doi: 10.53846/goediss-9589

GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN IN PUBLICA COMMODA SEIT 1737

Emergent processes as means of uncertainty reduction in group decision making

Dissertation
for the award of the degree
"Doctor rerum naturalium" (Dr.rer.nat.)
of the Georg-August-Universität Göttingen

within the doctoral program “Behavior and Cognition”
of the Georg-August University School of Science (GAUSS)

submitted by
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from Leipzig, Germany
Göttingen, 2022

 doi: 10.53846/goediss-9589

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Date of the oral examination: October 19, 2022

doi: 10.53846/goediss-9589

to Ronja -

We did this together.

doi: 10.53846/goediss-9589

 doi: 10.53846/goediss-9589

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Acknowledgements

First of all, I want to thank Prof. Dr. Margarete Boos who has guided me over the last four years and has always believed in me and my work. Dear Margarete, this project would not exist without you and neither would my continued love for science and academia. Some of my most treasured memories are of us discussing science in your kitchen and I am forever grateful for that.

I want to thank Prof. Dr. Julia Fischer and Dr. Claudia Fichtel who have shaped this doctoral project with their insightful questions, comments, and recommendations in our thesis committee meetings. I also want to thank Prof. Dr. Sabine Bergner, Prof. Dr. Kilian Bizer, and Prof. Dr. Dirk Semmann for agreeing to serve on my examination committee. I thank Dr. Valerie Liebs and Dr. Rebecca Jürgens for their support from the beginning to the end of this journey.

Importantly, I want to thank all of my colleagues, past and present: Jan Lehrke, Gertrud Degen, Julia Speckmann, Dr. Stefan Klötzer, Jan Mücher, Phuong Anh Tran and Jan-Filip Tameling. Academia is certainly no picknick, but if it were, there is no one I would rather have it with.

I want to thank Johannes Pritz for our discussions, collaboration, and for countless cups of very good coffee. You always asked the hard questions about our projects and they were so much better for it. I also thank Paul Pritz for our discussions and his insightful comments on our manuscripts.

I want to thank my students who I was privileged enough to work with in our projects and in our seminars. Thank you for inspiring me and shaping our work together. I want to thank everyone who has participated in our experiments – you are what makes science get ahead!

I dedicate this dissertation to my wonderful daughter Ronja Mathilda. You were on my arm on the day I started this project and slept right beside me while I worked late nights to finish it. Your love and laughter gave me the strength I needed.

Thank you, Paul, for your love and support, and for simply being your wonderful self. Whatever I needed – a good listener, a shoulder to cry on, a home-cooked meal, or simply a hot cup of tea –, I knew I could always find it with you. Thank you for keeping our family running over the last months. I could not have done this without you.

I want to thank all of my family for their support, especially: My mom Steffi - for believing in me, always being there when I needed you, and providing me with everything I could have ever asked for and more. Meine Großeltern Christel und Toni - für ihre Unterstützung, ihre Freude und ihren Garten, der seit meiner Kindheit Farbe in mein Leben bringt. My dad Manfred - for always asking the big questions about life. My siblings – for goofing off together. My aunt Tanzi – for phone support from around the world and being my doctoral role model since I was little.

I want to thank my friends, in Göttingen and beyond, for times of light and laughter, especially Tante Leo and Onkel Phil. No matter the circumstances, the times we spent together were always beams of light between everyday life and I look forward to more of exactly the same!

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Abstract

This dissertation investigates how emergent processes can reduce uncertainty in group decision making. Emergent processes are processes that arise from individual characteristics and social interactions and result in higher level properties of a group. The following three research questions are addressed: Can groups reduce uncertainty through emergent processes? Which emergent processes can be identified? How can we analyze and visualize these emergent processes?

An interdisciplinary theoretical framework was developed (Chapter 2), spanning theory and empirical evidence from biology, machine-learning, and psychology. Uncertainty is distinguished into informational uncertainty (i.e., uncertainty about the environment) and personal uncertainty (i.e., uncertainty about relationships and group characteristics). The effects of three emergent processes (collective cognition, group cohesion, and leader-/followership) on uncertainty reduction are investigated in groups.

Chapter 3 presents two empirical papers in which groups were faced with informational uncertainty in an intellective problem-solving task within the HoneyComb paradigm (Boos et al., 2019). The HoneyComb paradigm is a virtual game platform in which participants, represented by an avatar on the playing field, can interact only through movement on the playing field while solving group tasks. Specifically, groups had to infer the best out of four options presented to them on the playing field by repeatedly choosing from the options (exploration). Groups in these studies reduced informational uncertainty by inferring the best option through collective cognition (i.e., pooling of individual information on the collective level) and exhibited exploration/exploitation patterns. The quality of information available to the groups impacted the group decision process: Information that was corrupted by group incentives (i.e., rewards for staying close to other group members on the playing field) led to sub-optimal decisions. A simulation study using the ε-greedy algorithm exhibited similar results. Behavioral leader-/followership patterns emerged spontaneously within most groups and were associated with self-reported leader-/followership. However, behavioral leadership was not associated with typical personality trait correlates (self-confidence, achievement maximization, decisiveness, and risk propensity). Behavioral group cohesion was associated with self-reported group entitativity and interactivity. Chapter 3 concludes that groups effectively reduce informational uncertainty using emergent processes (i.e., group cohesion, leader-/followership), although the differential contribution of single processes remains to be investigated.

Chapter 4 presents empirical findings on the reduction of personal uncertainty through the emergence of collective trust. Collective trust is defined as a collective cognitive construct that emerges through repeated interactions of a group and reflects the shared level of trust a group holds for another individual, group, or organization. In Chapter 4, groups had to make investment decisions in the Collective Trust Game (CTG), a collective economic game, constituting a judgmental task. Findings suggest that collective trust, as a collective cognitive construct, emerged through interaction and reduced personal uncertainty in the CTG. This was indicated by an increase in consensus decisions and a decrease in the decision times necessary to reach a consensus on investment decisions. Chapter 4 concludes that collective trust, as an emergent cognitive construct, can reduce personal uncertainty within groups.

Chapter 5 describes the methodological contributions of this dissertation. The HoneyComb paradigm (Boos et al., 2019) is presented as a tool to investigate emergent group processes using spatio-temporal data. Three levels of analysis are presented and combined with four analytical approaches based on network and visual analytical strategies. An example illustrates how the presented approaches can be used to investigate emergent processes in group decision making under uncertainty.

This dissertation concludes: Groups can groups reduce informational and personal uncertainty through emergent processes. These processes include collective cognition, group cohesion, and leader-/followership. The identified processes, and possibly more, can be analyzed and visualized using network and visual analytic strategies as presented in this dissertation. The distinct contributions of each of those processes to uncertainty reduction should be the topic of future research.

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Zusammenfassung

Diese Dissertation untersucht, wie emergente Prozesse Unsicherheit in Gruppenentscheidungen reduzieren können. Emergente Prozesse sind Prozesse, die aus individuellen Charakteristika und sozialen Interaktionen entstehen und sich in übergeordneten Eigenschaften der Gruppe manifestieren. Die folgenden drei Forschungsfragen werden adressiert: Können Gruppen Unsicherheit durch emergente Prozesse reduzieren? Welche Prozesse sind identifizierbar? Wie können emergente Prozesse analysiert und visualisiert werden?

Ein interdisziplinärer theoretischer Rahmen wurde entwickelt (Kapitel 2), der Theorie und empirische Befunde aus den Feldern Biologie, Machine-learning und Psychologie umfasst. Unsicherheit wird in informationelle (Unsicherheit über die Umwelt) und persönliche Unsicherheit (Unsicherheit über Beziehungen und Gruppencharakteristika) unterteilt. Die Effekte von drei emergenten Prozessen (kollektiver Kognition, Gruppenkohäsion und Führen/Folgen) auf Unsicherheitsreduktion werden in Gruppen (also, Gruppen, die Informationen frei in Interaktionen austauschen können) untersucht.

Kapitel 3 zeigt zwei empirische Artikel, in denen Gruppen eine Problemlöseaufgabe im HoneyComb-Paradigma (Boos et al., 2019) unter informationeller Unsicherheit lösen mussten. Das HoneyComb-Paradigma ist eine virtuelle Spielplattform, auf der durch einen Avatar repräsentierte Studienteilnehmer*innen nur über Bewegungen auf dem Spielfeld interagieren und Gruppenaufgaben lösen müssen. Gruppen mussten die beste aus vier auf dem Spielfeld präsentierten Optionen identifizieren, indem sie wiederholt aus den Optionen wählten (Exploration). Die Gruppen in diesen Studien reduzierten informationale Unsicherheit, indem sie die beste Option durch kollektive Kognition (Zusammenfassen individueller Informationen auf Gruppenebene) identifizierten und Explorations-/Exploitationsmuster zeigten. Die Qualität der für die Gruppen verfügbaren Informationen beeinflusste den Gruppenentscheidungsprozess: Informationen, die durch Gruppenbelohnungen (Belohnungen für Nähe zu anderen auf dem Spielfeld) beschädigt waren, führten zu suboptimalen Entscheidungen. Eine Simulationsstudie mit dem ε-greedy-Algorithmus bestätigte dies. Führungsverhalten zeigte sich spontan in den meisten Gruppen und war mit selbstberichtetem Führen assoziiert. Allerdings zeigte sich keine Assoziation von behavioraler Führung und typischen Korrelaten von Führung (Selbstbewusstsein, Leistungsmotivation, Entscheidungsfreude und Risikobereitschaft). Behaviorale Gruppenkohäsion war mit selbstberichteter Entitativität und Interaktivität von Gruppen assoziiert. Kapitel 3 kommt zu dem Schluss, dass Gruppen informationale Unsicherheit mithilfe emergenter Prozesse (kollektive Kognition, Gruppenkohäsion, Führen/Folgen) reduzieren können, auch wenn die spezifischen Anteile der Einzelprozesse noch zu untersuchen sind.

Kapitel 4 zeigt empirische Befunde zur Reduktion von persönlicher Unsicherheit durch die Emergenz von kollektivem Vertrauen. Kollektives Vertrauen ist ein kollektives kognitives Konstrukt, welches durch wiederholte Interaktion einer Gruppe entsteht und das geteilte Vertrauensniveau der Gruppe gegenüber einem anderen Individuum, einer anderen Gruppe oder einer Organisation beschreibt. In Kapitel 4 mussten Gruppen Investitionsentscheidungen im Collective Trust Game (CTG) treffen, einem ökonomischen Spiel, das eine wertende Aufgabe darstellt. Die Ergebnisse zeigen, dass kollektives Vertrauen, als geteiltes kognitives Konstrukt, durch Interaktion emergiert und persönliche Unsicherheit im CTG reduzieren kann. Dies zeigte sich in dem Anstieg der einvernehmlichen Investitionsentscheidungen und dem Abfall der Entscheidungslatenzen. Kapitel 4 kommt zu dem Schluss, dass kollektives Vertrauen als ein emergentes kognitives Konstrukt persönliche Unsicherheit in Gruppen reduzieren kann.

Kapitel 5 beschreibt den methodologischen Beitrag dieser Dissertation. Das HoneyComb-Paradigma (Boos et al., 2019) wird als ein Werkzeug zur Untersuchung von emergenten Gruppenprozessen mithilfe von raumzeitlichen Daten vorgestellt. Drei Analyseebenen werden gezeigt und mit vier Analyseansätzen kombiniert, die auf visuellen und Netzwerkanalysemethoden beruhen. Ein Beispiel illustriert, wie die vorgestellten Ansätze genutzt werden können, um emergente Prozesse in Gruppenentscheidungen unter Unsicherheit zu untersuchen.

Diese Dissertation kommt zu folgendem Ergebnis: Gruppen können informationale und persönliche Unsicherheit durch emergente Prozesse reduzieren. Diese Prozesse beinhalten kollektive Kognition, Gruppenkohäsion und Führen/Folgen. Die identifizierten sowie weitere Prozesse können mithilfe von visueller und Netzwerkanalyse analysiert und visualisiert werden wie in dieser Dissertation dargestellt. Die spezifischen Anteile der einzelnen Prozesse an Unsicherheitsreduktion sollten durch zukünftige Forschung untersucht werden.

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Overview of publications

This is a publication-based, cumulative dissertation. The following chapters have been published in or were submitted to peer-reviewed scientific journals:

Chapter 3.1:
Ritter, M., Wang, M., Pritz, J., Menssen, O., and Boos, M. (2021). How collective reward structure impedes group decision making: An experimental study using the HoneyComb paradigm. *PLoS ONE, 16*(11), e0259963. https://doi.org/10.1371/journal.pone.0259963

Chapter 3.2:
Ritter, M., Pritz, J., Morscheck, L., Baumann, E., and Boos, M. (2022). In no uncertain terms: Group cohesion did not affect exploration and group decision making under low uncertainty. Submitted to *Frontiers in Psychology*.

Chapter 4.1:
Ritter, M., Kroll, C. F., Voigt, H., Pritz, J., and Boos, M. (2022). The Collective Trust Game: An online group adaptation of the Trust Game based on the HoneyComb paradigm. *Journal of Visualized Experiments, 188*, e63600. https://doi.org/10.3791/63600

Chapter 4.2:
Ritter, M., Fritsch, M., Komes, H., Komes, M., Pritz, J., and Boos, M. (2022). Collective trust as an emergent construct: An investigation using the Collective Trust Game (CTG). Under review at *Journal of Experimental Social Psychology*.

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Chapter 1: Introduction

Let me introduce you to a group of people: Christie, Jeff, Henry, and Laura recently moved to a new city for their studies. They meet at an academic event and decide to head out for a nice dinner afterwards. However, being new to the city, they do not know which of the restaurants they should choose. An awkward silence emerges – what now?

Christie thinks that they will need to gather some information about the nearest restaurants before making a decision. Jeff is agonizing about a proposal as he would love to know more about what kind of food the others like. Henry wishes someone would just take initiative and choose so that he can tag along. Laura does not really care about the restaurant, she will be fine as long as they are all together.

These four people are faced with the non-trivial task of making a group decision under uncertainty. Most people will have experienced a situation like this in which the group has not enough information about either the environment (the restaurants), each other (the group members' food preferences), or both. In fact, situations like this will have been familiar to our ancestors. Group-living animals, such as some primates (e.g., Fichtel et al., 2011; Fischer & Zinner, 2011), birds (e.g., Nagy et al., 2010), or fish (e.g., Kareklas et al., 2018), often need to decide collectively on when a group starts to move (e.g., Montanari et al., 2019) or where it moves to (e.g., Boinski & Garber, 2000; Kappeler, 2010).

Looking back to our human group, we can see that the four group members' thoughts exemplify processes a group might use to deal with uncertainty: Christie wishes for more information about the available restaurants to base their decision on. This could be interpreted as the motivation to explore their surroundings in order to reduce so-called informational uncertainty (van den Bos & Lind, 2013). The group might decide to simply pick a restaurant at random and try out different alternatives over the next weeks to identify the best place to eat. This is called exploration (Mehlhorn et al., 2015) and is a central mechanism of uncertainty reduction in both individual and group decision making. Once the group finds a restaurant they like, they could make this their weekly meet-up spot, thereby exhibiting so-called exploitation (Mehlhorn et al., 2015). The group might decide to visit all restaurants together or to try out different ones individually and report back with their experiences. On a large scale, this is what online rating systems are based on: Individuals gather information to benefit the larger group. This process of information gathering has been termed collective cognition (Couzin, 2009) or collective

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induction (Laughlin, 2011). Collective cognition and exploration/exploitation patterns are one way a group might reduce uncertainty.

Jeff is worried about not knowing anything about his fellow group members' preferences. This group has only known each other for a couple of hours so Jeff has no information if the others like Italian or Asian food, want to be seen at fancy bars or prefer to order in. What Jeff is experiencing has been called personal uncertainty (van den Bos & Lind, 2013). Whenever individuals interact with others, they have to engage in predictions and assumptions about the others' thoughts, feelings, and planned behaviors (Yamagishi et al., 1998). When first getting to know someone, these predictions will often be false: Jeff could assume that Laura loves Italian food because she was born in Florence, when Laura actually prefers Thai curry over pizza. With repeated interactions (Berger & Calabrese, 1975), Jeff's ability to predict the preferences of his companions will improve so that Jeff's personal uncertainty is reduced.

Henry wishes that someone would simply pick so that the group can move forward. In that, Henry wishes that some form of spontaneous leadership should emerge. This can often be seen in both human and animal groups (e.g., Couzin et al., 2005; Gavrilets et al., 2016). If no preexisting hierarchical structure exists, as is the case in our group of new friends, leadership often emerges when a group member makes a first move (Boos et al., 2014; Conradt et al., 2009). In most cases, the rest of the group will follow and thereby reduce the imminent uncertainty of the situation. Hence, the emergence of leadership and followership in groups might also be used to reduce uncertainty.

Laura is very flexible with her food choices and her main motivation is that the group stays together. This social motivation has been termed group cohesion (Casey-Campbell & Martens, 2009). Group cohesion can be a powerful motivator in animal and human groups (Cartwright, 1968; Couzin & Krause, 2003) and can affect group decision making for better or for worse (e.g., Simons, 2004; van Ginkel & van Knippenberg, 2012). For example, it might turn out that Christie and Jeff would like to try out the Thai restaurant around the corner, but Henry has a hard time eating spicy food. If Laura motivates everyone to stay together, Henry might have to compromise his own preferences. On the other hand, however, Laura might motivate everyone to talk it out until they find the best decision for the whole group.

What this perhaps overly simplistic example shows is how groups – and individual group members – might use emergent processes (collective cognition, leader-/followership, group cohesion) to deal with both personal and informational uncertainty. However, emergent processes are notoriously difficult to measure (Kozlowski et al., 2013) so that only little empirical research has been able to target these processes specifically.

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In this dissertation, I will aim to illuminate the processes groups use to decide under uncertainty. To reach this goal, I address the following three central questions:

1. Can groups reduce uncertainty through emergent processes?
2. Which processes can be identified?
3. How can we analyze and visualize the emergent processes in group decision making under uncertainty?

In Chapter 2, I will lay out the theoretical basis for this research. To this end, I will draw on theoretical and empirical work from the psychological, organizational, and biological sciences to define the key concepts of this dissertation: personal and informational uncertainty, group decision making, emergence, collective cognition, leader-/followership, and group cohesion. Additionally, I will discuss methodological aspects such as group decision task design and the measurement of emergent processes. In doing so, I want to provide an interdisciplinary theoretical framework in which the subsequent chapters should be understood.

In Chapter 3, I will address the first two research questions and present two empirical projects that focus on the investigation of how human groups cope with informational uncertainty. Both studies employ a movement paradigm, the HoneyComb paradigm (Boos et al., 2019), that allows researchers to observe the unfolding of emergent processes. Chapter 3.1 presents a study that mainly focuses on how group members identify the best leader. This study has important methodological implications on the design of group decision tasks. Chapter 3.2 presents a project including one simulation and two empirical studies. Based on findings from Chapter 3.1, the processes that influence group decision making are investigated. Specifically, this chapter shows that groups can use collective cognition processes to reduce informational uncertainty. I present findings on the relationship of group cohesion, exploration, and group decision making. Furthermore, the effect of emergent group cohesion and leader-/followership will be investigated.

In Chapter 4, I will present two papers addressing the first two research questions with a focus on personal uncertainty. Specifically, these papers will present findings on collective trust and how the emergence of collective trust can reduce personal uncertainty. Chapter 4.1 presents the Collective Trust Game (CTG) that was developed as part of this dissertation and allows the observation of emerging group processes within the trust game (Berg et al., 1995). Chapter 4.2 uses the CTG to observe whether collective trust will emerge spontaneously in investor groups and reduce personal uncertainty.

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In Chapter 5, I will present methodological approaches to analyze and visualize emergent processes in groups in order to address the third research question. This chapter will draw on data from Chapter 3 to illustrate three different levels of analysis and four different approaches to analyzing emergent processes. Next to classical inferential statistics, Chapter 5 will present methods based on network analysis (Butts, 2008; Wasserman & Faust, 1994) and visual analytics (Rack et al., 2019). This chapter will address calls for new methodologies to provide insights into emergent group processes (Kozlowski, 2015).

