents.

### 5.2.2. Experiment Setup and Parameters

In Chapter 3, we recruited participants to search for targets alongside nine autonomous agents across four separate movement conditions. Here, we recruited 10 new human players to search alongside nine non-memory agents with the top ranked configuration. The human players experienced the same setup as those in Chapter 3. Players controlled their agent with the use of a computer mouse, and their agent would follow a straight line heading toward the current position of the mouse at the same constant velocity as the other nine simulated agents. Like in Chapter 3, the movements of the human players remained completely unrestricted and uninfluenced by any other agent in the task, however, the other nine simulated agents did take the human's agent into account when calculating their next movement. The only functional difference these human players experienced that differed from those in Chapter 3 is that these participants were also subject to the initial separation-distance parameters following a target repopulating. Any remaining feature of the human player was also replicated from Chapter 3. These three intervention conditions allow us to compare how the non-memory, memory, and human players affected individual and collective performance.

## 5.3. Results

### 5.3.1. Collective Measures of Performance

Here, we repeated the same overall measures of performance for each game session like those used in Chapter 3. The primary measure of collective performance was the total number of targets found (session duration was constant). This measure relates to the time needed to find and then consume each target. Search and consumption times were computed on a per-target basis, and then averaged for each session. Put together, these measures create the average total trial time, i.e., the sum of search and consumption time, where lower times corresponded with better performance.

One primary factor was manipulated to test the role of memory and strategy in collective foraging. To do this, we compared different types of intervention for autonomous search agents across different sessions, varying the movement rules governing the behaviors of an agent depending on the intervention type. The role of memory and strategy was tested by comparing sessions with and without memory agent or human intervention.

#### 5.3.1.1. Targets Found varied by Intervention

First, we compared collective performance based on the total number of targets found. To compare the effects of different intervention types, we conducted a one-way ANOVA with the number of targets found as a dependent measure, and intervention type (no memory, memory, or human) as an independent variable. All agents in the no memory condition moved using the same governing movement rules. Agents in the memory and human intervention conditions moved using these same rules except for the memory agent and human players, respectively. See Figure 1 for the average number of targets found by intervention type.

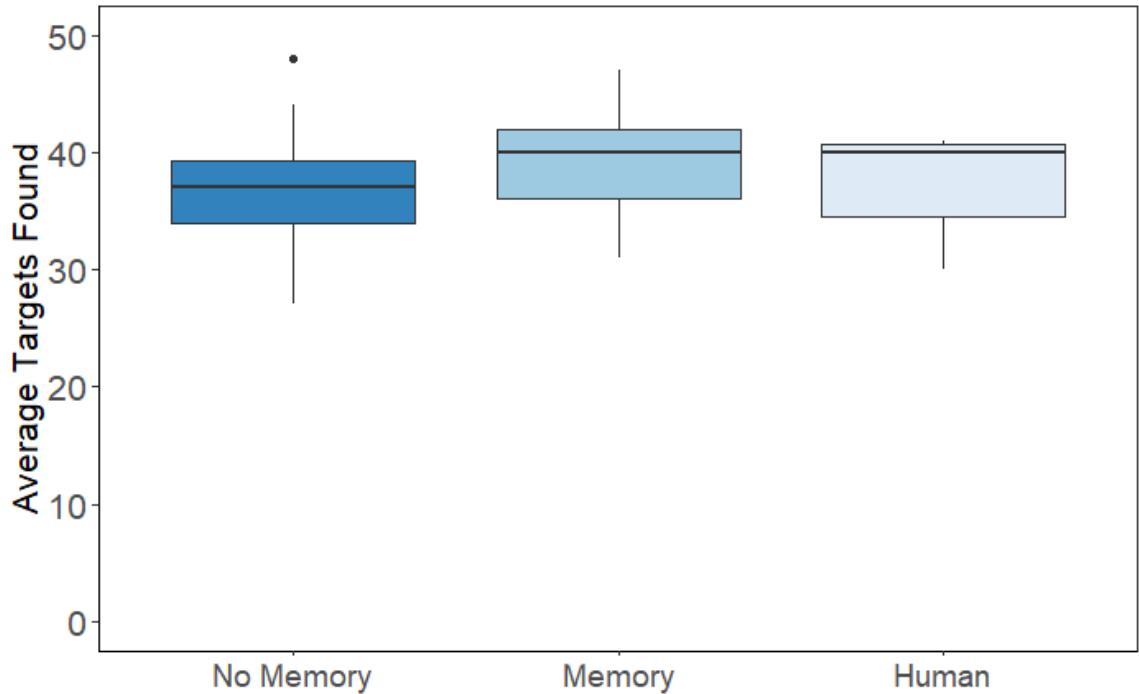


Figure 5. 1. Mean targets found per session by intervention type (no memory, memory, or human).