In Chapter 6, I will present an overview of the findings of this dissertation and relate them to each other and to previous research as discussed in Chapter 2. Within this chapter, the contributions of this work to answering the guiding research questions shall be summarized and evaluated. Additionally, Chapter 6 will reflect on limitations of the present work and discuss future directions.

It is the aim of this work to bridge the gap between psychological conceptualizations of uncertainty and group decision making and the emergent processes identified in animal behavior (Boos et al., 2011). To answer the three research questions, this dissertation will draw on theory and empirical evidence from biology, machine-learning, organizational behavior, and psychology. Within this dissertation, I want to illuminate how groups might use collective cognition, group cohesion, and leader-/followership processes in decision making to reduce both informational and personal uncertainty.

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 doi: 10.53846/goediss-9589

Chapter 2: Theoretical Background

The aim of this dissertation is to describe group decision making under uncertainty as an emergent phenomenon and to empirically identify relevant emergent processes and mechanisms that groups might use to reduce uncertainty. Within this chapter, I will draw on theory and empirical evidence from biology, machine-learning, organizational behavior, and psychology to lay the theoretical basis for the coming chapters on the reduction of informational (Chapter 3) and personal uncertainty (Chapter 4), and the measurement of emergent group processes (Chapter 5).

Grand and colleagues (2016) advise that a theory of emergent processes should "identif[y], operationaliz[e], and justif[y] both the core concepts involved in emergent phenomena as well as the 'rules' or process mechanisms that describe what, when, and how lower-level entities think, behave, and/or react" (p. 1355). This dissertation aims to contribute to the empirical evidence that is needed to build this theory in the future. In doing so, I will follow Grand and colleagues' advice to identify and define the core concepts of the group decision making under uncertainty as well as the involved emergent phenomena.

This dissertation will explore three candidate emergent processes (collective cognition, group cohesion, and leader-/followership) that groups might use to reduce uncertainty during decision making. These processes were chosen to allow for "multiple 'pathways' through which an emergent construct might unfold" (Grand et al., 2016, p. 1355), instead of confining investigation to only one process. I will begin by defining uncertainty, group decision making, and the emergent processes (collective cognition, group cohesion, leadership) individually. Throughout this chapter, I will explain how the discussed concepts were operationalized in the empirical studies presented in Chapter 3 and 4. Lastly, I will integrate the concepts to demonstrate the gap in the literature that this dissertation aims to fill and outline how the following chapters will address this gap.

Uncertainty

A fundamental human motivation is to feel safe and certain so that feelings of uncertainty are a highly aversive state (Hogg & Zanna, 2007; Kagan, 1972). Uncertainty can arise from a myriad of sources: insufficient communication (Berger & Calabrese, 1975), ill-defined norms of performance standards (Diekmann et al., 2004), changes within the work environment (Allen et al., 2007), or instability on a political or societal scale (Milliken, 1987). To reduce or manage

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uncertainty is a major concern for most humans (Berger & Calabrese, 1975; Hogg, 2000; Kagan, 1972; Lind & van den Bos, 2002).

Uncertainty can be differentiated into different types. Knight differentiated three types of probability situations (as cited in Boeckelmann et al., 2011): logical probabilities that can be calculated a-priori, statistically inferred probabilities, and estimated probabilities that rely on intuitive judgments. While logical and statistical probabilities can be subsumed under the term risk, estimated probabilities are termed (true) uncertainty. Group decision making usually deals with (true) uncertainty: Even though environmental outcomes can theoretically be calculated, the actions and behaviors of other group members cannot be known (von Ameln & Iwers, 2021). This is sometimes also called radical uncertainty (Magnani & Zucchella, 2018) and can stem from a number of sources, such as unpredictable environmental developments (e.g., complexity or dynamics), uncertainty about the behavior of other actors (e.g., conflict, lack in familiarity), or uncertainty due to not knowing (i.e., incomplete information). Further sources of uncertainty can be inadequate integration of information, unknown values of possible outcomes, lack of clarity about an appropriate decision process, unknown preferences, or insecurity about one's own ability to influence future events (Humphreys & Berkeley, 1985). This shows that our environment is characterized by ambiguity and equivocality (Tolman & Brunswik, 1935): A given environmental stimulus can precede a multitude of outcomes, while many different stimuli can precede a similar outcome, so that no clear causal inferences can be drawn. To make sense about the environment and other people in it, humans need to formulate and test hypotheses, as proposed by the causal uncertainty model (Weary & Edwards, 1996). This model predicts that humans will attend more to cues of social information, compared to environmental cues, to test the formed hypotheses about the social world.

Lind and van den Bos (2002) split (true) uncertainty into informational and personal uncertainty to reflect the separate sources of uncertainty. This dissertation follows this distinction as groups might deal differently with uncertainty about their environment (informational) and uncertainty about relationships and individual characteristics within the group (personal).

Informational uncertainty

Informational uncertainty is experienced when an individual or group has too little information to confidently and reliably form a judgment about their environment (van den Bos & Lind, 2013). Therefore, informational uncertainty is the individual's inability to predict, evaluate, or affect their environment or their future states (Tversky & Kahneman, 1974). This means that informational uncertainty in group decision making will mostly arise from the different options that a group can choose from. This dissertation will include two works on informational

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uncertainty in Chapter 3. In these empirical studies, informational uncertainty is represented within the decision options: In the beginning of the experiments, participants have no information about the quality of the different options and, therefore, are unable to predict the outcomes of choosing any of these options.

Personal uncertainty

According to van den Bos and Lind (2013), personal uncertainty incorporates both relational and self-uncertainty and refers to an individual's doubts or instability regarding their own attitudes or behaviors (self-uncertainty) as well as those of their social surroundings (relational uncertainty). Relational uncertainty refers to the inability to predict other's actions or preferences (Yamagishi et al., 1998) as well as to the experienced ambiguity about the quality of relationships with others, especially during early stages of a relationship (Berger & Calabrese, 1975). This dissertation extends the concept of personal uncertainty (van den Bos & Lind, 2013) to the group level in the investigation of collective trust (Chapter 4 and Kramer, 2010). In the two presented studies, personal uncertainty can be seen in (a) the inability of the investor group to predict the behavior of the trustee (Are they trustworthy?; relational uncertainty) and (b) ambiguity about one's own and the group's trust level (How much do we, as a group, trust?; self-uncertainty). As personal uncertainty is experienced as particularly aversive (Calcutt et al., 2019; van den Bos, 2009; van den Bos & Lind, 2013), investors should be highly motivated to reduce it by establishing collective trust.

It has been shown that personal uncertainty can be reduced during initial interactions (Berger & Calabrese, 1975; Rempel et al., 1985) by gathering relational information (Kramer et al., 2001; Weary & Edwards, 1994). This means that investor groups in the Collective Trust Game (CTG; Chapter 4) should be able to reduce personal uncertainty by interacting with each other during the first rounds of the game. These interactions can reduce personal uncertainty as individuals can compare their own trust level with that of the other investors (compare to Festinger, 1954), communicate their own trust level to interaction partners (Berger & Calabrese, 1975), or establish routines on how a collective trust response is determined in the group (compare to Becker & Knudsen, 2005). The studies presented in Chapter 4 will explore the process of personal uncertainty reduction on the group level through collective trust and its impact on the group decision process (e.g., decision latencies).

Group decision making (under uncertainty)

Group decisions are pervasive in everyday life and have been studied by different fields for many years (Tindale & Winget, 2019). Group decisions, by definition, are social and involve multiple group members (Tindale & Winget, 2019). Within the (psychological) literature, the study of

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group decision making has focused on two dimensions of group decisions (Tindale & Winget, 2019): How much exchange is allowed (or necessary) for group decision making? And how is the final decision made? Depending on the decision task and context, these dimensions have different implications for the quality and process of group decision making. Generally, research has shown that groups often perform well, but not optimally, on group decision tasks (Tindale & Winget, 2019).

From an evolutionary perspective (e.g., Van Vugt & Kameda, 2012), living and deciding in groups can be an advantage as group members can learn from each other (Mesoudi, 2011; Rendell et al., 2010; Wisdom et al., 2013) and share resources, labor, and knowledge (Kozlowski and Chao, 2012). Group synergy is reached when groups outperform individuals[1] and this "gain in performance is attributable in some way to group interaction" (Larson, 2010, p. 4). This could be due to motivational gains (e.g., Torka et al., 2021), identification of most expert members (e.g., Baumann & Bonner, 2013), or the adherence to statistical dominance instead of individual judgment errors (Charness et al., 2007). Groups often decide more rationally in a game-theoretic sense, compared to individuals, as they might be able to overcome individual cognitive biases of their members (Charness & Sutter, 2012), although this might not always maximize social welfare. Moreover, groups can rely on the pooling of private information (Kameda et al., 2011; Moussaïd, Garnier, et al., 2009; Moussaïd et al., 2017) as a successful strategy that can outperform individual trial-and-error learning (Rendell et al., 2010). The successful pooling of information has sometimes be coined the wisdom of the crowds (Couzin, 2009; Kao & Couzin, 2014). Schauenburg (2004) conceptualizes groups as information-transformation systems that can use collective information sampling strategies by incorporating individual cognition (evaluation and use of information) and social cognition (sharing of information). Groups do not always succeed in this pooling of information as the goals of a group can influence the decision to share information and the selection of which information is shared for better or for worse (as evidenced by hidden-profile paradigms; Stasser & Titus, 2003).

Over the years, research on group decision making has employed various paradigms or tasks and it has been shown that, depending on the decision task, different processes might influence group decision performance (Kerr et al., 1996; Moussaïd & Yahosseini, 2016; Stasser & Abele, 2020; Yahosseini & Moussaïd, 2019). Steiner (1972) proposed to categorize tasks according to component (i.e., is the task divisible between group members or does it need to be solved together), focus (i.e., does the task require a "good" solution – optimizing, or does it require

[1] It should be noted that synergy is often applied more strictly to only those instances in which groups can outperform their best individual member.

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many different solutions – maximizing), and interdependence (i.e., in which way can group members combine their different contributions to the task). Additionally, work on social decision schemes (Davis, 1973) and collective induction (Laughlin, 1999, 2011) has distinguished between intellective and judgmental tasks. While intellective tasks have one objectively correct answer (e.g., a mathematical problem), judgmental tasks (e.g., jury tasks) do not have an objectively correct answer but rely on the consensus or the aggregation of individual judgments of group members. Some group decision tasks fall in between those categories. These are often termed problem-solving tasks (e.g., those in Chapter 3; Laughlin, 1999). While they have an objectively correct or optimal solution, groups have to infer it through collective induction. "Collaborative problem solving is predicated on the presumption that there is a correct answer (or at least, defensible answers), and the task of the group is to combine their information and expertise to identify the best answer" (Stasser & Abele, 2020, p. 591). If the task is less demonstrable (i.e., tasks that require repeated hypothesis testing), it can exhibit qualities of a judgmental task. However, if the solutions of the task are clearly demonstrable (e.g., in an insight problem), the task can seem more like an intellective task (Laughlin, 2011). The more information is available to a group, the closer the task will be to an intellective task (Stasser & Abele, 2020). Yahosseini (2019) defined collective problem solving as a search process. He distinguishes between three types of groups in problem-solving tasks in terms of how much groups can interact: First, non-interacting groups make decisions without any information exchange between individual members. Second, social groups freely exchange information before deciding. Third, solution-influenced groups repeatedly contribute after one another in so-called transmission chains (Yahosseini & Moussaïd, 2020). Additionally, some gradient exists between tasks in terms of how much interaction is allowed. Note that these group distinctions are mainly distinctions of group task design (e.g., within an experiment) and do not necessarily emerge during group interaction. The different task types will affect group decision making in the way they structure a group's environment and either enable or constrain individual contributions (Yahosseini & Moussaïd, 2019).

This dissertation will present different task types: In Chapter 3, groups are faced with generally intellective tasks (i.e., tasks that have objectively correct solutions) that require inference of the best option and are low on demonstrability. Therefore, the tasks presented in Chapter 3 will fall somewhere between an intellective and judgmental task according to the amount of (social) information that is available to group members. Chapter 4 will present the Collective Trust Game (CTG) that is considered a judgmental task. Note that according to game theory (e.g., Morgenstern & Von Neumann, 1953; Osborne, 2009), one might consider economic games like the trust game (Berg et al., 1995) to be intellective tasks as one or more Nash equilibria exist that

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participants could base their behavior on. In terms of group type, Chapter 3 and Chapter 4 present studies using groups between the non-interacting and social group categories: The studies conducted using the HoneyComb paradigm (Boos et al., 2019) could be classified as social group studies as participants were able to exchange information through movement even though the amount of information that could be exchanged was restricted in Chapter 3.1. Additionally, two comparison studies (Study 2 in Chapter 3.2 and 4.2) are reported. In these studies, groups could exchange only very limited information so that these tasks should be classified as closer to non-interacting groups. The distinctions between different task types are important to consider as group processes and their effect on group performance may vary according to task type. Emergent processes that guide group decision making might be advantageous for one task type, but not for the other (Yahosseini, 2019). For example, it has been shown that groups often outperform individuals in complementary intellective tasks (i.e., exhibiting true group synergy), while groups perform equal to or below the level of the best individual member on other task types (Stasser & Abele, 2020). Furthermore, it has been found that biases in judgment tasks are predominantly determined by the process that groups used to determine their final answer (Kerr et al., 1996). Lastly, groups organized as transmission chains outperform individual problem-solvers in environments in which confidence is a reliable indicator of performance (Moussaïd & Yahosseini, 2016). These examples illustrate that divergent effects should be expected of experimental manipulations on group decision making, depending on task type. For example, environmental or task information should have a larger effect on group decision performance within the intellective tasks used in this dissertation (Chapter 3) but not the judgmental tasks (Chapter 4).

Emergent processes

At the core of group processes is interaction (Lehmann-Willenbrock et al., 2017). During group decision making, individual decision rules and dynamic group processes interact to form so-called "socio-spatial geometries" (Kenrick et al., 2003) that constitute emergent constructs. Emergence is defined as "a bottom-up process whereby individual characteristics and dynamic social interaction yield a higher level property of the group" (Kozlowski et al., 2013, p. 584). The result of emergence or an emergent process, therefore, is an emergent construct. Emergent processes that might affect group decision making are, among others, collective cognition (e.g., Couzin, 2009), group cohesion (e.g., Couzin & Krause, 2003), or leader-/followership behaviors (e.g., Conradt et al., 2009).

While the input and output of group processes (McGrath, 1964) in humans are researched fairly well, the process itself has long been treated like a black box (Kolbe & Boos, 2019). While the

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study of emergence has picked up speed over the last decade (e.g., Grand et al., 2016; Lehmann-Willenbrock et al., 2017; Lehmann-Willenbrock & Allen, 2018; Riethmüller et al., 2012), more psychological research needs to investigate group processes in their dynamic, emergent, and fluid qualities (Keyton, 2016; Kolbe & Boos, 2019; Kozlowski, 2015; Kozlowski et al., 2013; Kozlowski & Chao, 2012; Leenders et al., 2016; Roe, 2008). As described in the beginning of this chapter, three candidate emergent processes (collective cognition, group cohesion, and leader-/followership) shall be described and operationalized in the following.

Collective cognition

Groups are often described as an information-processing body (Hinsz et al., 1997; Larson & Christensen, 1993; Schauenburg, 2004; Stasser & Abele, 2020). This means that human and animal groups can combine information that individual members hold on the group level and use it to inform group decisions (Couzin et al., 2002; Couzin, 2009; Moussaïd, Garnier, et al., 2009). A group's success in this task is based on the capacity to communicate in order to exchange information and reach a consensus based on the pooled information (King et al., 2011). This process is called collective cognition and has been found across a range of domains from animal groups (e.g., Couzin, 2009; Couzin et al., 2002; Feinerman & Korman, 2017), over mathematical models of knowledge propagation in human populations (Billiard et al., 2020) and simulated cognitive organisms (Hornischer et al., 2019), to entrepreneurial teams (West, 2007). Collective cognition is "grounded in yet transcending the underlying mental states of the interacting agents" (Panzarasa & Jennings, 2006, p. 402) and comprises the processes involved in acquiring, storing, transmitting, manipulating, and using information within a group (e.g., Hinsz et al., 1997). Other related concepts are collective induction (Laughlin & Hollingshead, 1995), collective memory (Couzin et al., 2002), collective intelligence (Moussaïd & Yahosseini, 2016), team learning (Lehmann-Willenbrock, 2017), judgment propagation (Moussaïd et al., 2017), knowledge emergence (Grand et al., 2016), and cultural cognition (Sharifian, 2009). The breadth of these terms shows how widely the concept of collective cognition is investigated. According to Feinerman (2017), collective cognition relies on individual cognition as well as the connectivity between individuals. Collective cognition serves the essential purpose of integrating both environmental and social information (King & Sueur, 2011). In order to identify which individuals might hold pertinent information, groups can rely on verbal or nonverbal signaling, inadvertent social cues (e.g., starting order or group position), behavior reading, or the establishment of social communication networks (Faria et al., 2010; Fischer & Zinner, 2011; King et al., 2011; Momennejad, 2022). Sridhar and colleagues (2021) suggest that group decision making relies on geometric principles of information pooling through ego-centric spatial relationships. Notably, the gathering of information on the collective level might scale some

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form of certainty about how profitable an option is (Thomas et al., 2013): The more individuals share a piece of information, the more likely it is that this information will be used as a coordination cue. While the terms used in the cited literature might differ, all of them describe a process that integrates individual knowledge on the collective level. Some of these constructs shall be explained in more detail.

Collective induction was introduced by Laughlin and Hollingshead (1995) and is the "cooperative search for descriptive, predictive, and explanatory generalizations, rules, and principles" (p. 94). During collective induction, groups form hypotheses and test them. Laughlin (1999) describes a number of strategies (or social decision schemes, Davis, 1973) a cooperative decision making group can use to resolve disagreement: Random selection of options, voting, turn-taking, demonstration, and generation of new options are possible. The empirical studies presented in Chapter 3 are collective induction tasks: Groups need to identify the best option through hypothesis-formation and testing. In the beginning of the task, groups might rely on random selection of options (exploration; see Mehlhorn et al., 2015). Once individual members might have formed hypotheses about the different options, the groups in Chapter 3 could rely on voting (e.g., by a quorum response; compare to Ward et al., 2008) or possibly demonstration (e.g., via mimetism, Sumpter, 2006; or observational learning, Wang et al., 2021) and can exploit their choices.

The *pooling of collective information* in moving groups has been investigated in animal (Conradt, 2012; Conradt & Roper, 2005; Couzin, 2009; Couzin et al., 2002, 2005; Couzin & Krause, 2003; Hoare & Krause, 2003; Pyritz et al., 2011; Seeley & Buhrman, 1999) and human groups or crowds (Belz et al., 2013; Dyer et al., 2009; Helbing et al., 2005; Moussaïd, Garnier, et al., 2009; Moussaïd et al., 2016). A general principle of information transfer within groups seems to be the local information transfer between neighbors (e.g., Kolpas et al., 2013), so that, for example, the information of movement direction is transmitted via the alignment of one's own movement direction with that of one's neighbor. In this way, small changes in individual behavior can impact the whole group (Couzin et al., 2002) so that a small subset of a group can influence the decision of the collective (e.g., Boos et al., 2014). The groups in the empirical studies presented in this dissertation might have used alignment processes during group decision making. For example, to follow the pre-programmed leaders, participants in Chapter 3.1 might have chosen to align their movement directions to that of their preferred leader or that of their closest neighbor.

The *emergence of knowledge* seems to rely on the sharing of information through intentional, overt acts through a medium of communication (Grand et al., 2016). With repeating interactions,

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information is transferred between individuals so that collective knowledge emerges. Groups in Chapter 4 might have relied on movement to signal their preferred level of trust to each other. Over repeated interactions, all group members could collect information about each other's trust level and build a shared level of trust.

While collective induction (Laughlin, 1999) refers more specifically to the process investigated in Chapter 3, it is ill-suited to explain personal uncertainty reduction through the emergence of collective trust (Chapter 4). Collective trust as an emergent construct might be best described as knowledge emergence (Grand et al., 2016), specifically, reflexive knowledge of the group about its own level of trust. Lastly, the term collective information pooling (Moussaïd, Garnier, et al., 2009) might be best to describe the behavior of moving groups. However, this dissertation will mainly use the term collective cognition in order to subsume processes of information transfer from the individual to the collective level that might reduce both informational (Chapter 3) and personal uncertainty (Chapter 4).

Until now, I have described how information might be integrated from the individual to the collective level. In the following, I briefly discuss how groups might generate knowledge in the first place (exploration), before deciding to pursue the profitable option (exploitation), and how the construct collective trust relates to collective cognition.

Exploration/exploitation patterns

Exploration and exploitation patterns have been investigated using machine-learning algorithms (Sutton & Barto, 2018; see Chapter 3.2), animals (e.g., Franks et al., 2003; Seeley & Buhrman, 1999; Stahl et al., 2001), and humans (e.g., Bechara et al., 1994; Mehlhorn et al., 2015; Yahosseini et al., 2018). Logically, groups should have an advantage during exploration as they can "send out" individuals to gather information that can then be aggregated to collective cognition. In this way, groups could reduce uncertainty early on and, once sufficient information is gathered, transition to exploitation of an option quickly as seen in individuals (e.g., Bechara et al., 1994). This strategy seems to be employed by barnacle goose flocks, for example (Stahl et al., 2001): Subordinate geese scout food sources that are then exploited by higher-ranking individuals. Alternatively, groups could prioritize group cohesion early on and explore options (such as feeding sites) together (van der Post & Semmann, 2011). This strategy might be employed by groups in which the benefits of group cohesion outweigh the benefits of early uncertainty reduction. This means that, depending on the environmental context, the exploration strategy that groups use might vary as will the strategy to identify the ideal point of transition from exploration to exploitation (Cohen et al., 2007; Tickle et al., 2021). Within the empirical studies presented in this dissertation (Chapters 3 and 5), it was investigated whether

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groups use strategic exploration of options in the beginning of the task before exploiting the best option.

Collective trust

Collective trust is, as defined in Chapter 4, "a psychological state shared among a team or group of humans and formed in interaction among this group." As previously discussed, the CTG (Chapter 4) allows the investigation of personal uncertainty on different levels: on the individual level between investor and trustee, and on the group level between members of the investor group. The group-level personal uncertainty stems from the circumstance that investors are unable to predict the level of trust fellow investors hold for the trustee. As personal uncertainty can be reduced by gathering relational information about others during interactions (Dirks & Ferrin, 2001; Lind & van den Bos, 2002), I argue that the emergence of collective trust through repeated interactions will reduce personal uncertainty within investor groups. This argument is an extension of previous research that has mainly focused on the concept of interpersonal (dyadic) trust as means of personal uncertainty reduction (Jannssen, 2011). In this way, collective trust can be subsumed under the definition of collective cognition in that it emerges through the aggregation of individual information (trust levels) on a collective level.

Group cohesion

Group cohesion, in addition to alignment and collision avoidance, is one of the three basic principles guiding swarm behavior in animal (Couzin & Krause, 2003) and human groups (Belz et al., 2013). Many animal groups rely on consensus decision making so that group cohesion can be maintained (Conradt, 2012; Conradt et al., 2013; Conradt & Roper, 2005, 2007; Simons, 2004). High levels of group cohesion can improve cooperation (Cone & Rand, 2014) and information exchange between individuals (Cartwright, 1968; Conradt, 2012; Derex & Boyd, 2015; Mason & Watts, 2012). Additionally, individuals in highly cohesive groups might prioritize social information above their own goal-orientation (Boos et al., 2014; Sridhar et al., 2021) and reduce maladaptive following behaviors (Ward et al., 2008). All this might improve group decision performance under uncertainty (Casey-Campbell & Martens, 2009). For example, more homogeneous fish shoals outperformed more heterogeneous groups in a collective learning task. However, studies investigating group decisions under time pressure show that group cohesion can have a detrimental effect on group decision making (Conradt et al., 2013; Gavrilets & Richerson, 2017; Yahosseini et al., 2018) and information transfer (e.g., Pasquaretta et al., 2014; van Ginkel & van Knippenberg, 2012). Especially larger groups seem to suffer from disadvantageous mutual enhancement when group cohesion is high (Kao & Couzin, 2014). Regardless of its impact on decision performance, I argue that group cohesion can serve to reduce uncertainty in group decision making. When groups are highly cohesive, the social

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motivation to stick together might to overpower the goal-orientations of individual members (Sridhar et al., 2021) with negative effects on decision performance (Conradt et al., 2013). Therefore, group members can rely on the collective to determine the next steps, reducing perceived uncertainty, be it informational or personal. For example, a participant in Chapter 4 can reduce their personal uncertainty by simply deciding to go along with the other group members. Their next steps will be clear alleviating them of the aversive, uncertain state. The effects of group cohesion shall be investigated in detail in Chapter 3.

Leader-/followership

According to Conradt and colleagues (2013), leadership is most likely to emerge when a group is faced with informational uncertainty and internal conflicts. While groups with only basic social structure can usually rely on principles of self-organization (e.g., Couzin & Krause, 2003; Helbing et al., 2005), socially more complex groups might rely on leader-/followership processes (King & Cowlishaw, 2009; Lozano et al., 2018). According to Hooper and colleagues (2010), leadership is a possible solution to typical challenges of group living, such as conflict and coordination failures. Additionally, leadership can aid information transfer between individuals and groups, for example, when an informed minority can elicit followership from an uninformed majority and guide them to profitable options (Boos et al., 2014; Couzin et al., 2005). We define a leader according to Pyritz and colleagues (2011) as an "individual eliciting follower behavior or exerting social influence on others, by its rank into the progression, its behavior, or its socials status" (p. 1270). Importantly, both consistent and distributed or variable leadership seem to be able to reduce uncertainty in animal group decision making (Conradt & Roper, 2005; Couzin et al., 2005; Sridhar et al., 2021). In psychological terms, consistent leadership would correspond to hierarchical leadership (e.g., Morgeson et al., 2010), while distributed or variable leadership would correspond to shared leadership as an informal and dynamic process (Bachmann, 2022). Notably, distributed leadership is often assigned to individuals holding crucial information or possessing relevant abilities to cope with the situation a group is faced with (Moe et al., 2009; Van Vugt, 2006). Interestingly, this assignment of leadership can emerge on its own and does not require that the group can explicitly identify the individual holding the most information (Couzin et al., 2005). This illustrates how distributed leadership can go hand-in-hand with the emergence of collective cognition and reduce uncertainty in group decision making.

Effective leadership requires that leaders balance goal-directed with socially-oriented behavior so that other group members can be enticed to follow (Ioannou et al., 2015; Sridhar et al., 2021). Therefore, leadership can be partially costly for leading individuals while providing a benefit for the group as a whole (Gillet et al., 2011; Sridhar et al., 2021). For example, participants in Chapter 3.2 who were motivated to lead the other participants to their preferred option might need to

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use specific behavioral patterns in order to signal other participants to follow (see Boos et al., 2014). Couzin and colleagues (2002) show that highly cohesive, but leaderless groups only exchange little information between individuals. Leadership could enhance the information transfer and support the emergence of collective cognition. It has been shown that hierarchically organized groups might be more efficient during group movement than egalitarian ones (Nagy et al., 2010). This seems to be true for decision making in groups in organizations as well: Leaderless teams might engage in excessive exploration of options, while hierarchically structured groups reduce uncoordinated exploration and promote fast transitions to the exploitation phase (Koçak et al., 2022). However, other studies contradict this finding, indicating that groups perform better on complex problem-solving tasks before a formal structure has emerged (Bachmann, 2022). Once a structure has emerged, it seems to be crucial whether the emerged leader is fit to lead.

In sum, leadership seems to impact the reduction of uncertainty in group decision making both directly and indirectly. The direct effect of leadership seems to emerge when an individual with superior knowledge or skills emerges. This direct effect could emerge in the empirical study presented in Chapter 3 in cases in which a certain individual has identified the best option early on (during exploration) and can elicit followership from the other group members. For the indirect effect, leadership seems to mediate the effect of other emergent processes (i.e., group cohesion and collective cognition) on uncertainty reduction. For example, an emergent leader might facilitate the emergence of collective trust in the CTG (Chapter 4).

Measuring emergent processes

Within this chapter, I have presented three emergent processes (collective cognition, group cohesion, and leader-/followership) that might serve as strategies and/or mechanisms to reduce uncertainty in group decision making. Interestingly, many studies investigating emergent processes in animal group decision making (Conradt & Roper, 2010; King & Sueur, 2011; Nagy et al., 2010) use high-resolution spatio-temporal data. The use of spatio-temporal data as a measurement of group decision making seems to be wide spread in the field of animal behavior but only few studies have employed this approach for emergent processes of human group decision making (e.g., Boos et al., 2014; Dyer et al., 2009; Moussaïd et al., 2016). While there are a number of alternative analytical approaches to emergent processes (Lehmann-Willenbrock & Allen, 2018), they are often time-consuming and laborious (Kolbe & Boos, 2019). The difficulty of assessing emergent processes within human interaction could explain why there seems to be comparatively little psychological research on the emergent processes that guide group decision making under uncertainty (Kozlowski, 2015; Kozlowski & Chao, 2012). One way to bridge this gap might be to apply findings and methodologies from the study of animal group decision

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making to the psychological realm to measure emergent processes through observation of human moving groups (Moussaïd, Garnier, et al., 2009). In fact, studying movement behavior using spatio-temporal data can provide insights into group processes above and beyond verbal communication (Helbing et al., 2005; Jelić et al., 2012; Moussaïd, Helbing, et al., 2009). Advancements in virtual tools, such as the HoneyComb paradigm (Boos et al., 2014), facilitate the investigation of human moving groups or crowds (Moussaïd et al., 2018). This dissertation will extend this work. Specifically, the work presented in this dissertation shall apply theoretical and methodological advances from the field of biology to psychological research questions.

Research Objective

Within this chapter, I have aimed to summarize previous findings on group decision making under uncertainty and the emergent processes that guide it. Drawing on theory and empirical evidence from biology, machine-learning, organizational behavior, and psychology, I have illustrated how groups might use collective cognition, group cohesion, and leader-/followership processes to reduce both informational and personal uncertainty during decision making. What this work will contribute to the development of a unified theory of emergent processes in group decision making are insights into the three research questions: (1) whether emergent processes can reduce both informational and personal uncertainty in human decision making groups (Chapter 3 and 4), (2) which of the identified candidate processes can be detected in human decision making groups (Chapter 3 and 4), and (c) how advantages of analysis and visualization methods can be leveraged in the investigation of human groups (Chapter 5). Based on the current state of the psychological literature, there are too many unknowns about how human groups use emergent processes to cope with uncertainty. Where psychological evidence is lacking, literature from the biological sciences and machine-learning can provide a strong basis on which psychological research can build. It is, therefore, the objective of this dissertation to bridge the gap between psychological conceptualizations of uncertainty and group decision making in human groups and the emergent processes identified in animal behavior. As such, this dissertation follows in the large footsteps of Boos, Kolbe, Kappeler, and Ellwart (2011) who, in their book collection on coordination processes in human and primate groups, bring together the expertise of neighboring fields to illuminate basic group processes.

The three research questions of this dissertation are:

1. Can groups reduce uncertainty through emergent processes?
2. Which processes can be identified?
3. How can we analyze and visualize the emergent processes in group decision making under uncertainty?

 doi: 10.53846/goediss-9589

The first and second question will build heavily on the theoretical background laid out in this chapter in order to venture into the study of informational uncertainty (Chapter 3) and personal uncertainty (Chapter 4). While the single presented studies will focus on smaller objectives, the contributions that each of these studies makes to the investigation of these research questions will be discussed in Chapter 6.

The third research question will be addressed in Chapters 3 through 5. While Chapter 3 and 4 will mainly contribute to the investigation of the first two research questions, they will employ analysis and visualization techniques that contribute to answer the third research question as well. Chapter 5, however, will focus specifically on analytical and visualization methods of emergent processes and how they can contribute to the investigation of group decision making under uncertainty. The methods presented in Chapter 5 aim to transpose established methods from the biological sciences (i.e., analysis of group movement) into the study of psychological phenomena.

The last chapter (Chapter 6) will review the evidence that was gathered within this dissertation and apply it to the three research questions. Additionally, Chapter 6 shall give an outlook on future research and outline implications for a unified theory that might continue the fruitful exchange between disciplines in order to shed light onto the emergent processes that reduce uncertainty in group decision making.

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 doi: 10.53846/goediss-9589

Chapter 3: Reduction of informational uncertainty

Chapter 3.1: Reduction of informational uncertainty in followers

Ritter, M., Wang, M., Pritz, J., Menssen, O., and Boos, M. (2021). How collective reward structure impedes group decision making: An experimental study using the HoneyComb paradigm. *PLoS ONE, 16*(11), e0259963. https://doi.org/10.1371/journal.pone.0259963

PLOS ONE

doi: 10.53846/goediss-9589

RESEARCH ARTICLE

How collective reward structure impedes group decision making: An experimental study using the HoneyComb paradigm

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Abstract

This study investigates if and under which conditions humans are able to identify and follow the most advantageous leader who will them provide with the most resources. In an iterated economic game with the aim of earning monetary reward, 150 participants were asked to repeatedly choose one out of four leaders. Unbeknownst to participants, the leaders were computer-controlled and programmed to yield different expected payout values that participants had to infer from repeated interaction over 30 rounds. Additionally, participants were randomly assigned to one of three conditions: single, independent, or cohesion. The conditions were designed to investigate the ideal circumstances that lead to identifying the most advantageous leader: when participants are alone (single condition), in a group that lets individuals sample information about leaders independently (independent condition), or in a group that is rewarded for cohesive behavior (cohesion condition). Our results show that participants are generally able to identify the most advantageous leader. However, participants who were incentivized to act cohesively in a group were more likely to settle on a less advantageous leader. This suggests that cohesion might have a detrimental effect on group decision making. To test the validity of this finding, we explore possible explanations for this pattern, such as the length of exploration and exploitation phases, and present techniques to check for confounding factors in group experiments in order to identify or exclude them as alternative explanations. Finally, we show that the chosen reward structure of the game strongly affects the observed following behavior in the group and possibly occludes other effects. We conclude with a recommendation to carefully choose reward structures and evaluate possible alternative explanations in experimental group research that should further pursue the study of exploration/exploitation phases and the influence of group cohesion on group decision making as promising topics for further research.

OPEN ACCESS

Citation: Ritter M, Wang M, Pritz J, Menssen O, Boos M (2021) How collective reward structure impedes group decision making: An experimental study using the HoneyComb paradigm. PLoS ONE 16(11): e0259963. https://doi.org/10.1371/journal.pone.0259963

Editor: The Anh Han, Teesside University, UNITED KINGDOM

Received: February 22, 2021

Accepted: October 29, 2021

Published: November 16, 2021

Data Availability Statement: All data files, the analysis script, the figures, and all Supporting information are available from the OSF project (https://osf.io/btruw/?view_only=c4c137fce44548e9a6021e9eb8e9dff4, DOI 10.17605/OSF.IO/BTRUW).

Funding: The study was partially funded for participant reimbursement by the Fachgruppe Psychologie of the University of Göttingen (https://fgpsygoettingen.wordpress.com/). MW was the grantee. We acknowledge financial support of

Introduction

Democracies rely on the basic idea that elections will lead to the establishment of a government most likely to make the best decisions on behalf of its voters. Voters supposedly choose their representatives on an estimate of how well they will provide themselves and their demographic group with benefits [1] based on public information and their previous experience with the

publication costs by the Open Access Publication Funds of the Göttingen University. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. There was no additional external funding received for this study.

Competing interests: The authors have declared that no competing interests exist.

party [2]. Thus, the election is presumed to manifest a pooled "wisdom of the crowd" judgment that surpasses individual judgments and thereby contributes to the entire group's welfare [3]. However, history and recent examples have demonstrated that election choices are observably more complex and often fail to produce leaders that are beneficial to their followers [4].

In this study, we investigate how human groups coordinate when faced with a number of differently advantageous leaders and need to infer each leader's qualities from their continuously observed behavior. Specifically, we examine the participants' ability to identify the leader that will see them to their best possible result under three different conditions.

Leadership as a result of group decision making

Leadership can be construed as the result of choices followers make in consideration of their objective to maximize their own and their group's advantage. Leaders and followers emerge in everyday decision making as an adaptive solution that enables groups to decisively initiate, arrive at, and complete the best possible collective action goals [5]. In other words, leadership and followership occur as they are part of the same interdependent agreement that groups form to coordinate significant collective actions that provide all group members with benefits upon completion [6,7]. Previous studies have shown that leadership can emerge in accordance with followers' needs [8,9].

An extensive body of literature in evolutionary psychology has proposed that leader-follower interactions arise naturally in (leaderless) animal groups with coordination needs such as joint migration or foraging [10,11]. For humans, evolutionary adaptation took place in small, semi-nomadic family groups [12]. In these environments, leading and following behaviors provided humans as a group living species with fitness advantages such as higher group effectiveness [12–20]. As there was no formalized leadership, leaders gained their influence on collective action by demonstrating their expertise [21–25]. Thus, evolutionary research would suggest the existence of an evolved psychological mechanism that enables followers to assess different potential leaders and to select the most appropriate individual to follow [26].

Applied to human behavior today, these findings indicate that humans can use heuristics and decision rules in choosing their leaders which can increase the efficiency of leaders and followers in their respective roles [15,18]. Using these psychological mechanisms, humans are able to reap the benefits of coordinated group actions while at the same time mitigating its costs, such as coordination efforts.

Finding the best leader

When presented with a number of options and no information on which option is best, individuals still arrive at economically sound decisions by adjusting their behavior to maximize the overall or average benefit a choice offers [27–30].

Previous work has shown that other people's behavioral tendencies (i.e., typical behaviors) are stored and represented on a neural basis [31,32]. This is especially true in iterative economic games, where the profit outcome of the entire game is dependent on both one's own recurrent action and how other parties respond [33]. In such games, a player's ability to anticipate the behavior of other players often correlates with their potential to maximize personal profit [34]. Existing research has shown that predictions of someone else's behavioral tendencies rely on learning from this person's past behavior [35]. Several studies suggest that with repeated exposure to another's behavior, participants are able to infer how others are likely to behave in a given context [36]; participants are more likely to continue associating with those individuals with whom previous interactions yielded a positive outcome [37–39].

Similar processes may be at play when followers are predicting prospective contributions of specific leaders to the achievement of collective group goals from a leader's past behavior. In repeated encounters with distinct leaders, group members may develop an internal model of expected value attainable by aligning their own action to the leader's behavior. This internal model may facilitate a comparative process, allowing the individual to adaptively identify the leader with the highest potential for contributing towards a given task.

. . . in moving human groups

The aforementioned "wisdom of the crowd" might also play a role in movement behavior. For example, group navigation performance is improved through "the pooling of information from many inaccurate compasses" [40] and group cohesion can suppress navigation errors in groups that allow individuals to make independent suggestions on which direction to take [41]. This "many wrongs principle" of navigation has been confirmed empirically in groups of both birds and humans [42,43]. Moussaid and colleagues show that self-organized collective behavior rely on local interactions between individuals who then integrate this information on the collective level [44]. It seems that interactions on a movement-only basis result in an averaging process that combines individual information to arrive at the optimal choice.

For human groups, using a multi-client simulated environment of a visual field, Boos and colleagues demonstrated that followers are indeed able to identify advantageous leaders by their movement patterns and, thereby reach an optimal goal [45]. A minority of informed group members who were given information about the location of a more profitable reward field were able to make an uninformed majority follow by displaying certain movement patterns (moving first and moving cohesively). This finding is in line with previous results using face-to-face groups [46,47].

These simple decision rules (e.g., the first-mover effect) are crucial in explaining how collective movement decisions are made. Additionally, some studies illuminate how people move when a group incorporates several potential leaders [46,48]. Consensus exists in literature that movement direction of the group reflects an aggregate decision-making process where each individual balances their indented movement direction with the movement direction of other group members. Moreover, group movement is influenced by the quorum response [49]: Group movement decisions toward one direction are adhered to by subsequent decision makers once a certain threshold of decision makers has been met. Ultimately, decisions of individuals incorporate their responses to both the environment and other individuals' movement choices [44,48]. This means that individuals may need to find an appropriate balance between acquiring private information about prospective leaders through exploration and relying on social information from observing others.