We found a significant effect of intervention type,  $F(2,127) = 3.85$ ,  $p = 0.024$ ,  $\eta^2 = 0.06$ . The specific direction of effects was supported by post-hoc Tukey HSD comparison tests which showed that the memory agents and the human were not significantly different from each other,  $p = 0.543$ . Surprisingly, human intervention was not different from the no memory agents,  $p = 0.908$ . This lack of differences for the human condition likely resulted in part from the small initial sample size. With more individuals, we would have a clearer picture of their performance distribution. However, the memory agents were significantly different than the no memory agents,  $p = 0.018$ , supporting our initial assumption that an improved agent with memory would benefit collective performance.

### 5.3.1.2. Search Time Improved with Memory Intervention but at a Cost

Next, we compared the effect that intervention type had on performance by comparing mean search, consumption, and trial times across conditions as dependent measures in a one-way ANOVA. Intervention type served as the independent variable again. Results showed that searching performance as measured by mean search time was significantly better with memory intervention,  $F(2,127) = 4.309$ ,  $p = 0.015$ ,  $\eta^2 = 0.06$ . Post-hoc Tukey HSD comparison tests showed that the intervention of a memory agent significantly decreased search times compared to no memory intervention,  $p = 0.013$ , however, the human players did not significantly differ from either memory or no memory intervention conditions, both  $p > 0.4$ . As anticipated, the memory agent helped facilitate lower overall search times beyond the no memory condition by being biased towards searching yet-unsearched areas based on their theoretically perfect but locally situated spatial memory.

Separately, we conducted the same ANOVA with “consumption time” as a dependent variable and “intervention type” as an independent variable. We found the opposite pattern of effects than those we saw for search time, indicated by a significant main effect of intervention type,  $F(2,127) = 5.968$ ,  $p = 0.003$ ,  $\eta^2 = 0.09$ . The no memory intervention condition had significantly lower consumption times than the memory intervention condition,  $p = 0.002$ . Like the search time results, the human player is not significantly different in consumption times than the other intervention types, both  $p > 0.35$ . Interestingly, we see the no memory intervention condition improve consumption times over the memory condition. This likely results from the memory agents searching independently when search times run long, resulting in them consuming targets alone more often than the no memory agents.

When summed together to construct the mean trial time, there was not a significant main effect of intervention type,  $F(2,127) = 1.187$ ,  $p = 0.309$ ,  $\eta^2 = 0.02$ . Unlike the individual measurements of search and consumption times, the sum of these two values does not differ as a function of intervention type, all  $p > 0.37$ . The benefits provided by the inclusion of a memory agent helped improve search times, but this may have resulted in the memory agent consuming targets alone, which would increase consumption times. The improvements to search times were washed out by increased consumption times, as seen in Figure 2.

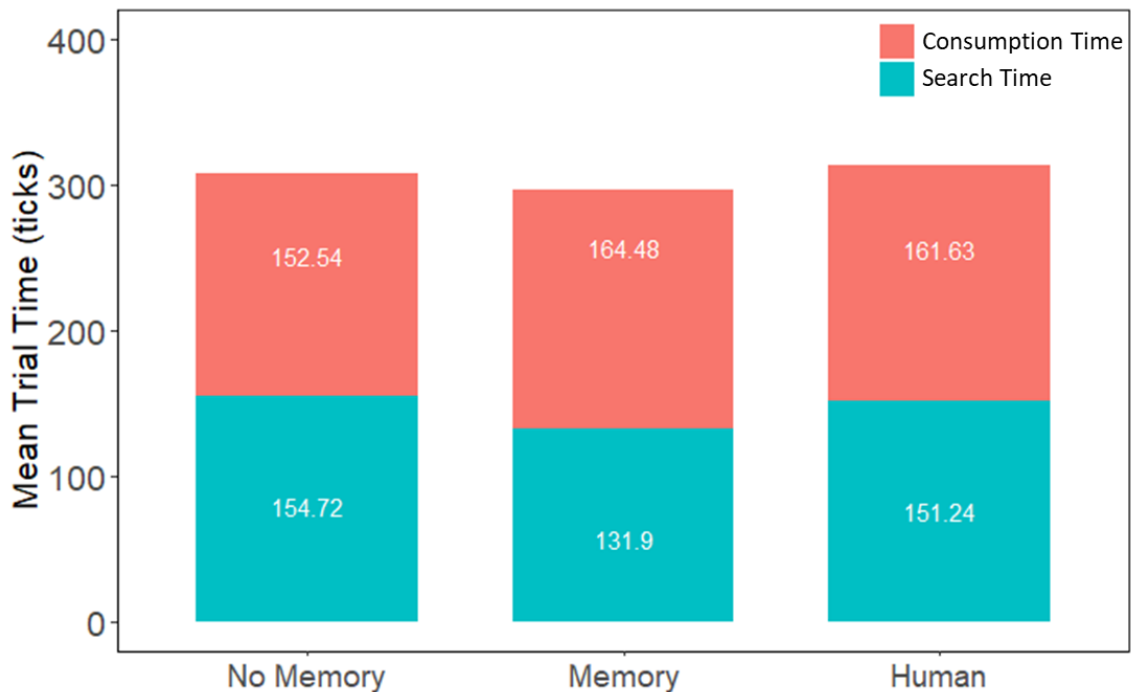


Figure 5. 2. Mean trial time per session by intervention type (no memory, memory, or human). Mean trial times are divided into their composite search times (teal) and consumption times (red).

### 5.3.2. Individual Measures of Performance

Here, we repeated the same primary individual measures of performance as in Chapter 3. We conducted analyses on the average grouping entropy and area-search rate on individual agents across intervention types. These measures provide evidence related to the group-size diversity and searching effectiveness for an individual agent, respectively. The efficacy of loose coupling, memory, and strategy was tested by comparing sessions with and without a memory agent or human intervention. This factor of agent type was used as the independent variable within each respective one-way ANOVA.

#### 5.3.2.1. Memory Agents group like Humans

Thus far, we have seen that intervention types are more beneficial for separate parts of collective performance measures. Memory intervention improved search times, while non-memory improved consumption times. This likely relates to the way in which agents are searching on an individual basis. To measure how an individual searches the space, we used two primary measures. The first measure is the grouping entropy value, based on the distribution of counts relating to the number of agents in view while searching for targets. Based on a visual inspection, we can see that the memory agent and the human searched in similarly diverse group sizes, contrasted by the more collectively oriented non-memory agents, as seen in Figure 3.

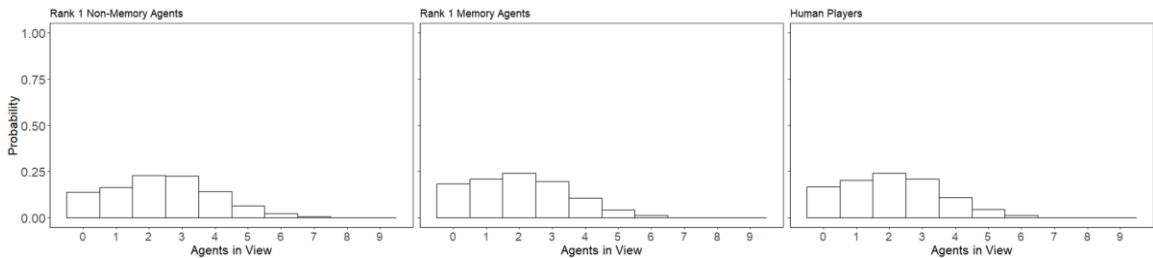


Figure 5.3. Normalized histogram of the number of agents in view during the search time period respective to one agent per session. Human players and simulated agents differ only by agent type (non-memory, memory, or human).

To test the significance of any difference across intervention type on grouping diversity, we used the same grouping entropy measure from Chapters 3 and 4 (i.e.,  $-\sum[p(x_i) \log(p(x_i))]$ , where  $x_i$  is the number of agents viewed by agent  $i$  over time, and  $p$  is the associated proportion of time that  $x_i$  agents were in view). This measure provides a value for the overall stability of the distribution associated with the number of agents in view over time while searching for targets (see Figure 4).