Current study

In the current study, we adapted the HoneyComb paradigm by Boos and colleagues [45,50] to serve as our investigative platform. The HoneyComb paradigm is a multi-agent computer-based virtual game platform that was designed to eliminate all sensory and communication channels except the perception of participant-assigned avatar movements on the playfield. We decided to use the HoneyComb paradigm in this study as we assume that it is a highly suitable tool to research the process of group decision making. To do that, the HoneyComb paradigm records spatio-temporal data to track the movement of members of a real group. In fact, we believe that only few other tools are suitable to investigate the process of group decision making, such as group interaction analysis [51]. However, this requires time-intensive analysis and

introduces confounds into communication between group members that the restricted experimental environment of HoneyComb can control.

In the adapted version of the HoneyComb paradigm, participants were asked to move on a virtual playing field where they had to repeatedly choose between following four distinct leaders. These leaders appeared to know the location of four reward fields that participants themselves could not see. Unbeknownst to the participants, the four leaders were computer-controlled and had different predefined chances of arriving at a profitable reward field. Consequently, participants could maximize their profit by learning about the leaders' overall decision quality. Using this paradigm, we aim to test if and under what conditions followers can learn from repeatedly experiencing the consequences of their following behavior. In particular, we aim to investigate if followers can learn to follow those leaders more frequently whose decisions result in the followers' greatest overall payoff.

We expect that participants will be able to identify the most advantageous leader. Specifically, we hypothesize that participants will more frequently follow the computer-controlled leader who is programmed to yield the highest expected reward for their followers. Note that we explicitly define following as a behavior (i.e., an individual gives his/her support to an initiator for a certain activity) and not as a motivation or preference [52].

To further explore participants' behavior in different contexts, we created three conditions: In the first condition, participants played the game by themselves (*single condition*). The preprogrammed leaders were the only others that were visible in this condition. In the second condition, participants played the iterative game in the presence of five other participants (*independent condition*). In the third condition, participants also played the game in the presence of five other participants but were rewarded on a group level when they moved cohesively towards a reward field (*cohesion condition*). With this design, we aim to find optimal conditions for participants to identify the best leader; either by themselves (single condition), in a group that favors private experience over social information from the group in the pooling of information (independent condition), or a condition that emphasizes cohesion early on (cohesion condition) and may in this way reduce the individuals' propensity to gather private information.

Methods

Sample

Overall, we recruited 156 participants (51.3% female) in groups of twelve. Six participants had to be excluded because they left before completion of the experiment. The remaining sample consisted of 150 participants (M = 21.90, SD = 3.05), of which 50.7% were female. Participants were compensated according to the amount of virtual money they earned through their in-game behavior. All participants were informed about the procedure of the study and gave written consent to participate. Data collection and data analysis procedures in this study were approved by the Ethics Committee of the Georg-Elias-Müller Institute for Psychology of the University of Göttingen (proposal 10/2016).

Procedure and experimental setup

The HoneyComb virtual experiment paradigm [45,50] was adapted to the purpose of the current study in the following way: This Iterated HoneyComb Game consisted of 30 consecutive rounds of the same virtual computer game. The game was played on a virtual field in the form of a honeycomb. On this virtual playing field, participants controlled avatars in the form of differently colored dots via the movement of their mouse. Communication among players was restricted to the visual perception of each other's movements within a visual radius of two

doi: 10.53846/goediss-9589

adjoining spatial fields surrounding their own avatar. The rules of the virtual game remained the same throughout the 30 rounds. Players were initially endowed with a small amount of money and were then instructed to maximize their payoff by arriving at fields that yielded a monetary reward at the end of each round. In order to counterbalance income effects, half of the participants were initially endowed with 50 cents, while the other half received 250 cents. A screenshot showing the virtual playing field can be seen in Fig 1; a detailed description of the experimental setup and procedure can be found in the S1 and S2 Texts, while an interactive payout matrix can be accessed in the S2 Table.

Participants were led to believe that four people in their group were chosen to receive additional information. These informed players were supposedly able to see fields with monetary rewards beyond other players' visual radius and were allowed to move first. The instructions delineated that the four informed players were not allowed to aim toward the same reward field.

In reality, these four players were potential leaders with pre-programmed strategies of reward attainment of their followers with different expected values over the entire 30 rounds (EV, i.e., the average payout this leader would yield): The "incompetent" leader paid the

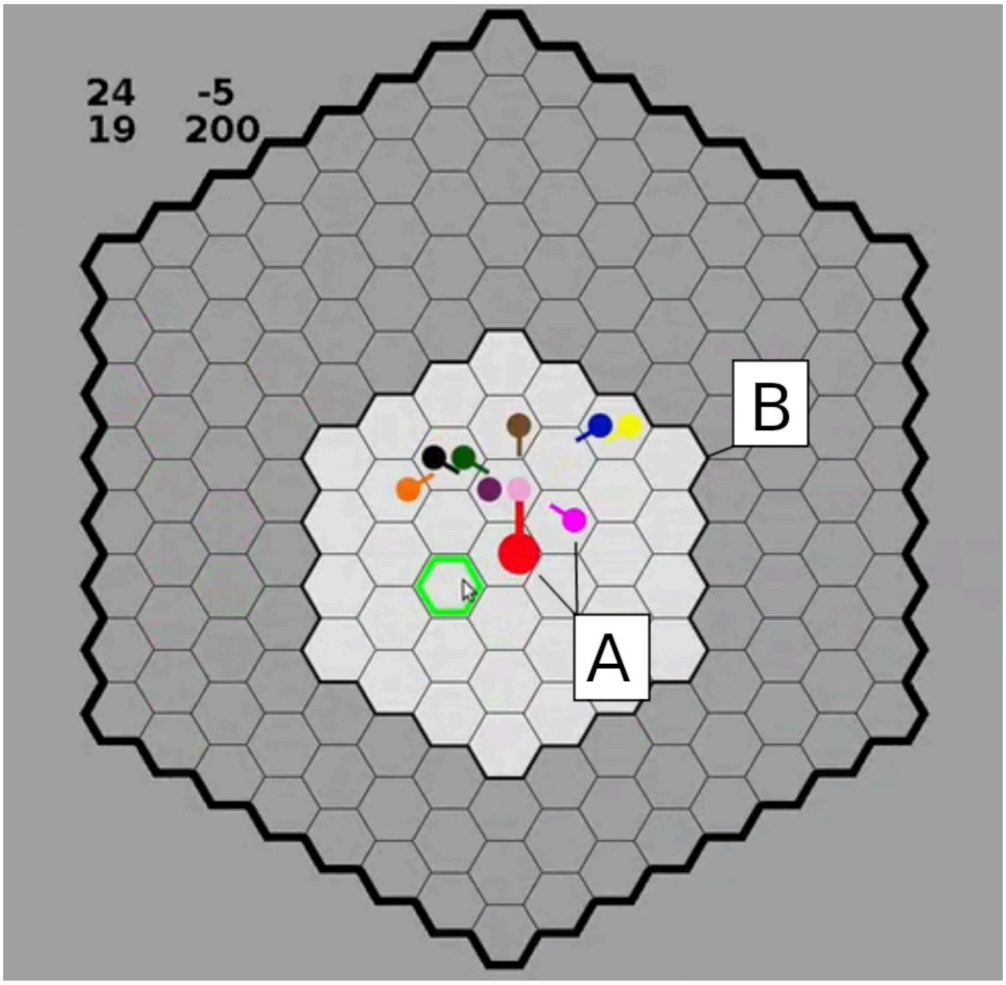

Fig 1. The HoneyComb virtual playing field. A–Each player controlled a differently-colored avatar. B–A visual radius of two fields surrounded each player.

https://doi.org/10.1371/journal.pone.0259963.g001

participants 20 cents 20% of the time (EV = 120 cents). The "risky neutral" leader paid the participants 20 cents 45% of the time (EV = 270 cents), while the "secure neutral" leader paid 10 cents 90% of the time (EV = 270 cents). Lastly, the "competent" leader paid 20 cents 80% of the time (EV = 480 cents).

The participants were told that they could find the reward fields by following one of the four informed players. At the end of every round, players received feedback on their gains, losses, and the total amount of money on their account.

In order to explore the conditions under which participants are most likely to identify the competent leader, we designed three between-subject conditions (single, independent, and cohesion condition): In the single condition, participants played the game with only the four leaders present, while in the independent and cohesion condition, participants played the game with the four leaders and five other players.

In the independent condition, the rewards participants attained by arriving at a reward field were simply added to their in-game account. No further instructions or incentives to behave in a certain way were given. In contrast, participants in the cohesion condition received further reward for arriving on a reward field with other players. This additional reward was computed by multiplying the individual reward gained on the field by the number of players who arrived there. For instance, when four players arrived at the same reward field paying out 10 cents, each player received 10 cents x 4 players = 40 cents.

A post-game questionnaire assessed risk propensity [53], self-esteem [54], embodiment [55], and additional demographic questions (see S3 Text). As the results from the questionnaires are not relevant to the argument made in this report, they will not be reported here.

Data analysis

Both, initial data processing and data analyses, were conducted using the statistics program R (R Core Team, 2018). A complete list of the used R packages can be found in the S4 Text.

Results

In this section, we will first report the result of our hypothesis test. Subsequently, we will report the results of analyses that explore five further possible explanations for the difference in behavior between the independent and cohesion condition.

Confirmatory analysis: Group members find the best leader

As was shown by a Chi-square test, there were significant differences between the frequency with which leaders were followed; $\chi^2(4) = 1518.3$, $p < .001$. Across rounds and conditions, participants followed both the competent and the secure neutral leader more frequently compared to the risky neutral leader (784 times, $p < .001$; p-values corrected for multiple comparisons with Bonferroni method) and the incompetent leader (394 times, $p < .001$), while participants generally followed the competent leader approximately as often (1543 times) as they followed the secure neutral leader (1474 times, $p = 1$). However, Fig 2 shows differences between conditions: Participants in the single and independent conditions followed the competent leader with the highest frequency, while participants in the cohesion condition mostly followed the secure neutral leader.

We fitted a logistic mixed model (estimated using ML and BOBYQA optimizer) to predict the following of the competent leader with condition and round, excluding the intercept (formula: Following of Competent Leader (0 or 1) ~ -1 + condition * round). The model included round, participant id and group as random effects. Participants in the single condition were randomly grouped in pseudo-groups for this analysis. The model's total explanatory power is

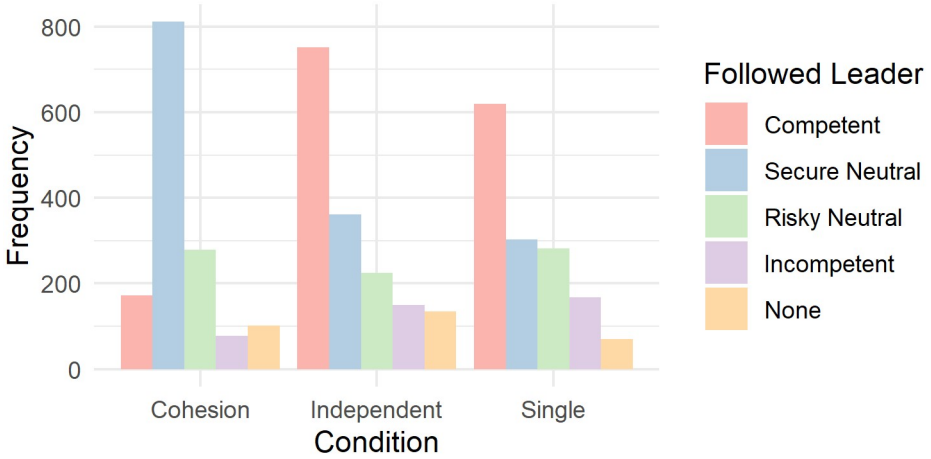

Fig 2. Overview over following behavior according to condition and leader.

https://doi.org/10.1371/journal.pone.0259963.g002

substantial (conditional $R^2 = 0.70$) and the part related to the fixed effects alone (marginal R^2) is of 0.21. We fitted the same model for the other three leaders (secure: conditional $R^2 = 0.64$, marginal $R^2 = 0.15$; risky: conditional $R^2 = 0.53$, marginal $R^2 = 0.03$; incompetent: conditional $R^2 = 0.36$, marginal $R^2 = 0.15$). Detailed results on the effects within these models are shown in the S1 Table and Fig 3. From these, it can be observed that the cohesion condition differed in remarkable ways from both the single and independent condition. While in both, the single and independent condition participants showed a significant increase in advantageous decisions over the 30 rounds (following the competent leader) and a decrease in disadvantageous decisions (following the risky or incompetent leader), participants in the cohesion condition showed an increase in mediocre decisions over the 30 rounds (following the secure neutral leader) and a decrease in advantageous decisions (following the competent leader).

To further investigate the key factors behind these observations, we explored further possible explanations. In the following, we will focus on the comparison of the independent and cohesion condition as some of the following analyses would require to form pseudo-groups of separate participants in the single conditions. We believe that statistically created pseudo-groups of separate players in the single condition are not meaningfully comparable to conditions where participants played in real groups and, therefore, choose to focus on the comparison between the cohesion and the independent conditions.

Exploratory analysis

Control for payout realization. Participants were rewarded according to the payout structure of the pre-programmed leaders. Because these were defined via random draws from a binomial distribution, it is possible that unlikely realizations may have caused unexpected rewards for participants. For example, in an unexpected realization the secure neutral leader might have paid out more over 30 rounds than the competent leader. Therefore, we investigated whether games played in the cohesion condition had more unlikely payout realizations compared to those in the independent condition. The leader payout averages over 30 rounds were calculated for all games. On the accumulated level, leader payout realizations were always close to the theoretically expected values as can be seen in the S1 Fig. In no game did we find that the order of leaders in terms of expected payout was changed (sorted from competent to incompetent). Hence, we are able to exclude this as an explanation for our findings.

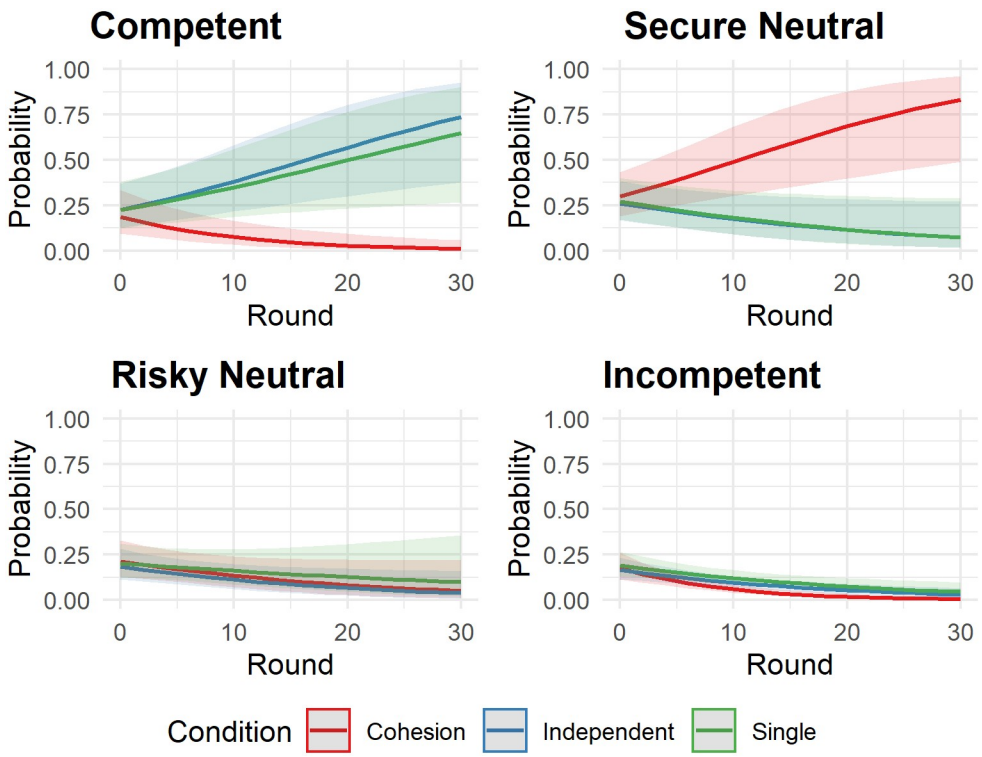

Fig 3. Predicted probability to follow leaders. Plot shows the predicted values for the probability to follow the individual leaders depending on condition and round. Shaded areas represent the 95% C.I.

https://doi.org/10.1371/journal.pone.0259963.g003

Rewards after leader-change. While we did not find unlikely payout realizations in between games, specific payout realization on a per-round-level might still be present. An especially critical point, where unlikely payout realizations might have a significant effect, is the moment after a participant has changed the leader he/she had followed before. A leader change is identified whenever a participant (a) followed one leader in a given round and this leader was not followed in the subsequent round or (b) followed no leader in a given round and followed any leader in the subsequent round. Random disproportionate punishment or reward of leader changes could then serve as an explanation for the differences observed between the independent and the cohesion condition. Especially, disproportionate punishment of leader changes in the cohesion condition might have discouraged participants in this condition to try out other leaders.

We conducted a Breslow-Day-Test of homogeneity of odds ratios that did not support this explanation: There was no significant difference in the odds ratio between the cohesion (odds ratio = 0.535) and independent condition (odds ratio = 0.594); $\chi^2(1) = 0.347$, $p = 0.55$. This means that participants in the cohesion and independent condition were equally likely to receive a payout (or not) after a leader change. In fact, it seems as if not receiving a payout after a leader change was less likely than receiving a payout after a leader change as can be seen in Table 1. Hence, we reject this explanation for our data as well.

Exploration and exploitation phases. Participants in the current study might have gone through an initial trial-and-error-phase (exploration) before sticking with the option they believed to have the most advantageous outcome (exploitation). In the exploration phase, participants would be expected to show more frequent leader changes compared to the

Table 1. Contingency tables for cohesion and independent condition.

		Cohesion		Independent	
Leader Change		Yes	No	Yes	No
Payout	Yes	325	787	508	805
	No	122	158	220	207

Chi-Square Test of Independence showed a significant difference between observed and expected cell values in both cohesion (χ^2 $(1)_{Coh}$ = 20.46, p < .001) and independent condition ($\chi^2(1)_{Ind}$ = 21.28, p < .001).

https://doi.org/10.1371/journal.pone.0259963.t001

exploitation phase [27]. Differences between the independent and cohesion conditions could have resulted from the cohesion reward inadvertently shortening the exploration phase of participants in the cohesion condition, as has been shown in previous research [56]. We explore this hypothesis in the following.

First, we checked whether we could identify exploration and exploitation phases in the behavior of participants. To this end, the metric "half-change-round" was defined. The half-change-round is defined to be the round in which at least half of all leader changes of one participant had occurred. For example, within 30 rounds one participant changes the leader 15 times in total. After 10 rounds, this participant has already changed the leader 8 times (15/2 = 7.5, rounded 8). Hence, by round 10, the participant has already performed at least half of all leader changes. Consequently, round 10 would be defined as that player's half-change-round. It should be noted that the half-change-round does not correspond to the length of the exploration phase as still half of leader changes happen after this point of time.

We found that on average, participants made half the leader-changes after 10 or 11 rounds (half-change-round = 10.82) which, according to a one sample t-test testing (μ = 15), lies significantly below the midpoint of the game at 15 rounds (difference = -4.18, 95% CI [9.70, 11.95], t(107) = -7.33, p < .001; Cohen's d = -0.71, 95% CI [-0.92, -0.50]), confirming that participants are more likely to change their leader in the early phases of the game. However, when conducting a Welch two-sample t-test, we did not find a significant difference in half-change-rounds between the independent (11.1 rounds) and cohesion condition (10.48 rounds); difference in means = -0.62, 95% CI [-2.94, 1.69], t(94.47) = -0.53, p = 0.596; Cohen's d = -0.10, 95% CI [-0.49, 0.28]. This means that on average participants in the cohesion and independent condition stayed in the exploration phase equally long, so that this could not explain the difference in following behavior between the conditions.

Clustering. We explored whether clustering of the participants might be the cause of the observed effects. Due to the collective reward structure, groups in the cohesion condition might have stayed together as a group throughout the game, thereby inhibiting individual exploration. If this were true, we would expect that clustering on the playfield would at least partially mediate the relationship between condition and following behavior. It should be noted that we understand clustering ("staying in close spatial distance") as a procedural pattern of group decision making in HoneyComb, comparable to concepts of interdependence in group processes [57] or local information exchange through direct interaction [44]. Based on this, clustering might influence participants behavior on the playfield additional to goal-directed behavior ("finding the best leader"; [58]), for example, as collective feedback [44]. Clustering, therefore, is a variable describing the spatial clustering of participants on the playing field, similar to "flocking" [59], and has no connection to statistical cluster analysis of certain variables of those participants. Clustering is understood as a variable on the group level (global clustering), compared to clustering around a certain participant (local clustering).

Hence, clustering does not only take the movement of one individual participant into account, but the movement of the whole group.

We operationalized clustering of the participants as transitivity in a network based on the final movement coordinates of participants and leaders. More information on how the networks were constructed is given in the S5 Text. In this network, the nodes are agents (participants and leaders), while the edges indicate the distance between two participants or a participant and a leader. The strength of the edge between two nodes representing a participant or leader was set to be the inverse of the shortest path between these two (closeness = 1/(shortest path + 1); addition of 1 to prevent division by zero). For example, if Participant A finished the round on the same field as Participant B (shortest path = 0 fields) and within three fields of Participant C (shortest path = 3 fields), the connection (the edge) between A and B would be stronger than the connection between A and C. Specifically, the weight of the edge between nodes A and B would be set to 1 (1/(0 + 1) = 1), while the weight of the edge between A and C would be 0.25 (1/(3 + 1) = 0.25). Transitivity is defined as the overall probability in a network (or graph) that adjacent nodes are interconnected. Under perfect transitivity, if a node A is connected (by an edge) to B, and B is connected to C, then A and C are also connected. High transitivity in a group of HoneyComb players would indicate that its members often moved together throughout the game. In order to reflect our understanding of clustering as a procedural pattern, we calculate a moving average of transitivity over five rounds (transitivity in round 5 (6, 7, . . .) = mean of transitivity in round 1–5 (2–6, 3–7, . . .). In doing so, we incorporate the fact that participants' behavior in a given round is also informed by experience about other participants' behavior in previous rounds. Further information on how transitivity was calculated can be found in the S5 Text. We also note that this operationalization of clustering is close to the concept of crowd density that is often used in research of moving human groups [60–62].

We did not find a significant difference in transitivity between the independent and cohesion conditions when conducting a Welch two-sample t-test between the mean transitivity in the cohesion and independent condition; $t(100.77) = 0.00$, $p > .999$. This means that even though cohesion was not incentivized in the independent condition, participants often moved closely together as had already been observed in previous HoneyComb experiments [59]. We further explored the effects of condition, transitivity, and round on following behavior (i.e., which leader a participant followed) by fitting a logistic mixed model (estimated using ML and BOBYQA optimizer) to predict following the competent leader with condition, round and transitivity (formula: Following the competent leader (0 or 1) ~ condition * round * transitivity). The model included round, participant id and group as random effects. The model's total explanatory power is substantial (conditional $R^2 = 0.76$) and the part related to the fixed effects alone (marginal R^2) is of 0.25. In order to identify whether the additional inclusion of transitivity as an explanatory model increases model fit, we compared this model to a model including only condition and round as explanatory variables. Both models were then compared using the likelihood ratio test. We repeated this procedure for the other three leaders (secure: conditional $R^2 = 0.72$, marginal $R^2 = 0.17$; risky: conditional $R^2 = 0.62$, marginal $R^2 = 0.04$; incompetent: conditional $R^2 = 0.36$, marginal $R^2 = 0.08$). The complete results can be seen in Table 2.

On the one hand, neither condition, round, nor transitivity had any effect on how likely participants were to follow the secure neutral or the incompetent agent. On the other hand, we found that participants were more likely to follow the competent leader in the cohesion condition when transitivity was high during early rounds ($b = 0.49$, $p = .035$), as can be seen in Fig 4. During later rounds, the effect of transitivity ceased. The opposite was true for participants in the independent condition: During the early rounds, they were less likely to follow the competent leader if transitivity was high. During later rounds, however, participants in the

Table 2. Results of logistic regression model of probability to follow different leaders.

Predictors	Beta (SE)	p	Overall model[a]
Competent			
Condition[b]	7.66 (3.06)	**.012**	$\chi^2(4) = 9.91$ p = **.042**
Round	0.16 (0.15)	.291	
Transitivity	8.10 (3.40)	**.017**	
Condition x Round	-0.20 (0.18)	.272	
Condition x Transitivity	-9.59 (4.03)	**.017**	
Round x Transitivity	-0.35 (0.20)	.078	
Condition x Round x Transitivity	0.49 (0.23)	**.035**	
Secure Neutral			
Condition[b]	-4.49 (2.70)	.096	$\chi^2(4) = 14.22$ p = **.006**
Round	0.019 (0.11)	.865	
Transitivity	2.85 (2.44)	.243	
Condition x Round	0.21 (0.15)	.179	
Condition x Transitivity	3.76 (3.51)	.283	
Round x Transitivity	-0.00 (0.14)	.991	
Condition x Round x Transitivity	-0.36 (0.20)	.077	
Risky Neutral			
Condition[b]	-5.83 (2.70)	**.031**	$\chi^2(4) = 19.66$ p < **.001**
Round	-0.28 (0.13)	**.032**	
Transitivity	-11.90 (3.00)	< **.001**	
Condition x Round	0.17 (0.17)	.325	
Condition x Transitivity	10.41 (3.76)	**.006**	
Round x Transitivity	0.43 (0.18)	**.015**	
Condition x Round x Transitivity	-0.38 (0.22)	.092	
Incompetent			
Condition[b]	0.42 (3.58)	.906	$\chi^2(4) = 2.45$ p = .653
Round	0.14 (0.21)	.498	
Transitivity	2.27 (3.99)	.569	
Condition x Round	-0.10 (0.24)	.677	
Condition x Transitivity	0.50 (4.84)	.918	
Round x Transitivity	-0.26 (0.28)	.352	
Condition x Round x Transitivity	0.14 (0.32)	.656	

For all models, the outcome variable was set to 1 when a participant had arrived at a specific leader and set to 0 when he/she had arrived at a different or no leader. The explanatory variables were condition (independent vs. cohesion), round, and transitivity, as well as their interactions. Playgroup, participant id and intercept were included as fixed effects but are not reported here. Round was included as a random effect.

[a]Model selection for inclusion of transitivity in the model based on likelihood ratio test.

[b]Cohesion condition was dummy coded 0, independent condition as 1.

https://doi.org/10.1371/journal.pone.0259963.t002

independent condition were more likely to follow the competent leader if transitivity was high. For the risky leader, we found that participants in both conditions were more likely to follow during early rounds and when transitivity was low ($b = 0.43$, $p = .015$).

The explanatory value of transitivity is further corroborated by the fact that in three out of four models (competent, secure neutral, and risky neutral leader), the inclusion of transitivity improved the model fit significantly (see Table 2). In order to check whether this additional explanatory variable was due to a mediation effect, we conducted a mediation analysis, including the explanatory variables condition and round, the mediator transitivity, and the outcome

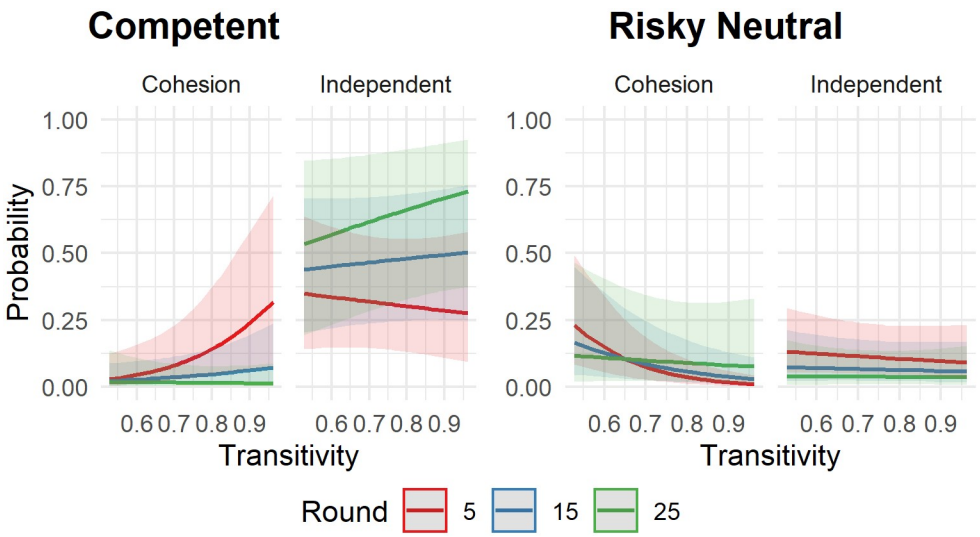

Fig 4. Predicted probability to follow competent or risky leader. Plot shows the predicted values of the probability to follow either the competent or risky neutral leader in relation to condition, round, and transitivity. Shaded areas represent the 95% C.I. Round 5, 15 and 25 represent an early, middle, and late round in the game, respectively.

https://doi.org/10.1371/journal.pone.0259963.g004

variable of following a leader. We did not find any significant mediation effects for any of the leaders. For the purpose of readability of this manuscript, we report the detailed information of the fitted models as well as results of these analyses in the S6 Text.

In sum, transitivity seems to play a role in group decision making as it adds explanatory value to our analyses. However, the results on transitivity should be interpreted with caution as they remain correlational and the direction of influence between the outcome variable, the decisions to follow a leader, and transitivity remain unclear. This will be discussed in further detail in the Discussion section. It seems clear, however, that transitivity does not fully account for the differences in following behavior between the independent and cohesion condition.

Reward structure. Finally, we explored whether the reward structure itself might have driven the difference between the independent and the cohesion conditions. Since the payout participants received was their main source of information about the leaders, there should be a direct impact on the participants' behavior. To accurately identify the best leader, participants would have needed precise information on the leader's payout properties. However, in the cohesion condition, rewards were multiplied by the number of participants who received it. Thus, participants in the cohesion condition might not have received adequate feedback as the number of participants following one leader and, therefore, the multiplication factor of the rewards could have varied strongly–especially during the exploration phase.

To operationalize the decision behavior of a participant throughout the game, we calculated participants' choice score using a point system: For each round in which a participant followed the competent leader, two points were awarded. For rounds in which participants followed the neutral leaders (secure or risky), the participants were awarded one point, while receiving zero points for following the incompetent or no leader. The sum of all points over 30 rounds was then set to be the participant's choice score. We argue that if participants did receive accurate feedback through rewards, payout should only depend on the participants' behavior (measured by the choice score) and not the condition. However, if the reward structure occluded crucial information from participants in the cohesion condition, we should see a moderation effect of condition on the effect of choice score.

To test this explanation, we fitted a linear mixed model (estimated using REML and nloptwrap optimizer) to predict earnings (corrected for initial endowment) with condition and choice score (formula: earnings ~ condition * choice score). The model included group as random effect. The model's total explanatory power is substantial (conditional $R^2 = 0.88$) and the part related to the fixed effects alone (marginal R^2) is of 0.80. The model's intercept, corresponding to condition = Cohesion and choice score = 0, is at 809.10 (95% CI [579.01, 1039.19], t(102) = 6.89, $p < .001$). Within this model, the effect of condition [Independent] is statistically significant and negative (beta = -958.30, 95% CI [-1240.75, -675.84], $p < .001$; Std. beta = -1.85, 95% CI [-2.16, -1.53]), showing that condition did have an unintended effect on payout and, therefore, on the feedback participants received from the leaders they followed. The effect of choice score is statistically non-significant (beta = -0.04, 95% CI [-8.22, 8.13], p = 0.992). The interaction effect of choice score on condition [Independent] is statistically non-significant (beta = 7.36, 95% CI [-1.82, 16.53], p = 0.116).

Additionally, we calculated two Pearson's product-moment correlation tests between earnings (corrected for initial endowment) and choice score separately for the independent and the cohesion condition. For the independent condition, the correlation is positive, statistically significant, and very large (r = 0.87, 95% CI [0.79, 0.92], t(58) = 13.37, $p < .001$), while statistically not significant and tiny for the cohesion condition (r = -0.03, 95% CI [-0.31, 0.26], t(46) = -0.20, p = 0.840). We note that these correlations should be interpreted with care as they do not include the nesting of participants within their groups.

These findings fit well to the relationship between choice score and earnings as shown in Fig 5. While we see a very close relationship in the independent condition, the data in the cohesion condition are much more scattered showing a high range in earnings but a comparatively low range in choice score. While it is surprising that this was not represented in a significant effect in the linear model, we can conclude that the reward structure might have interfered with the participants' estimation of who the best leader could be.

Discussion

In this study, we used an adapted version of the HoneyComb paradigm [45,50] to investigate whether participants are able to identify the most advantageous of four leaders by gathering

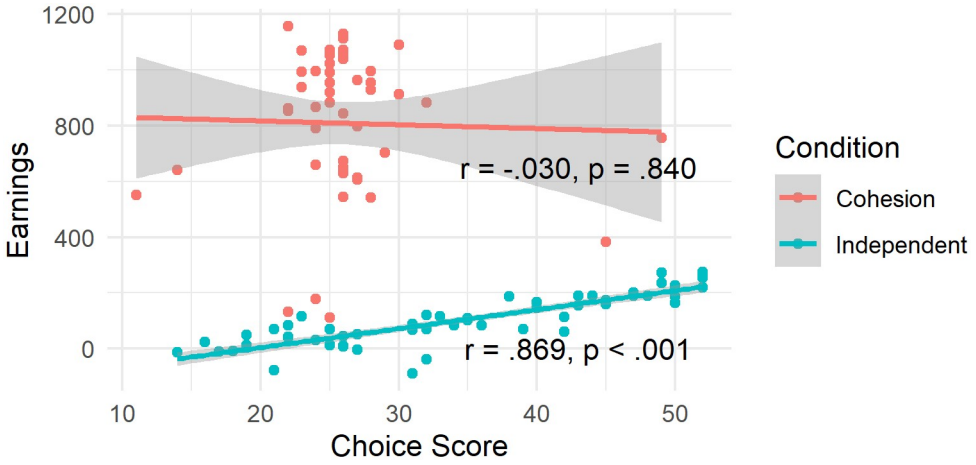

Fig 5. Earnings of participants according to condition and choice score. In the cohesion condition, choice score and earnings (corrected for initial endowment) do not correlate, while in the independent condition, there exists a strong relationship between earnings and choice score. The plot shows the choice score and earnings after 30 rounds, corrected for initial endowment.

https://doi.org/10.1371/journal.pone.0259963.g005

information through following and observing others follow these leaders. Additionally, we investigated under which circumstances participants are able to find the best leader: alone or in a group, as independent group members or in a group that rewarded cohesion.

Our results show that group members who repeatedly interact with different leaders are indeed able to identify the leader that is most beneficial to themselves and the group. This holds true, even if they do not have any prior knowledge about the leaders' abilities but need to infer them from their experience. This is consistent with studies showing that the ability to find the best possible leader in a group might have been a crucial evolutionary advantage [12,14,16].

Apart from this general result, this study shows the impeding effects different circumstances might have on group members. While participants who played alone and participants who played as independent group members followed the most advantageous leader, participants who played in a group that was rewarded for cohesive behavior frequently followed a less advantageous leader. To further explore the reasons for this difference, we conducted a series of exploratory analyses.

The aim of our initial analysis was to rule out confounding factors as explanations for the data observed in the experiments. Our results show that there was no systematic difference between the cohesion and independent condition in the realization of either leader payouts or random punishments of leader changes through non-payouts in the subsequent round. Therefore, we conclude that we can exclude these confounding factors as suitable explanations for the differences between the independent and cohesion condition.

Next, we investigated the possibility that participants in the cohesion condition might have exhibited a shorter exploration phase, compared to participants in the independent condition, as was suggested by previous research [56]. To this end, we developed the metric of the half-change-round to operationalize the length of both exploration and exploitation phases in the HoneyComb paradigm. Our results show that in both the independent and cohesion condition participants first explore the behavior of different leaders and, afterwards, exploit the leader they believe to be best. However, our results do not show shorter exploration phases for the cohesion condition. This is surprising as we expected that a more cohesive group might suppress the gathering of private information for the benefit of cohesive behavior as suggested by previous studies on group decision making [56], hidden profiles [63], or groupthink [64]. We believe that this area is an interesting subject for further investigation, aided by the newly developed half-change-round metric.

In an attempt to explain the surprising effects, we then investigated the influence of clustering, a measure of how closely group members stick together, on a group's following behavior. Our results show that clustering does play a role for an individual's ability to identify the most advantageous leader. For independent group members, a high clustering seems to be disadvantageous during early phases, but advantageous during later phases. The opposite seems to be true for groups with a high incentive to act cohesively: High clustering is advantageous during early phases but has no effect later on. This might be explained in the following way: When no pressure to act cohesively exists, participants are free to try out different and also less advantageous leaders in the beginning, gathering private information. When group members learn who the most advantageous leader is, others can learn from them, thereby integrating private information on the collective level [44]. When more individuals follow one leader, others are reinforced to do the same, creating a positive reinforcement loop that has been observed in collective animal movement and crowd behavior [44]. In this manner, more and more group members join into the cluster, following the best leader. However, when acting cohesively is incentivized, as in the cohesion condition, clustering might not be a result of individual decisions but rather the basis on which group decisions are made [56]. As a result, a group might

cohesively explore some leaders during early phases but the one they settle on in the exploitation phase might not be the most advantageous one. This explanation is in line with studies which show that a high emphasis on group cohesion can be detrimental to group decision making [56], a prominent example being groupthink [65].

Contrary to this explanation, the effect of condition on the ability to find the best leader was not significantly mediated by clustering. This might be due to the effect that no meaningful difference in clustering was found between conditions. We could explain this in two ways: First, other HoneyComb studies have found that participants generally exhibit high levels of clustering on the playfield, even if they are not instructed or rewarded to do so [59]. Second, we cannot draw definite conclusions about the causal direction of the relationship between clustering and following behavior. We assume that participants in the cohesion condition moved as a group because they were incentivized for this behavior and that clustering had an effect on the participants' ability to find the best leader. Alternatively, it could be argued that the clustering was a side-effect of multiple participants following the same leader. This could explain why groups in the independent condition also exhibited high levels of clustering. Multiple participants independently identified the competent leader as the most advantageous option and then continuously followed that leader. Through repeatedly following the same leader, participants inadvertently also moved as a group. Because of the correlational nature of our data on this relationship, we cannot rule out either explanation.

However, as we did not find consistent effects of transitivity on following behavior towards the different leaders, we do not believe that this can explain the remarkable difference between the cohesion and independent groups. Therefore, we investigated whether the reward structure might be the driving force behind these results. The results seem to substantiate this explanation: The financial outcome is not influenced by the participants' following behavior, but rather by the membership in either the independent or cohesion condition. Additionally, we might have expected a moderator effect of condition because participants in the independent condition received unadulterated monetary feedback from the leaders, while the monetary feedback given to participants in the cohesion condition was occluded by the multiplication of rewards. We did not find support for this in the linear model. However, we could show in a further exploratory analysis that choice score and earnings did highly correlate in the independent condition, while they did not correlate in the cohesion condition. We note that these correlations do not take nesting of data into account so that they should serve solely as an illustration while we rest the following conclusions on the results of the linear model. From it, we assume that in the current experiment participants' earnings were mainly determined by experimental condition and not participants' decision behavior. This is problematic as the financial outcome is the central feedback that participants can receive from the leaders they followed and, therefore, the basis of their estimation of which leader is most advantageous. If this source of information is faulty (i.e., not reflective of the individuals' behavior) then participants are deprived of the only way to make an informed decision about the leaders. Our results show that the reward structure we implemented–multiplying a reward by the number of group members on the same reward field to encourage cohesive action–has likely occluded the information participants need to make an informed decision. We believe that this information was occluded, but not inaccessible altogether as, theoretically, participants in the cohesion condition could have been able to infer the differences between the leaders. As can be seen in the S2 Table, participants in the cohesion condition might have earned less when they followed the competent leader alone, compared to when following the secure leader with other participants. However, they would have earned even higher payouts when following the competent leader. Thus, participants should have been able to infer the best leader, albeit it might have been more difficult (participants would have to divide the reward by the number of co-players

on the field to get a better estimate). Moreover, participants in the cohesion condition might have felt satisfied with the high rewards they earned by following less advantageous leaders, thereby reducing the need to gather more information about the other leaders, which in the end cost them the knowledge of the most advantageous outcome.