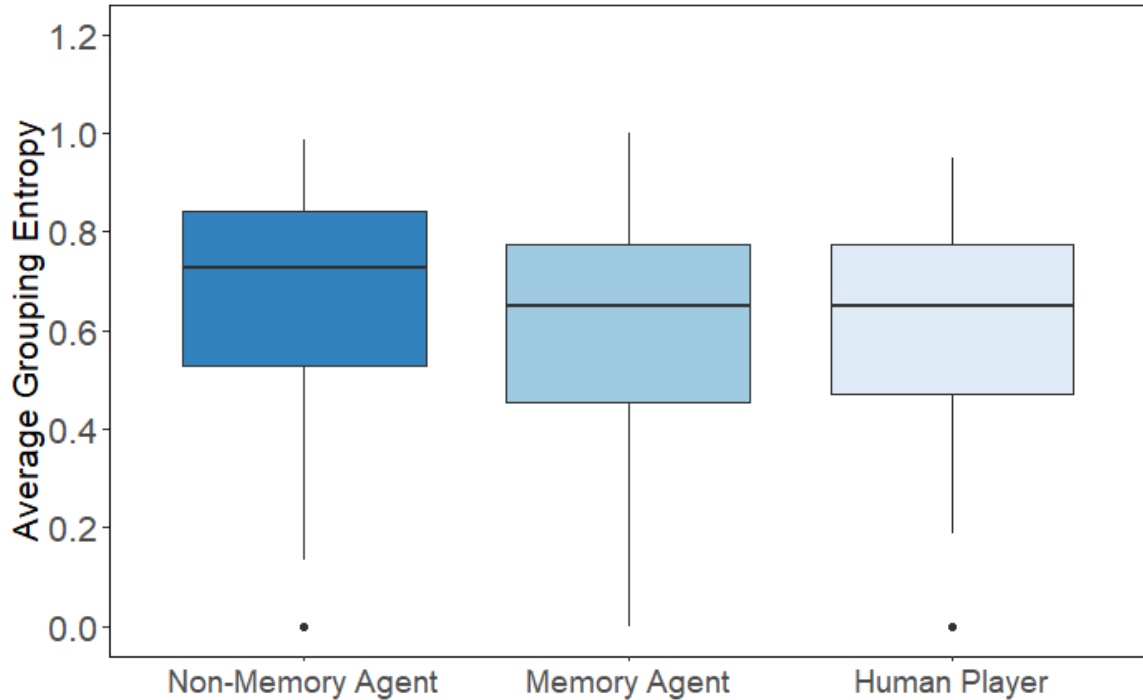


Figure 5. 4. Average Grouping Entropy of the number of agents in view during the search time period of the task for individual autonomous agents or human players. Human players and simulated agents only differ based on the agent type (non-memory, memory, or human).

Results showed that there is a significant main effect of Agent Type,  $F(2,4390) = 2.386$ ,  $p < 0.001$ ,  $\eta^2 = 0.01$ . Post-hoc Tukey HSD comparison tests showed the non-memory agent was significantly different than both the memory agents and human players, both  $p < 0.001$ . Interestingly, the memory agents were not significantly different in grouping diversity than the human players,  $p = 0.986$ . This is an interesting result because, by including the memory parameter to adjust the memory agents' searching behaviors, the memory agents searched in similar configurations to how a human player decided to search.

### 5.3.2.2. Area Search Rate

Lastly, we measured the individual ability of an agent to cover the space using the area-search-rate measure used before. This is an important measure for comparing effects of agent type because the area-search rate captures the individual quality an agent has for covering the space. The higher the rate an agent can search the space, the better able they are at covering ground within the time it took to find the target (see section 3.4.3. for more details about area-search rate). To evaluate the effect of Agent Type as an independent variable, we conducted the same one-way ANOVA, with area-search rate as a dependent variable.

Like grouping entropy, results showed a significant main effect of Agent Type,  $F(2,5057) = 123.1$ ,  $p < 0.001$ ,  $\eta^2 = 0.05$ , where the non-memory agent had a significantly



slower area search rate than both the memory agent and human players, both  $p < 0.001$ . Consistent with previous results, the memory agent searched the space as effectively as the human player based on the non-significant difference in their respective area search rates,  $p = 0.8$ . These results are supported visually in Figure 5.