Lastly, we want to draw attention to the fact that humans are a species, naturally living in groups [12]. As such staying together as a group throughout the game might be rewarding in and of itself. We find support for this argument in the fact that participants in the independent condition clustered about as much as participants in the cohesion condition. This conforms with findings from previous experiments in the HoneyComb paradigm in which participants were found to move relatively cohesively ("flock") even though they did not receive any special instruction to do so [59].

Implications and conclusion

Our findings show that group members are able to find the most advantageous leader by exploring different possible leaders and later exploiting the one they believe to be best. We show that these results are observable in a reductionist paradigm like HoneyComb [45,50] that allows researchers to control the experimental environment closely and even remove most of the communication channels that are typically used in group interaction (visual and auditory verbal and nonverbal communication), so that participants can only communicate through movement.

Furthermore, we developed a new metric to quantify and compare the length of exploration and exploitation phases in group decision making: the half-change-round. We note that while other scientific fields may have used similar constructs to quantify phases (e.g., transition phases in physical systems), the half-change round constitutes, to the authors' knowledge, the first application of such an approach to quantify the phases of a group decision making process. Using this tool, we could show that group decision settings can be divided into an exploration and exploitation phase.

Lastly, our results shine a spotlight on a number of confounding factors in group experiments, including reward structures that are used in order to create certain group behaviors. In this paper, we present ways to check for and either identify or exclude them as alternative explanations for results of group experiments. We specifically want to draw attention to the setup of reward structures in group experiments. We argue that researchers need to take a close look into how reward structures might inadvertently affect the phenomena that researchers wish to investigate. In our case, creating cohesion through multiplication of rewards impeded participants in the cohesion condition in their gathering of essential information, thereby influencing behavior directly rather than through the creation of a cohesive group behavior. Retrospectively, a more suitable option than multiplication of rewards might have been to create cohesion through a shared group account or fixed group bonus.

As a result of this, we believe that while some of the mentioned results were driven by the chosen reward structure, other results (e.g., length of exploration phases or effect of transitivity) might be partially occluded by the strong influence of reward structure on behavior. Hence, we suggest that the concept of differing exploration and exploitation phases, as well as the influence of clustering warrant further investigation in future research. In doing so, researchers should be especially careful when choosing a reward structure to not cost their participants the best behavior, by giving them rewards "for free".

Supporting information

S1 Fig. Overview of payout realization for all games played. This overview includes the averages of all payouts leaders made during a game, regardless of condition and whether the leaders were followed.
(PNG)

S1 Table. Results of logistic regression model of probability to follow different leaders. For each leader type, a separate generalized logistic mixed-effect regression was estimated. The probability to arrive at that leader were set to be the outcome variable; condition and round were included as explanatory variables. Participants in the single condition were put into pseudo-groups for comparison. The intercept was excluded in this model. Round was included as a random effect and group and participant ID were included as grouping variables. Numbers in the table are parameter estimates (standard errors in parentheses). $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
(DOCX)

S2 Table. Interactive table of payout matrix.
(XLSX)

S1 Text. Detailed description of technical setup and game software.
(PDF)

S2 Text. Additional information on experimental procedure.
(PDF)

S3 Text. Summary of questionnaires.
(PDF)

S4 Text. List of used R-packages.
(PDF)

S5 Text. Description of how networks and transitivity were computed.
(PDF)

S6 Text. Detailed information on mediation analysis.
(PDF)

Acknowledgments

We thank Paul Pritz for his helpful comments and proof-reading on the manuscript, Daniel Hautz for his help with reference-management, Inga Neubauer and Xaver Franiel for their help with data collection.

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 doi: 10.53846/goediss-9589

Chapter 3.2: Reduction of information uncertainty through emerging group processes

Ritter, M., Pritz, J., Morscheck, L., Baumann, E., and Boos, M. (2022). In no uncertain terms: Group cohesion did not affect exploration and group decision making under low uncertainty. Submitted to *Frontiers in Psychology*.

Figures and Supplementary Material:
https://s.gwdg.de/koB92J (DOI 10.17605/OSF.IO/86GUX)

 doi: 10.53846/goediss-9589

In no uncertain terms: Group cohesion did not affect exploration and group decision making under low uncertainty

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Keywords: group cohesion, exploration, group decision making, uncertainty, HoneyComb paradigm, leadership, collective induction, ε-greedy.

Abstract

Group decision making under uncertainty often requires groups to balance exploration of their environment with exploitation of the seemingly best option. In order to succeed at this collective induction, groups need to merge the knowledge of all group members and combine goal-oriented and social motivations (i.e., group cohesion). This paper presents three studies that investigate whether more cohesive groups perform worse at collective induction tasks as they spend less time exploring possible options. Study 1 simulates group decision making with the ε-greedy algorithm in order to identify suitable manipulations of group cohesion and investigate how differing exploration lengths can affect outcomes of group decisions. Study 2 (N= 108, 18 groups á 6 participants) used an experimental manipulation of group cohesion in a simple card choice task to investigate how group cohesion might affect group decision making when only limited social information is available. Study 3 (N = 96, 16 groups á 6 participants) experimentally manipulated group cohesion and used the HoneyComb paradigm, a movement-based group experiment platform, to investigate which group processes would emerge during decision making and how these processes would affect the relationships between group cohesion, exploration length, and group decision making. Study 1 found that multiplicative cohesion rewards have detrimental effects on group decision making, while additive group rewards could ameliorate negative effects of the cohesion reward, especially when reported separately from task rewards. Additionally, exploration length was found to profoundly affect decision quality. Studies 2 and 3 showed that groups could identify the best reward option successfully, regardless of group cohesion manipulation. This effect is interpreted as a ceiling effect as the decision task was likely too easy to solve. Study 3 identified that spatial group cohesion on the playing field correlated with self-reported entitativity and leader-/followership emerged spontaneously in most groups and correlated with self-reported perceptions of leader-/followership in the game. We discuss advantages of simulation studies, possible adaptations to the ε-greedy algorithm, and methodological aspects of measuring behavioral group cohesion and leadership to inform empirical studies investigating group decision making under uncertainty.

doi: 10.53846/goedis-9589

1 Introduction

From an evolutionary perspective, humans naturally live in groups in which individual members contribute to group tasks (van Vugt and Ronay, 2014). This creates an advantage as individuals can share resources, labor, and knowledge (Kozlowski and Chao, 2012) and less experienced group members can learn successful behavior from others, avoiding the costs of trial-and-error (Rendell *et al.*, 2010; Mesoudi, 2011; Wisdom, Song and Goldstone, 2013). When groups make decisions in an uncertain environment, they can draw on the knowledge or experience of individual members in order to learn about their decision options. This has been termed collective cognition (Couzin, 2009) or collective induction (Laughlin and Hollingshead, 1995; Laughlin, 1999). Understanding how collective induction emerges remains one of the central questions of unraveling group decision making under uncertainty (King and Sueur, 2011; Grand *et al.*, 2016) and phenomena like groupthink (Janis, 2008) suggest that group cohesion might play an important role. The aim of this paper is to investigate the role of group cohesion in group decision making under uncertainty and illuminate the emergent mechanisms behind it. Specifically, we use three studies to examine whether more cohesive groups perform worse as they forego chances of exploring different options in an uncertain environment.

While the relationship between group cohesion and performance has been researched extensively over the last years, findings are all but consistent (Casey-Campbell and Martens, 2009). Some studies suggest that high group cohesion will improve group communication (i.e., information transfer), lead to effort gains, and higher performance (Cartwright, 1968). It has been shown that groups who successfully pool private information, so information that is available to individual members, achieve higher performance or efficiency in decision making (Tomasello, 1999; Helbing, Farkas and Vicsek, 2000; Couzin *et al.*, 2002; Boyd, Richerson and Henrich, 2011; King and Sueur, 2011; Laughlin, 2011; Van Vugt and Kameda, 2012; Moussaïd *et al.*, 2016; Sridhar *et al.*, 2021). Further, tightly knit social networks facilitate the exchange of information and enhance group performance (Mason and Watts, 2012; Derex and Boyd, 2015). In moving groups, group cohesion (i.e., staying closely together) can facilitate the "pooling […] from many inaccurate compasses" (Simons, 2004) and help less knowledgeable individuals prioritize social information (i.e., information that is shared by other group members) and motivations above their own private information and goal-directed behavior (Boos *et al.*, 2014; Sridhar *et al.*, 2021). Individuals might balance social and goal-oriented motivations by observing their neighbors and adapting their own movement direction accordingly (Couzin and Krause, 2003; Conradt and Roper, 2009; Sridhar *et al.*, 2021).

In contrast, it has been shown that group cohesion can negatively impact group decision performance and information transfer (March, 1991; van Ginkel and van Knippenberg, 2012; Mehlhorn *et al.*, 2015). Some studies suggest that sparser or loosely coupled social networks sometimes outperform more connected ones (Mason, Jones and Goldstone, 2008; Fang, Lee and Schilling, 2010; Derex and Boyd, 2016). The detrimental effect of group cohesion is most pronounced when decision speed is prioritized (Gavrilets and Richerson, 2017; Yahosseini *et al.*, 2018), as can be seen in phenomena like groupthink (Janis, 1972, 2008) or hidden-profile experiments (Stasser and Titus, 2003). Recent research suggests that the context of a group or team likely determines whether group cohesion positively or negatively affects effort (Torka, Mazei and Hüffmeier, 2021) or group decision making (Casey-Campbell and Martens, 2009). Perhaps paradoxically, it has been shown that individuals are more motivated to follow a group when they experience uncertainty (Hogg, 2000), aggravating the already disadvantageous effect of group cohesion.

doi: 10.53846/goedss-9589

In sum, when social orientation (group cohesion) outweighs goal orientation, group members might forego their personal preference to stick with the group (e.g., Sridhar *et al.*, 2021). This means that cohesive groups might miss important information. On the other hand, however, completely disjoint groups will not be able to share information between group members to engage in collective induction (Laughlin, 1999) and to build collective information. This means that the "right balance of interdependence and independence" (Conradt, 2012, p. 1) appears crucial.

A key element in the relationship between group cohesion and group decision performance is the amount of exploration undertaken by the group or its individual members. The decision to stop accumulating more information about the environment (exploration) and commit to one option (exploitation) is a central challenge for individuals (Cohen, McClure and Yu, 2007; Tickle *et al.*, 2021). Individuals faced with an uncertain decision task will usually engage in exploration in the beginning before transitioning to exploitation of the option they estimate to be best (Bechara *et al.*, 1994). This has been investigated in computational models of reinforcement learning (e.g., ε-greedy algorithms; Sutton and Barto, 2018) that predict the best outcomes for a medium amount of exploration (i.e., an inverted U-relationship between exploration and decision outcome). However, if group cohesion is high, individual group members might rely on the knowledge of others instead of exploring on their own (Bolton and Harris, 1999; Yahosseini *et al.*, 2018). It has been shown that high group cohesion and resulting mutual reinforcement of sub-optimal choices prevents groups from exploring more profitable options (Bala and Goyal, 1998; Giraldeau, Valone and Templeton, 2002; Salganik and Watts, 2008).

Ritter and colleagues (2021) used the HoneyComb paradigm, a multi-agent virtual game platform, to investigate conditions under which humans are able to identify the most advantageous leader. In the experiment, the leaders were four pre-programmed agents and differed in expected values (i.e., in the probability and amount of pay-out). In order to infer which leader was best, participants had to explore by following the leaders in repeated interactions (i.e., 30 game rounds). After an initial exploration period, participants settled for one leader and exploited this option for the remaining part of the game. Within this experiment, three experimental conditions were tested: In the single condition, one participant played alone. In the independence condition, six participants played the game at the same time and each participant could simultaneously observe the movement of all other players. In the cohesion condition, six participants played the game as in the independence condition but received a cohesion reward for following a leader together with other participants. The incentive was implemented by multiplying the reward gained from the leader with the number of participants who had followed this leader. It was found that participants in the cohesion condition were more likely to settle on a less advantageous leader (Ritter *et al.*, 2021). While the effect of the implemented reward system (multiplicative cohesion reward) drove this effect, exploratory results suggested that high group cohesion might negatively affect group decision making.

In the current paper, we want to investigate whether increased group cohesion has a detrimental effect on group decision making by prioritizing social information over individual exploration, as previous work suggests (e.g., Yahosseini *et al.*, 2018). To this end, we conducted three studies: In the first study, we aimed to identify key parameters of the group decision making process under uncertainty using a simulation study. We use the ε-greedy algorithm (Sutton and Barto, 2018) to investigate findings about the influence of the cohesion reward structure (Ritter *et al.*, 2021), demonstrate the effects of exploration on group decision making, and inform following behavioral studies. Based on findings of Study 1, we designed the group decision making tasks used in in Study 2 and 3.

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In the second study, we empirically investigate whether groups who are incentivized to behave cohesively perform worse at a collective induction task, and whether this can be attributed to differences in exploration times. To test this prediction, we used a repeated card-choice task (similar to the Iowa Gambling Task, Bechara *et al.*, 1994). Participants explored the options individually but were given social information (i.e., information about the choices of other group members). The study investigated whether participants in groups incentivized to choose the same card would prioritize social information over individual exploration.

In the third study, we investigate emergent group processes affecting group decision making by implementing the decision task of Study 2 within the HoneyComb paradigm (Boos, Pritz and Belz, 2019). In this study, players were faced with the same choice options as in Study 2 but could communicate through movement on the playing field. All other verbal and nonverbal communication was blocked. By using the HoneyComb paradigm, we were able record spatio-temporal data to observe the group processes in real time. With these three studies, we aim to answer the basic question: How does group cohesion affect group decision making under uncertainty? In Study 1, we provide a detailed view of group decision making processes dependent on key parameters, such as exploration length, through a simulation study. In Study 2, we investigate this question in a simplistic choice task to investigate the influence of basic social information. In Study 3, we extend the choice task of Study 2 to a movement paradigm in order to investigate in detail which emerging group processes can be identified in group decision making under uncertainty. In this way, these three studies address the question at hand with increasing complexity.

2 Study 1

The purpose of this study was to identify key parameters of the group decision making process as investigated by Ritter and colleagues (2021). They implemented a multiplicative cohesion reward: In the cohesion condition, the rewards were multiplied by the number of participants arriving at the same reward field. Due to this reward inflation, participants in the cohesion condition were not able to accurately infer the value of the different options. We aim to substantiate these claims and identify additional parameters that could affect collective induction. To this end, we adapted the ε-greedy algorithm, a popular reinforcement learning algorithm, to model decision making under uncertainty (Sutton and Barto, 2018). The ε-greedy algorithm serves as a formalization of the previously used group decision making task (Ritter *et al.*, 2021) in which exploration/exploitation trade-offs had to be made by a group. As a detailed account of the ε-greedy algorithm is beyond the scope of this paper, we refer interested readers to introductory literature (e.g., Sutton and Barto, 2018) and limit ourselves to a basic explanation of the simulation algorithm, its parameters, and its relation to our psychological research question.

The ε-greedy algorithm is a reinforcement learning optimization method. It is often applied to so-called multi-armed bandit problems that are used to investigate decision making under uncertainty. A multi-armed bandit problem contains *k* different options and one agent that aims to find the best option. All *k* options have underlying reward distributions that are unknown to the agent. The multi-armed bandit problem can be extended to include multiple agents *n*: a multi-agent multi-armed bandit problem. In order to maximize their reward, agents need to discover the option that yields the highest reward through iterated trial-and-error choices (exploration). An important assumption of the basic ε-greedy algorithm is that the reward distributions underlying each of the options are stationary (i.e., are not subject to change from one iteration to the next). This means that each option follows a predefined reward distribution and that the parameters defining these distributions should not change. For example, the option of following the competent leader (Ritter et al., 2021) was defined by a

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binomial distribution with 80% success rate ($C \sim B(n, p)$, $p = 0.8$, $n = 30$ rounds). The expected value of this option $E[C]$, in the independence condition, was $E[C] = n * p = 24$ multiplied by the amount of payout $E[C] * 20$ cent = 480 cent. To satisfy the assumption of stationary reward distributions, this distribution should be constant across all iterations (or rounds). In principle, the Ritter and colleagues' (2021) experiment task constitutes a multi-armed bandit problem: The four leaders are the different options ($k = 4$) and their underlying reward probability is unknown to participants at the beginning of the game. The six players are the agents ($n = 6$) and they need to repeatedly choose from the four options in order to infer the option that yields the highest reward. Importantly, the assumption of stationary reward distributions is met in the independence condition (i.e., no cohesion reward), but not in the cohesion condition (i.e., multiplication of rewards with number of participants choosing the same option). In the cohesion condition, the presence of others following the same leader affected the reward that could be gained from an option. This could be one reason for the suboptimal performance of participants in the cohesion condition. In the cohesion condition, participants' rewards incorporated pay-out from the leaders, on the one hand, and the cohesion reward, on the other hand, without separating the feedback from these two sources. This means that agents in the cohesion condition received information that was corrupted by the cohesion reward and was, therefore, not suited to reliably estimate the underlying reward distributions.

In a multi-armed bandit problem, the ε-greedy algorithm is one possible way to find the best out of the k options. The n agents strive to maximize their (numerical) reward gained from different choices. To do so, they need to balance exploring the different options and exploiting the option that seems best in a given iteration. This is implemented in the following way: Each agent starts out by assuming that all k options are equally profitable. With each iteration (or each choice) an agent makes, their knowledge about the different options is updated and will become increasingly accurate. We can find analogous processes in human decision making under uncertainty. For example, the updating of information one holds about different options enables human decision makers to infer the best card stack in the Iowa Gambling Task (Bechara *et al.*, 1994). Additionally, it has been shown that neural networks in the human brain encode accumulated evidence about different options in the form of estimated distributions (Beck *et al.*, 2008; Churchland, Kiani and Shadlen, 2008).

In order to refine their knowledge, agents need to explore different options (i.e., make a random choice independent of previous experience). The tendency to explore is implemented with the ε-parameter ($0 < \varepsilon < 1$). For each iteration t of the algorithm (i.e., every time an agent needs to make a choice), a random number p is drawn from a uniform distribution between 0 and 1. If $p < \varepsilon$, the agent will randomly choose one of the options; if $p > \varepsilon$, the agent will choose the option with the highest expected reward based on their current knowledge. This means that a small ε will result in few exploratory iterations (e.g., $\varepsilon = 0.01$: about 1% of trials will be used for exploration), a large ε in many exploratory iterations (e.g., $\varepsilon = 0.5$: about 50%). Due to the random nature of determining whether an iteration will be used for exploration or exploitation, exploration can also happen at late stages of the algorithm, contrary to findings about human exploration/exploitation patterns (Bechara *et al.*, 1994). Nonetheless, we argue that this algorithm is well suited to model known psychological repeated choice problems. In this way, the ε-greedy algorithm can provide an interesting point of comparison to decision making problems under uncertainty.