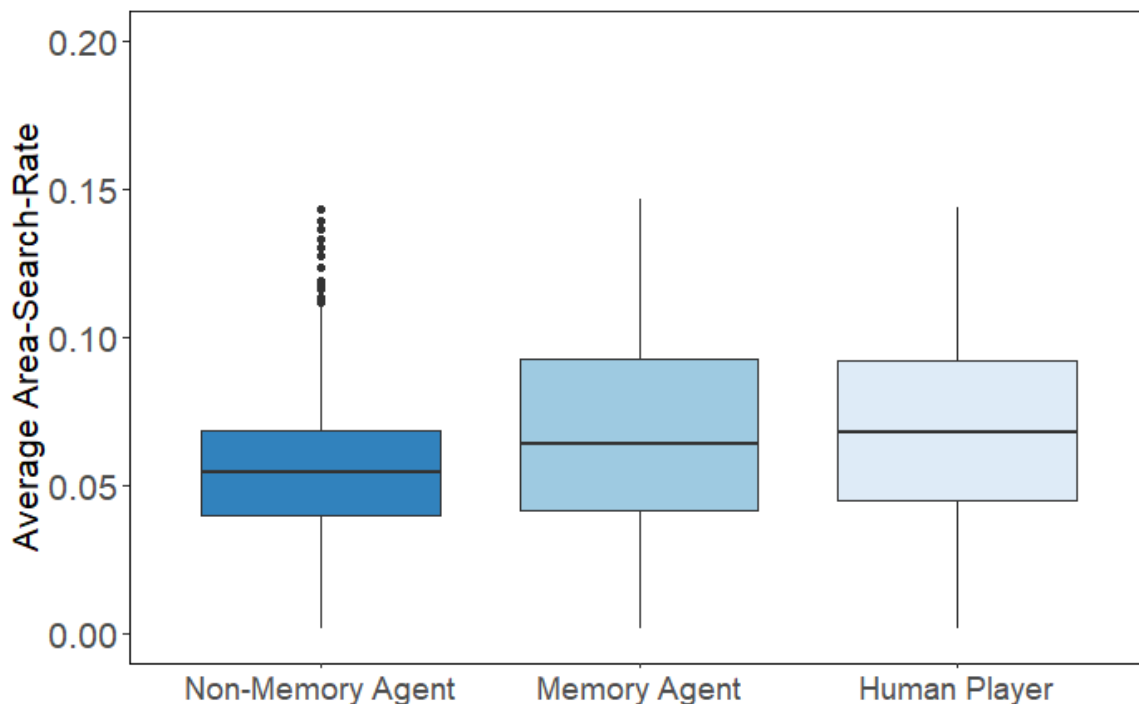


Figure 5. 5. The average area-search rate for individual autonomous agents or human players. Human players and simulated agents only differ based on the agent type (non-memory, memory, or human).

These results are striking because a simulated agent was able to perform similarly to the human player based on an individual-level measurement by including a primitive version of one quality that humans possess: memory. However, these results should be considered preliminary based on the relatively small sample size for the human players ( $n = 10$ ). Despite this limitation, we find these results to be promising based on the success we see in the memory agent differing from agents without memory, and the apparent similarities emerging between the memory agent and human players.

#### 5.4. Discussion

The intervention of the memory agent helped to improve both individual and collective performance during this cooperative search task. Human intervention with more-optimal loose-coupling agents did not have as much effect on collective performance as it did in Chapter 3, but as an individual, the human player continued to outperform non-memory agents. We saw a replication of our findings from Chapter 3 with the reduction in grouping entropy for human players when compared to the non-memory, loose-coupling agents. This supports the original interpretation that the human is varying their grouping diversity less than the autonomous agents, preferring to search in smaller group sizes. We also replicated

the area-search-rate findings, where the human players continued to search the space more effectively than the non-memory, loosely coupling agents. Supporting the idea that the human players are utilizing qualities beyond what the loose-coupling configuration is capable of on its own. Results relating to the human's performance are tentative due to the low sample size, but the initial pattern of results remains promising for the new memory agent. Our initial findings suggest the added memory parameter, in addition to the more-optimal loose-coupling movement configuration, resulted in the memory agent searching in more 'human-like' ways.

We saw the memory agent improve both its overall grouping entropy and area-search-rate to equal that of the human players. Both measures were designed to measure the strategies human players enacted back in Chapter 3. To see the memory agent be statistically equal to the human player on both measures is a promising preliminary result. Importantly, this does not mean that human players only used memory to guide their searching behaviors. Rather, this study provides evidence that memory is one quality of what makes human players successful. Obviously, human players possess additional qualities, like decision making and learning, that the memory agent does not possess.