2.1 Simulation

Starting from an existing Python script (Samishawl, 2020), we set up an ε-greedy simulation to include six agent ($n = 6$) and four options ($k = 4$). The four options followed the same reward distributions as in Ritter and colleagues' study (2021) as can be seen in Table 1. Additionally, three

doi: 10.53846/goedis-9589

different bonus types were implemented, corresponding to the different conditions (Ritter *et al.*, 2021): (a) no group bonus, (b) multiplicative group bonus (cohesion condition, reward multiplied by number of agents choosing an option), and (c) a new additive group bonus. With the additive group bonus, agents receive a fixed bonus (3 cent) for each other agent that chooses the same option. With the additive bonus, rewards are less inflated, compared to the multiplicative bonus. We included the additive bonus to explore whether it could be a viable alternative to the multiplicative cohesion reward in future experiments. Simulations included 30 iterations ($t_{max} = 30$), corresponding to the 30 rounds in the previous study. To compare the three reward structures, ε was kept constant (ε = 0.1) across three simulations. Additionally, we explored the influence of the ε parameter by running five different simulations (ε ϵ {0.01, 0.05, 0.1, 0.2, 0.5}). For these comparisons, we did not include any group reward to disentangle the effects of reward structure and exploration rates. In all simulations, agents explored for the first 3 iterations before continuing with the algorithm as described above. We recorded the number of agents choosing each option for each iteration of each simulation. Each simulation was repeated for 1000 runs (corresponding to groups in a human experiment). The Python script used for simulations, resulting data, and the analysis script can be found on our OSF project[1].

2.2 Results

Results can be seen in Figure 1. We fitted a Poisson mixed model (estimated using ML and BOBYQA optimizer) to predict the number of agents choosing the profitable field with bonus type (none vs. multiplicative vs. additive) and iteration, with simulation run as random effect. There was a significant effect of round, indicating that agents learned to choose the profitable option (β = 0.02, *95% CI* [0.02, 0.02], $p < .001$; std. β = 0.18, *95% CI* [0.17, 0.18]). Interaction effects showed that agents identified the best option faster when receiving no bonus (β = 0.001, 95% CI [0.00, 0.002], $p = .019$, std. β = 0.01), compared to the multiplicative and additive bonus, and slower when receiving a multiplicative bonus (β = -0.003, 95% CI [-0.004, -0.002], $p < .001$, std. β = -0.03), compared to the no bonus and additive bonus runs. For the secure neutral option, the main effect of round reversed (β= -0.003, *95% CI* [-0.004, -0.002], $p < .001$; std. β = -0.03, *95% CI* [-0.04, -0.02]) as well as the interaction effects; multiplicative bonus: β = 0.004, *95% CI* [0.003, 0.005], $p < .001$; std. β = 0.04, *95% CI* [0.03, 0.05]; no bonus: β = -0.003, *95% CI* [-0.005, -0.002], $p < .001$; std. β = -0.03, *95% CI* [-0.05, -0.02]. More details on the regression analysis can be found in the Supplementary Material 1.1.1.

While the overall differences between the frequency of chosen options seem very small, the regression analyses replicate the previous general finding (Ritter *et al.*, 2021): Runs that included the multiplicative bonus performed worse, compared to runs with no such reward. The additive bonus, while still producing suboptimal decisions, performs better, compared to the multiplicative reward. It is important to keep in mind that these results are produced by an algorithm designed to optimize rather than simulate decision problems, using the same decision task parameters as in the experimental study. Yet, the resulting patterns are comparable to those that can be found within human behavior (Ritter *et al.*, 2021).

Lastly, we explored how different exploration rates influence the decision making process. Simulations using intermediate levels of exploration usually fared best in (a) terms of overall choices and (b) learning rates in choosing the profitable and secure neutral options. These observations are corroborated by quantitative analyses (Supplementary Material 1.1.1) that consistently show no main

[1] https://s.gwdg.de/y0cOIu

doi: 10.53846/goedis-9589

effects for different ε-levels but interactions with round. This was true for both the number of agents choosing the profitable and the secure neutral option.

Results of this simulation study showed that simulated groups receiving a multiplicative or additive group bonus performed worse compared to groups receiving no such reward. However, when rewarding cohesion is a necessary experimental manipulation, an additive bonus should be implemented for better performance. Additionally, we advise that the bonus is reported separately from the choice reward (i.e., the reward stemming from the choice itself). Lastly, this study showed that the length of exploration is an important key element of group decision making under uncertainty that should be investigated in human behavior. This was done in Study 2.

3 Study 2

The aim of Study 2 was to investigate (a) whether more cohesive groups would perform worse in a group decision task, as found in previous work (Ritter *et al.*, 2021), and (b) whether this effect can be attributed to differences in exploration (Yahosseini *et al.*, 2018). In order to disentangle the effects of collective induction (Laughlin, 1999, 2011) and group cohesion, we amended earlier methodological limitations of the study by Ritter and colleagues (2021): In the current study, the feedback about how much money participants earned in a given round is shown separately for earnings from the reward field and the cohesion incentive. By separating the feedback, the reward distributions are constant across all rounds, eliminating problems of information occlusion (nonstationary reward distributions) as discussed in Study 1. The experimental design in the current study is restricted to two conditions: the independence and cohesion condition. Cohesion was manipulated using an additive cohesion reward (i.e., 3 cents for each additional player on the same reward field). It should be noted that groups in the independence condition might also exhibit some group cohesion, albeit less compared to groups in the cohesion condition. This should be ensured using a manipulation check. Additionally, we transformed the original task(Ritter *et al.*, 2021) into a card-choice paradigm (similar to the Iowa Gambling Task; Bechara *et al.*, 1994): The differently profitable leaders were transformed into differently profitable card stacks that participants chose from. In this way, this study excludes more complex emergent processes (e.g., leadership) to focus on clearly discernible effects of cohesion on the use of social information. More complex group processes are investigated in Study 3. A comparison of design aspects of the study by Ritter and colleagues (2021), Study 2, and Study 3 can be seen in Table 1.

In Study 2, the group decision process is investigated under minimal interaction. In the previous experiment (Ritter *et al.*, 2021), participants were able to communicate their decision preferences through movement, and possibly, use leader-/followership processes to guide group decision making. In contrast, communication between participants is blocked entirely in the current study. Participants were only informed about the choices other group members made. Therefore, the only social information available to participants was feedback about their own and other group members' choices.

This investigation aimed to replicate findings indicating a detrimental effect of group cohesion on group decision making (H1-4; March, 1991; van Ginkel and van Knippenberg, 2012; Mehlhorn *et al.*, 2015; Ritter *et al.*, 2021) and the mediating role of exploration (H5-6; e.g., Yahosseini *et al.*, 2018) as discussed in the theoretical background. The following hypotheses were formulated:

H1: Subjects will be more likely to find the profitable stack with increasing number of game rounds.

doi: 10.53846/goedis-9589

H2: There will be a stronger increase in finding the profitable stack with increasing number of rounds in the independence condition, compared to the cohesion condition.

H3: Subjects in the cohesion condition will have a shorter exploration phase measured by the half-change round (Ritter *et al.*, 2021), compared to those in the independence condition.

H4.1: Subjects will choose worse options overall, measured by choice score (Ritter *et al.*, 2021) in the cohesion condition, compared to those in the independence condition.

H4.2: Overall, subjects in the cohesion condition will choose the profitable stack less often, but the safe neutral stack more often compared to those in the independence condition.

H5: Participants with a longer exploration phase determined by the half-change round will make better decisions overall. We anticipate an inverted U-shape as predicted by ε-greedy algorithms (e.g., Sutton and Barto, 2018). The inverted U-shape suggests that the highest quality of decision occurs at an intermediate level of exploration while low and high levels of exploration will result in impaired decision quality. We therefore expect a negative square correlation between exploration and decision quality.

H6.1: The relationship between condition (cohesion vs independence) and the quality of decision making is mediated by the length of the exploration phase.

H6.2: The relationship between condition (cohesion vs independence) and choice of the profitable stack is mediated by the length of the exploration phase.

3.1 Methods

This study is designed as a mixed-design with a 2-level between-subjects manipulation (independence vs. cohesion condition) with repeated measures (30 rounds).

3.1.1 Sample

In this study, 108 participants (84 women, 23 men, 1 diverse; Age: M = 22.96 years, SD = 5.11) played the game in groups of six, resulting in a total of 18 groups (power analyses in Supplementary Material 1.2; additional sample information Supplementary Material 1.3.1). All data collection procedures were approved by the Ethics Committee of the Georg-Elias-Müller-Institute for Psychology (proposal 305/2022).

3.1.2 Procedure

Once participants signed up for the study, they received an e-mail with a link to an online meeting room (BigBlueButton). At the start of the experiment time slot, participants were asked to join this online meeting. To preserve anonymity, participants were prohibited from sharing their camera, microphone, or name. This meeting served to ensure that all six participants were present and to create social presence within the participant group. After some initial instructions, participants received a link to a form in which they had to give written consent in order to participate. Subsequently, another link was sent to participants that led them to the online experiment programmed within Labvanced (Finger *et al.*, 2017)).

doi: 10.53846/goedis-9589

Participants were shown instructions that explained that they would play a game during which no communication with the other participants would be allowed or necessary. It was explained that the game consists of repeated card choices with each card choice representing one round (see Figure 2).

The task of the participants was to earn as much money as possible by choosing cards from four card stacks labelled “A”, “B”, “C”, and “D”. The general setting consisted of four different stacks with different expected values (Table 1, Figure 2). In each round, participants had to choose from which card stack they wanted to draw with a mouse-click. A colored bar (green for pay-out, red for no pay-out) at the top of the screen informed them whether the card had paid out and, if so, how much. If participants failed to choose a card in the allotted time (40 seconds), the red bar showed the message “YOU DID NOT CHOOSE”. Participants who had not chosen a card in a given round did not receive payout in this round. Additionally, the feedback screen displayed the choices of all other players by printing the player number under the card they had chosen. This was done to provide a minimum of social information to participants. The player’s own choice was shown by printing “You” under the chosen card. In the cohesion condition, participants received an additional bonus of 3 cents for each other participant that had chosen the same card. A blue bar at the top of the screen informed participants about the earned group bonus so that the reward from the card choice and the group bonus were presented separately. In the independence condition, no such bonus was implemented. As in the study by Ritter and colleagues (2021), the participants played 30 repeated rounds of this game. After the last round, participants were informed about the total amount of money they had earned and were then led to a post-experiment questionnaire. Participants were then asked to return to the online meeting room, where they were thanked and dismissed.

3.1.3 **Operationalization.**

Decision quality is operationalized in two ways: choice of the profitable stack in each round and an overall choice score to quantify overall decision quality in the game. The *choice of profitable stack* is a binary variable in each round and the probability to choose the profitable stack (i.e., card stack with highest expected value) will be calculated within a logistic regression model. The *choice score* is the overall quality of card stack choices which is determined by a cumulative points system (Ritter *et al.*, 2021). To calculate the choice score, points were assigned to each card choice and summed over all rounds: For the profitable stack, participants received 3 points, for the neutral stacks, participants received 2 points, for the unprofitable stack, participants received 1 point. If participants failed to choose a card stack, they received 0 points. Note that the choice score is simply an overall operationalization of participants’ decision quality for analysis purposes and was not used to calculate participants’ earnings.

Group cohesion is operationalized as the manipulated independent variable condition. Half of the groups were incentivized with a group bonus to show group cohesion (cohesion condition), while the other half was not incentivized in this way (independence condition).

Exploration is operationalized using the *half-change-round* (Ritter *et al.*, 2021): the round in which at least half of all card stack changes of one participant had occurred. It is used to operationalize the end of the exploration phase and beginning of the exploitation phase.

doi: 10.53846/goedis-9589

3.1.3.1 Data preprocessing and analysis.

Data was preprocessed and analyzed using R, running in RStudio (R Core Team, 2020; RStudio Team, 2020). Used R packages can be found in the Supplementary Material 1.4. The analysis script and preprocessed data can be found on the OSF project[2].

3.2 Results

H1. As expected, participants were indeed significantly more likely to choose the profitable card stack in later rounds, compared to earlier rounds (β = 0.04, *95% CI* [0.02, 0.06], $p < .001$; std. β = 0.62, *95% CI* [0.39, 0.86]). To check this, we fitted a logistic mixed model (estimated using ML and BOBYQA optimizer) to predict choice of the profitable card stack with round (formula: choice of profitable card stack ~ -1 + round). The model included round, participant id and group as random effects. The model's total explanatory power is substantial (conditional $R^2 = 0.39$) and the part related to the fixed effects alone (marginal R^2) is of 0.02. Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation. All models reported in the following are fitted in the same way if not stated otherwise.

H2. Contrary to expectations, there was no difference in learning rates between the cohesion and independence condition. We fitted a logistic mixed model to predict choice of profitable card stack with condition (independence vs. cohesion) and round, with round, participant id, and group as random effects. The model's total explanatory power is substantial (cond. $R^2 = 0.42$; marg. $R^2 = 0.07$). The results can be seen in Figure 3. The main effect of round remained significant, showing that participants in both conditions were more likely to choose the profitable card stack in later rounds (β = 0.06, *95% CI* [0.03, 0.09], $p < .001$, std. β = 0.67), while no main effect of condition (β = -0.65, *95% CI* [-1.58, 0.27], $p = .167$, std. β = -0.09) and no interaction effect was found (β = -0.01, *95% CI* [-0.06, 0.04], $p = .670$, std. β = -0.26).

H3. Contrary to expectations, participants in the cohesion condition explored for a longer time (M = 13.56 rounds, SD = 5.23), compared to participants in the independence condition (M = 10.78 rounds, SD = 4.94). This was shown by a Welch two-sample t-test: $t(106) = 0.41$, $p = .003$, Cohen's d = -0.55.

H4. Contrary to expectations, participants in both conditions chose the card stacks about equally well as measured by choice score (*H4.1*) and card choice (*H4.2*). There was no significant difference in choice score between conditions (*H4.1*; M_{Coh} = 73.70, SD = 7.43; M_{Ind} = 74.25, SD = 6.72); $t(104.94) = 0.41$, $p = .342$; Cohen's $d = 0.08$. While there were differences between overall card stack choices (*H4.2*; Figure 3) as shown by a χ^2-test (H4.2; $\chi^2(3) = 18.231$, $p < .001$), there was no difference between conditions in how often participants chose the profitable card stack ($p = 1$, determined by post-hoc tests corrected with the Bonferroni method). However, we found that participants in the cohesion condition chose the secure neutral card stack significantly more often, compared to the independent condition ($p = .020$).

H5. Contrary to expectations, the length of the exploration phase (as measured by the half-change round) did not affect the overall decision quality (as measured by the choice score). There was neither a linear nor a quadratic relationship between these two variables, as shown by a linear mixed

[2] https://s.gwdg.de/y0cOIu

doi: 10.53846/goedoc-9589

model (estimated using REML and nloptwrap optimizer) to predict choice score with half-change round in a linear and quadratic term (formula: choice score ~ half-change round + half-change round^2), including group as random effect. The effect of both the linear term (β = -0.71, *95% CI* [-1.69, 0.27], $t(103) = -1.44$, $p = .153$; std. β = -0.53, *95% CI* [-1.26, 0.20]) and the quadratic term were statistically non-significant (β = 0.02, *95% CI* [-0.02, 0.05], $t(103) = 0.86$, $p = .390$; std. β = 0.32, *95% CI* [-0.41, 1.05]). However, when only including the linear term in the model, the model suggests that participants with longer exploration phases perform worse, measured by choice score (cond. $R^2 = 0.27$, marg. $R^2 = 0.05$; β = -0.30, *95% CI* [-0.54, -0.05], $t(104) = -2.41$, $p = .018$; std. β = -0.22, *95% CI* [-0.40, -0.04]). The model fit did not differ significantly between both models, as determined by a loglikelihood test ($\chi 2(1) = 0.765$, $p = .382$).

H6.1. We expected that the relationship of group cohesion and decision quality as measured by the choice score would be mediated by exploration[3]. However, no mediation effect was found. We performed a mediation analysis. The total effect (half-change round * condition on choice score) was significant (β = 2.79, *95% CI* [0.36, 5.33], $p = .030$) as was the direct effect (β = 2.79, *95% CI* [0.36, 5.33], $p = .030$). The indirect effect, however, remained nonsignificant (β = 0, *95% CI* [-0.00, 0.00], $p = 1$). The proportion mediated was 0.

H6.2. As for H6.1, a mediation of the relationship of group cohesion and decision quality (as measured by choice of the profitable reward field) by exploration was expected. However, no mediation effect was found. While the total effect (half-change round * condition on choice of profitable card stack; β = 2.810, *95% CI* [0.246, 5.07], $p = .030$) and the direct effect (β = 2.810, *95% CI* [0.246, 5.07], $p = .030$) were significant, no mediation effect could be found (proportion mediated = 0) with the indirect effect (β = 0, *95% CI* [-0.00, 0.00], $p = 1$) being nonsignificant.

4 Study 3

Emergent group processes (e.g., leader-/followership) were excluded in Study 2 to focus on the effects of group cohesion and exploration on group decision making. In contrast, the aim of Study 3 is to identify which processes emerge if participants are allowed to interact through movement and how these processes might guide the group decision process. In this way, Study 3 extends the reductionist paradigm of Study 2 to the HoneyComb paradigm (Boos, Pritz and Belz, 2019) that was previously used (Ritter *et al.*, 2021). This was done for three reasons: First, the HoneyComb paradigm allows participants to interact and therefore exchange social information according to processes that have been shown for moving (animal) groups (e.g., Couzin, 2009; Moussaïd *et al.*, 2009; Sridhar *et al.*, 2021). Second, using the HoneyComb paradigm allows researchers to analyze the emerging group processes (Boos *et al.*, 2014; Boos, Pritz and Belz, 2019) by recording spatio-temporal data. In this way, we aim to disentangle emergent processes from each other. Third, the HoneyComb paradigm allows researchers to implement the same decision task that was used in Study 2 (e.g., using the same reward structure; see Table 1 for a comparison of study designs). In order to allow for the emergence of processes such as leadership, aspects of Ritter and colleagues' study (2021) were adapted. In the current study, we allowed for a global visual radius. This means that participants can see movements of all other participants on the playfield, regardless of their distance to them. In this way, participants can sample as much social information as possible. Additionally, we used four reward fields instead of pre-programmed leaders. The differently

[3] We recalculated all mediation analyses (H6.1 & H6.2 in Study 2 and 3) using a quadratic term for exploration. However, the results remained the same so that we report the less complex models.

doi: 10.53846/goeduhs-9589

profitable leaders were transformed into differently profitable reward fields (analogous to card stacks in Study 2, see Table 1).

In this study, we aimed to investigate the effect of group cohesion on group decision making and the mediating effect of exploration. As in Study 2 and explained in the theoretical background, we hypothesized a detrimental effect of higher group cohesion on group decision making (H1-4) and a mediating role of exploration on this effect (H5-6). The study and the following hypotheses were preregistered: 10.17605/OSF.IO/3N5RA.

H1: Subjects will be more likely to find the profitable field with increasing number of game rounds.

H2: There will be a stronger increase in the likelihood of finding the profitable field with increasing number of rounds in the independence condition, compared to the cohesion condition.

H3: Subjects in the cohesion condition will have a shorter exploration phase measured by the half-change round (Ritter *et al.*, 2021), compared to those in the independence condition.

H4.1: Subjects will choose worse options overall, measured by the choice score (Ritter *et al.*, 2021) in the cohesion condition, compared to those in the independence condition.

H4.2: Overall, subjects in the cohesion condition will choose the profitable field less often, but the safe neutral field more often compared to those in the independence condition.

H5: Participants with a longer exploration phase determined by the half-change round will make better decisions overall. We anticipate an inverted U-shape. We therefore expect a negative square correlation between exploration and decision quality.

H6.1: The relationship between condition (cohesion vs independence) and the decision quality is mediated by the length of the exploration phase.

H6.2: The relationship between condition (cohesion vs independence) and choice of the profitable field is mediated by the length of the exploration phase.

Using a post-experiment questionnaire, subjective experiences during the experiment, measures of group cohesion and entitativity (i.e., a feeling of ‘groupness’; Blanchard, Caudill and Walker, 2020), and typical correlates of leadership behavior (decisiveness: Aramovich and Blankenship, 2020; achievement motivation: e.g., Karsudjono, Christiananta and Eliyana, 2013; self-confidence: e.g., García-Vidal *et al.*, 2019; risk: Baškarada, Watson and Cromarty, 2017) were collected. Note that leadership behavior in the HoneyComb paradigm has not been associated with personality traits (Boos *et al.*, 2014) as measured by the Big Five (Rammstedt and John, 2005) or agency and communion scales (Spence, Helmreich and Holahan, 1979). Therefore, more behavior-oriented traits that have been shown to correlate with leadership were investigated in this study. We hypothesize that behavioral leadership as measured by a leadership score (L-F-score) will correlate with typical personality correlates of leadership (H7-10). Additionally, we expect that subjective experiences of leader-/followership (H11) and group cohesion and entitativity (H12) will correspond to behavioral measures of leadership and group cohesion. Lastly, we expect that groups will need to find effective ways of communication in earlier rounds that can be used in later rounds. We therefore expect that participants rate cooperation and interaction to be lower during earlier rounds, compared to later rounds (H13).