There is an important difference between the memory of the human players and memory agents which separates them. The spatial memory of the memory agent was locally situated but globally perfect. The memory agent would only augment its heading based on the value of pixels within its field of view, but globally all pixels retained a value of 0 or 1 regardless of the memory agent's position. This fundamentally differs from the memories of humans, which are notoriously limited and imperfect. Despite this difference in memory capacity, the memory agent could find itself covering areas it had already searched by cornering itself into areas it had already been. In these moments, infrequent as they might be, the memory agents reverted to acting like regular non-memory agents.

By lacking a form of decision making, the memory agent could realistically find itself traveling over previously searched ground by cornering itself into searched areas. This is less likely to occur within the human players because of their capacity to enact higher-order decision making, planning, and learning. With additional parameters it is likely that a simulated agent could be made to outperform the human players. From what we have seen, adding one human-like quality improved the memory agent to match human performance. The memory agent benefited collective and individual performance by being biased towards unsearched ground. If it were given additional properties of learning and decision making, a simulated agent could potentially far-outperform a human player in future iterations of this study. As a note of caution, this may improve an agent's ability to search within this task space, but unless given qualities of equally general applicability to those of humans, the agents may continue to fundamentally differ in type from the human players by being overly specialized within this context. By contrast, the human player will remain a contextual generalist, able to flexibly and spontaneously reorganize themselves to reach their goals.

## Chapter 6

### Conclusions about Coordination and Loose Coupling

Throughout this dissertation, the underlying focus has been to deepen our understanding of the general principles and processes of coordination. To do this we have explored varying scenarios requiring multiple agents to cooperatively coordinate their actions to achieve some shared, common goal. We began with individuals and dyads coordinating their actions via a moving target, where the goal was to complete the aiming task as quickly as possible. We found that higher degrees of complexity matching occurred for individuals and dyads (Chapter 2). Response coupling, i.e., nested spatial and temporal variability, was required for the emergence of higher degrees of complexity matching in dyads. We interpreted these results to mean that complexity matching reflects a more “underlying” or fundamental process within coordination than other measures of coordination, which relate more to target predictability (i.e., phase matching). These results align with other research suggesting that complexity matching taps into a more sensitive and underlying process within coordinating complex systems (Marmelat & Delignières, 2012; Ramirez-Aristizabal, Médé, & Kello, 2018; Rigoli et al., 2014; Tononi, Sporns, & Edelman, 1996). Chapter 2 added to the literature by showing how interpersonal coordination benefits from being loosely coupled. Coordination was facilitated by the exchange of predictable information both within and between individuals, as measured by complexity matching. This research helped to further illuminate some of the principles of intrapersonal and interpersonal coordination.

In Chapter 3, to scale up the size of the interactions that occur within a shared space to reach a common goal, we constructed a cooperative search task to expand our findings from Chapter 2 to groups larger than two. To formulate a balance between collective and independent searching behaviors, we formulated movement rules that balanced a tendency toward distancing with a tendency toward flocking within autonomous searching agents. Our simulations showed that loose coupling among agents benefitted overall group performance. An analysis of group-size variability showed that loose coupling diversified the group sizes more than any other movement condition, resulting in the loose coupling condition covering a more diverse range of individual and collective search configurations over time. The diversity of search patterns did not come from decision-making of any kind—it was instead driven primarily by injecting noise with the CRW movement component, plus additional randomness from the positioning of targets.

The inclusion of a human player added to the benefits of loose coupling by engaging in even greater diversity of search configurations than loosely coupled agents. This resulted in the higher area-search rates with human intervention, especially in the loose-coupling condition. We found that human players exhibited a tendency to individually find and consume targets when agents either distanced too much or flocked too much, whereas they cooperated more equally when agents were loosely coupled. This finding suggests that intelligent agents can learn to leverage other agents for the good of the group, depending on their individual abilities.

Our initial simulations showed that loose coupling is beneficial even when agents are memoryless and unable to learn, adapt, or develop strategies through experience. Our simple model of loosely coupled foraging agents is useful in its economy of mechanism, however, humans and other social animals with extensive capacities use their memory, learning, and decision-making to drive their actions over longer spans of time. Theories of self-organization suggest that loose coupling may be generally useful for adapting coordinated behavior to respond to changes in conditions as they unfold (Van Orden et al., 2003). These results provide evidence that abilities like learning and memory may complement simpler rules of loose coupling to support cooperative coordination, rather than supplant them.

In Chapter 4, we investigated the effects of loose coupling by pursuing a more-optimal configuration of movement rules. The extended simulation resulted in a configuration of loosely coupled agents whose collective performance surpassed the original loosely coupled agents. The more-optimal configuration was benefited further by increased initial separation distances. Mid-ranged initial separation distances improved the distribution of agents over the space while maintaining multiple group configurations to consume targets cooperatively. The more-optimal attraction and repulsion parameters benefited individual measures of performance but continued to differ from individual human performance.

Individually, the more-optimal configurations lacked the searching effectiveness of the original human players from Chapter 3, those players were able to leverage their memory, learning, decision-making, and strategy, something the present iterations of the simulated agents lack the capacity to do. These qualities remained uniquely human, resulting in humans searching more effectively than any simulated agent until those discussed in Chapter 5.

With the intervention of a memory agent, we saw distinct improvements for both collective and individual performance for the more-optimal simulated agents. Human intervention with more-optimal loose-coupling agents did not have as large of an influence on collective performance as it did in Chapter 3, but as individuals, human players continued to outperform non-memory agents. Our initial findings suggest the added memory parameter, in addition to the more-optimal loose-coupling movement configuration, resulted in the memory agent searching in more ‘human-like’ ways.

With improved individual-based measurements, equal to that of the human players, Chapter 5 provides evidence that memory is one quality underlying human performance. Naturally, we possess additional qualities beyond simply memory, but even the added memory parameter suggests that human players utilize qualities beyond what the loose-coupling configuration was capable of on its own. If simulated agents were provided with additional parameters designed to simulate additional human-like qualities, the agents could potentially outperform the human players. Importantly, these qualities should be made as general as possible to avoid over-specifying the agents within a certain context. This would limit their general utility to be beneficial across a wider range of situations, situations that could benefit a lot from the intervention of autonomous agents (Lomonaco, Trotta, Ziosi, Ávila, & Díaz-Rodríguez, 2018; Mishra, Garg, Narang, & Mishra, 2020; Niu, Hollenbeck, Zhao, Wang, & Chen, 2020; Smith, John, Stark, Christensen, & Chen, 2016).

This dissertation focused on the nature of the connections that bind individuals together while cooperatively coordinating their actions to reach shared goals. This work fits within a broader picture about the underlying principles of interpersonal coordination. The joint Fitts' task results are consistent with emerging narratives about complexity matching and the effect that different modalities have on cooperative systems (Almurad, Roume, & Delignières, 2017; Coey et al., 2018, 2016; Fine et al., 2015; Marmelat & Delignières, 2012; Ramirez-Aristizabal et al., 2018; Zapata-Fonseca et al., 2016). Chapters 3–5 fit into a broader narrative about large-group teamwork coordination (Auletta et al., 2020; Lamb et al., 2017; Nalepka et al., 2019; Rigoli et al., 2020; Wiltshire et al., 2018, 2020), within a collective foraging scenario (Cortés-Avizanda et al., 2014; Farine, Strandburg-Peshkin, Couzin, Berger-Wolf, & Crofoot, 2017). These chapters probed further into the effects that loose coupling can have on individual and cooperative performance.

As the agents became more loosely coupled, they became more flexible in their grouping diversity, increasing their collective and individual performance. Taken together, this work supports a broader narrative that coordination depends on the loose and flexible alignment of available degrees of freedom (Glassman, 1973; Kloos & Van Orden, 2009), supported by an exchange of information dependent upon the connections linking complex networks together (Nordham et al., 2018; Rigoli et al., 2014; West et al., 2008). Whether interactions take place between multiple people, with people and autonomous agents, or within simulations alone – loose coupling has been shown to play a positive role within cooperative coordinated systems. It has helped coordinate the actions of two people working to reach a shared goal, as well as aiding many agents search effectively and efficiently across a large space. Regardless of the scenario we have shown here in this dissertation, loose coupling has helped improve cooperative performance between fellow group members. Benefiting both the performance of individuals and groups alike. Future work has ample ground left to explore to seek out the remaining unfound properties about the connections that help bind us together – connections that make us who we are in those coordinated moments, with other humans or not.

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