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H7: There will be a positive correlation between self-confidence and leadership as measured by L-F-profiles.

H8: There will be a positive correlation between decisiveness and leadership as measured by L-F-profiles.

H9: There will be a positive correlation between profit/achievement maximization and leadership as measured by L-F-profiles.

H10: There will be a positive correlation between risk propensity and leadership as measured by L-F-profiles.

H11: There will be a positive correlation between perceived leadership/followership and leadership as measured by L-F-profiles.

H12: Entitativity (as measured by the mean of all group members' reports) will be higher in the cohesion condition, compared to the independence condition.

H13: Cooperation and interaction (as measured by mean of all group members' reports) in the rounds 1 through 10 will be lower than in rounds 11 through 20 and 21 through 30; cooperation and interaction in the rounds 11 through 21 will be lower than the rounds 21 through 30.

4.1 Methods

This study employs a mixed-design with a 2-level between-subject manipulation (independence vs. cohesion condition) with repeated measures (30 rounds).

4.1.1 **Sample.**

Data was collected from 96 participants that played the game in groups of six (i.e., 16 groups). However, one person reported a level of German below B1 and was therefore excluded from the analysis. The resulting sample consists of 95 participants (62 women, 32 men, 1 diverse; Age: M = 24.55 years, SD = 7.76). Half of the groups (n = 8) were assigned to the cohesion condition, the other half played the independence condition. As this study is a conceptual replication of Study 2, the same a-priori power analysis applies (Supplementary Material 1.2, additional sample information in Supplementary Material 1.3.2). All data collection procedures were approved by the Ethics Committee of the Georg-Elias-Müller-Institute for Psychology (proposal 305/2022).

4.1.2 **Procedure.**

Upon signing up to participate, participants received an invitation e-mail detailing all necessary steps to prepare their laptop for participation and a link to an online meeting room. During the experiment slot, subjects needed to use a PC or laptop to join an online video conference (BigBlueButton). In order to ensure complete anonymity between participants, participants were prohibited from sharing their camera, microphone, screen, or name. The experiment was started using an online meeting to (a) allow the experimenter to check that all participants are present and provided written consent prior to starting the game, and (b) share instructions live with participants to create social presence.

Participants started the game by logging into a Remote Desktop Machine on which the experiment program was running. The program is an adaptation of the HoneyComb paradigm version used by Ritter and colleagues (2021) and was designed to eliminate all communication channels except the

doi: 10.53846/goedis-9589

visual perception of movements on the playing field. Participants were represented on the virtual playing field as colored avatars (see Figure 4) that they could move around on the playing field using mouse-clicks.

The game consisted of 30 consecutive rounds (as in Study 2) in which the rules of the game remained the same. The task for participants was to maximize their payoff by arriving at fields that yielded a monetary reward at the end of each round. There were four reward fields, represented by differently colored circles (colors were assigned randomly for each game). Participants played the game in the presence of five other participants and could observe each other's movement behavior on the whole playing field (global visual radius). In the cohesion condition, participants received an additional reward (3 cents) for arriving on a reward field with other participants to incentivize cohesive behavior in the game. This bonus was shown to participants separately from their winnings from the reward field itself. When participants had completed the 30 game rounds, they received a link to the post-experiment questionnaire which assessed subjective experience and strategy in the game, self-confidence, decisiveness, achievement motivation, and risk propensity. Furthermore, we asked participants to rate their perception of following and/or leading others in the game, entitativity, cooperation, and interaction. After completing the questionnaire, participants were thanked and asked to leave the online conference.

4.1.3 **Operationalization.**

Decision quality is operationalized analogous to Study 2.

Group cohesion is operationalized in three ways. First, as the manipulated independent variable condition in which half of the groups were incentivized with a group bonus, rewarding group cohesion (cohesion condition), while the other half was not incentivized in this way (independence condition). Second, cohesion as a dependent variable is operationalized as the *average distribution* of players across the playing field. The percentage of used fields on the playing field is a measure of spatial distribution of players, a behavioral marker of group cohesion. Third, group cohesion as another dependent variable is operationalized as *clustering* in terms of the global clustering coefficient of an undirected, weighted network: In the network, players are nodes and the closeness between players (inverted numbers of fields between two players) are differently weighted edges. The global clustering coefficient of the network (transitivity) is used as a measurement for spatial clustering of players on the playing field, a behavioral marker of group cohesion in the game.

Exploration is operationalized analogous to Study 2.

Leadership is operationalized with the *L-F-score* of each person in each round. This score is a measure of the open behavioral aspect of leader-/followership within a group. L-F-profiles are constructed as in the following example: At the beginning of a round, all players are assigned a L-F-score of zero. Whenever a player moves during the game, the resulting difference in distance to all other members is calculated. For example, player A has moved away one field from player B and C, thereby increasing the distance to them. Player A's L-F-score is increased by 1 point, players' B and C score is decreased by 1 point. Next, player B moves closer to player A, but away from player C. Again, player A's L-F-score is increased by 1 point (someone else "followed" them). Player B's L-F-score remains the same (moved away from C, but closer to A) and player C's score is further decreased by 1. For every move, the L-F-score for all players is updated. For each new round, a new L-F-score is calculated that is summed up to calculate the *overall L-F-score* measuring leadership over all 30 rounds.

doi: 10.53846/goedis-9589

Self-confidence was measured using the Multidimensionale Selbstwertskala (internal consistency: Cronbach's α = .76 - .87; retest reliability: r_{tt} = .69-.82; Schütz, Rentzsch and Sellin, 2016). ***Decisiveness*** was measured using the Decisiveness Scale (internal consistency: Cronbach's α = .82 - .87; Roets and Van Hiel, 2007). ***Achievement motivation*** was measured using the short version of the Leistungsmotivationsinventar (internal consistency: Cronbach's α = .68 - .86; retest reliability: r_{tt} = .66 - .82; Schuler and Prochaska, 2001). ***Risk propensity*** was measured with the R-1 measure (retest reliability: r_{tt} = .64; Beierlein *et al.*, 2014). Additionally, two scales assessed ***entitativity*** (Gaertner and Schopler, 1998; Blanchard, Caudill and Walker, 2020). All scales were validated and measurement criteria can be found in the cited original articles or manuals.

4.1.4 **Data preprocessing and analysis.**

Data was preprocessed and analyzed as described in the preregistration[4] using R, running in RStudio (R Core Team, 2020; RStudio Team, 2020), using the packages cited in the Supplementary Material 1.4. The analysis script and preprocessed data can be found on the OSF project[4].

4.2 Results

4.2.1 **Confirmatory analyses.**

Confirmatory analyses were run as described in the preregistration and are presented in order of the hypotheses.

Manipulation check. The manipulation check was successful. A one-sided Wilcox Rank-Sum Test with continuity correction, used since variables violated assumptions of normality, showed that groups in the cohesion condition used significantly fewer fields (*Mdn* = 12.14 % of all fields) than groups in the independence condition (*Mdn* = 20.86 %); $W = 2268$, $p < .001$. The same holds for the field distribution calculated on the move level (Mdn_{Ind} = 4.90 %; Mdn_{Coh} = 4.07%; $W = 2268$, $p < .001$) and clustering (Mdn_{Ind} = 0.80, Mdn_{Coh} = 0.85, $W = 0$, $p < .001$).

H1. As predicted, participants were more likely to choose the profitable reward field in later rounds. We fitted a logistic mixed model (estimated using ML and BOBYQA optimizer). In the model the choice of the profitable field could be predicted with round (formula: choice of field ~ -1 + round). The model included round, participant id and group as random effects. The model's total explanatory power is substantial (conditional R^2 = 0.66) and the part related to the fixed effects alone (marginal R^2) is 0.06. The effect of round is statistically significant and positive (β = 0.09, *95% CI [0.04, 0.14]*, $p < .001$; std. β = 0.47, *95% CI* [0.28, 0.67]). Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and p-values were computed using a Wald z-distribution approximation. All following models were fitted using the same method if not stated otherwise.

H2. Contrary to expectations, participants in both conditions were more likely to choose the profitable field in later rounds and there was no difference between conditions in this effect as can be seen in Figure 5. This was shown by a logistic mixed model, predicting choice of the profitable field with condition and round (fixed effects) and including round, participant id, and group as random effects. The model's total explanatory power is substantial (cond. R^2 = 0.68) and the marginal R^2 is 0.07. The effect of condition is statistically non-significant (β = -0.24, *95% CI* [-1.08, 0.60], $p = .570$, std. β = 0.40), and the effect of round is statistically significant and positive (β = 0.11, *95% CI* [0.04,

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0.17], p = .002, std. β = 0.46). The interaction effect is statistically non-significant (β = -0.03, *95% CI* [-0.13, 0.07], p = .535, std. β = 0.009).

H3. Contrary to expectations, no differences in the length of exploration phases were found between conditions, as shown by a one-sided Wilcox Rank-Sum Test with continuity correction. In both the cohesion and independence condition, the half-change round median was at 14 rounds (M_{Coh} = 11.21 rounds, M_{Ind} = 12.48 rounds); W = 1254, p = .776.

H4.1. Contrary to expectations, participants in both conditions scored about equally well on the choice scores. As shown by a Wilcoxon-signed rank test, the median choice scores for the cohesion and independence condition (M_{Ind} = 70.35 points, M_{Coh} = 71.52 points) did not differ significantly; W = 1095.5, p = .662.

H4.2. Contrary to predictions, there was no difference between the number of times participants in the cohesion condition chose the profitable reward field, compared to participants in the independent condition (post-hoc p = 1, Bonferroni corrected; Figure 5). Further, participants in the cohesion condition chose the secure neutral field less often, compared to the independence condition (post-hoc p = .023, Bonferroni corrected); $\chi^2(4) = 16.496$, p = .002.

H5. Contrary to expectations, a medium exploration length was associated with lower choice scores, while shorter and longer exploration lengths were associated with higher choice scores. We fitted a linear mixed model (estimated using REML and nloptwrap optimizer) to predict the choice score with the length of the exploration phase (half-change round) in a linear and quadratic term (formula: choice score ~ half-change round + half-change round^2). The model included group as a random effect. The model's total explanatory power is substantial (cond. R^2 = 0.65) and the part related to the fixed effects alone (marg. R^2) is of 0.42. The effect of the linear term is statistically significant and negative (β = -2.88, *95% CI* [-4.27, -1.49], $t(91) = -4.11$, $p < .001$; std. β = -1.29, *95% CI* [-1.92, -0.67]). The effect of the quadratic term is statistically significant and positive (β = 0.08, *95% CI* [0.02, 0.14], $t(91) = 2.57$, p = .012; std. β = 0.74, *95% CI* [0.17, 1.31]). This model was compared to a model using only the linear term: This model's total explanatory power was substantial (cond. R^2 = 0.60; marg. R^2 = 0.32). The effect of the liner term is statistically significant and negative (β = -1.13, *95% CI* [-1.50, -0.76], $t(92) = -6.13$, $p < .001$, std. β = -0.51). The quadratic model outperformed the linear model significantly in a Log-Likelihood comparison ($\chi^2(1)$= 6.62; p = .010) and on all model performance indices (RMSE, Sigma, AIC, BIC, cond. R^2, marg. R^2), except for the ICC (Supplementary Figure 1).

H6.1. Contrary to expectations, exploration did not mediate the relationship of cohesion and decision quality as measured by the choice score. A mediation analysis was performed, even though the general effect (condition – choice score) was not found. The total effect of condition on choice score (β = -1.37, *95% CI* [-5.77, 2.92], p = .520) was nonsignificant as were the direct effect (β = -1.37, *95% CI* [-5.77, 2.92], p = .520) and the indirect effect(β = 0, *95% CI* [-0.00, 0.00], p = 1). The proportion mediated was 0.

H6.2. Contrary to expectations, exploration length did not mediate the relationship of group cohesion on group decision making as measured by choice of profitable reward field. No mediation effect could be found (proportion mediated = 0) with the total (β = -1.33, *95% CI* [-5.75, 2.74], p = .520), direct (β = -1.33, *95% CI* [-5.75, 2.74], p = .520), and indirect effect (β = 0, *95% CI* [-0.00, 0.00], p = 1) being nonsignificant.

doi: 10.53846/goedss-9589

H7-H11. Contrary to expectations, the L-F-Scores did not correlate with self-confidence, achievement motivation, decisiveness, or risk propensity. However, the data showed that participants who reported following others, were more likely to have lower L-F-scores (indicating followership). Further, participants with higher (vs. lower) L-F-scores were also more likely to report taking a leading (vs. following) role, and vice versa. Results of the correlation analyses can be seen in Table 2.

H12. As expected, participants in the cohesion condition reported significantly higher levels of entitativity, compared to participants in the independence condition (M_{Coh} = 4.38, M_{Ind} = 2.73). A Welch Two-Sample t-test showed a positive and large effect: $t(91.46) = 7.17$, $p < .001$; Cohen's d = 1.46, *95% CI* [1.01, 1.91].

H13. As expected, participants reported that interaction increased over rounds (Figure 6). Three paired t-tests (Bonferroni corrected) showed that participants rated interaction higher in rounds 11-20 (M = 4.30), compared to rounds 1-10 (M = 3.14; $t(95) = -6.81$, $p < .001$); Cohen's d = -0.70, *95% CI* [-0.92,-0.47]. Interaction in rounds 21-30 (M = 4.92) was rated even higher, compared to both rounds 1-10 ($t(95) = -9.27$, $p < .001$; Cohen's d = -0.95, *95% CI* [-1.19, -0.70]) and rounds 11-20 ($t(95) = -5.48$, $p < .001$; Cohen's d = -0.56, *95% CI* [-0.77, -0.34]).

4.2.2 **Exploratory results.**

In our previous study (Ritter *et al.*, 2021), a major methodological drawback was the low correlation between the choice score and participants' earnings. This problem seems to have been eliminated in the current study: We fitted a linear mixed model to predict earnings with condition and choice score, including group as a random effect (cond. R^2 = 0.97, marg. R^2 = 0.87). While the effect of condition was non-significant (β = 117.19, *95% CI* [-151.44, 385.81], $t(90) = 0.87$, $p = .388$, std. β = 1.31), choice score was positively associated with earnings (β = 12.58, *95% CI* [11.19, 13.98], $t(90) = 17.92$, $p < .001$, std. β = 0.56). No significant interaction could be found (β = 3.18, *95% CI* [-0.39, 6.75], $t(90) = 1.77$, $p = .080$, std. β = 0.14).

We explored whether participants could indicate explicitly which reward field had been the most profitable one. We found that 70.5% of all participants were able to identify the profitable field explicitly with a self-reported certainty of 57.1% on average (SD = 30.76). Those participants who did not correctly identify the profitable field reported a significantly lower certainty (M = 27.5%, SD = 18.86); $t(79.95) = -5.71$, $p < .001$; Cohen's d = -1.16, *95% CI* [-1.59, -0.72].

We further explored the correlations between the measures of cohesion on the HoneyComb field (condition, field distribution, transitivity) and subjective cohesion measures. Results can be found in Table 3. Significant correlations were found between virtually all cohesion measures, except for ratings of similarity within a group and some interaction ratings. Notably, we found a significant medium association between cohesion (as measured by field distribution) and decision quality; r = -0.26, *95% CI* [-0.44, -0.07], $t(93) = -2.64$, $p = .010$.

Lastly, we explored whether we could find evidence that leader-/followership emerged over interactions. Leader and follower roles seem to have emerged in most groups (Figure 7), except for groups 3, 4, and 5. Notably, a significant difference in decision quality can be found between those three groups (choice score: M = 64.65, SD = 9.71) and groups in which leader-/followership emerged (M = 72.62, SD = 11.37); $t(93) = -2.68$, $p = .009$; Cohen's d = -0.72, *95% CI* [-1.25, -0.18]. However, there was no significant correlation between decision quality and leadership (as measured by L-F-scores); r = 0.007, *95% CI* [-0.19, 0.21], $t(93) = 0.07$, $p = .946$.

doi: 10.53846/goedis-9589

5 Discussion

The aim of this paper was to provide detailed insights into the relationships between group cohesion, length of exploration phases, and group decision making under uncertainty and the processes that might drive these relationships. Specifically, we conducted three studies with increasing complexity: Study 1, a simulation study, identified suitable cohesion manipulations and investigated how differing lengths of exploration would affect group decision making. Study 2 examined in a behavioral experiment how group cohesion can affect exploration lengths and the quality of group decision making when only limited social information is available. Study 3 used a group movement paradigm to identify and disentangle group processes that emerge in group decision making under uncertainty and to study how these processes might drive the relationships between group cohesion, exploration, and the quality of group decision making.

Specifically, we used the ε-greedy algorithm in Study 1 to identify a new cohesion reward (additive bonus) that was implemented in the empirical studies (Study 2 and 3). In the second study, the effect of group cohesion on exploration and group decision making was tested in a card-choice task. Here, group cohesion was manipulated experimentally by rewarding group members choosing the same option with an additive group bonus. In the third study, we implemented the task within the HoneyComb paradigm (Boos, Pritz and Belz, 2019) that allows participants to interact or communicate with each other via movement, while the emerging group processes can be observed in detail via analysis of the spatio-temporal data. In this way, we were able to identify which group processes emerged during group decision making under uncertainty (leadership, group cohesion) and how these processes might have affected the decision outcome.

The results of Study 1 corroborated claims that a multiplicative reward structure might not be suitable in group experiments. Results of the simulation indicate that successful inference of the best option is much harder with a multiplicative cohesion reward as the multiplication of rewards creates nonstationary distributions. This is in line with previous findings (Ritter *et al.*, 2021). With a multiplicative reward, each time agents in a simulation (Study 1) or human participants (Study 2 and 3) choose a certain option, the reward attributed to the option is obfuscated by the number of agents choosing the same option. This has been coined unexpected uncertainty (Cohen, McClure and Yu, 2007) or even volatility (Bland and Schaefer, 2012). In comparison, simulations using an additive cohesion reward fared better and simulations using no cohesion reward were the fastest to find the optimal solution (Study 1). It should be noted that including an additive cohesion reward will still violate the assumption of stationary distributions. However, with a small additive reward, the problem of non-stationarity is less pronounced as the actual option reward remains the dominant feedback. The additive bonus was implemented in Studies 2 and 3. Additionally, the separation of the feedback of the reward and cohesion bonus was introduced. In this way, we could empirically support the proposal that empirical studies can use additive cohesion rewards without hampering a group's ability for collective induction. That even an additive group bonus can successfully manipulate group cohesion was shown in Study 3 where groups receiving the additive bonus showed greater observed, spatial cohesion as well as self-reported cohesion and entitativity.

Additionally, Study 1 showed that how much agents explore during the decision task (as represented by the ε parameter) will strongly impact performance. Lower exploration rates (1% and 10% of trials used for exploration) produced suboptimal results in which agents were slower to identify the optimal solution. In contrast, higher exploration rates (20% and 50%) in the simulations led to agents finding the optimal solution more quickly. As an outlier to this general pattern, the simulation using $\varepsilon = 0.05$ performed about as good as the simulation with $\varepsilon = 0.5$. Future simulation studies might investigate

doi: 10.53846/goedis-9589

whether this is a systematic effect or, more likely, a random finding. After all, the amount of trials that agents use for exploration are determined randomly. Additionally, future simulations might investigate whether ceiling effects of exploration exist. The results of Study 1 suggest that higher exploration rates will lead to better optimization results. However, it seems implausible that this would generalize to other simulations or real-world decisions, as there is usually a trade-off between exploration and exploitation (e.g., Cohen, McClure and Yu, 2007; Tickle *et al.*, 2021). In fact, this inverted U-shape (high performance using a medium ε) is frequently found in applications of the ε-greedy algorithm (Sutton and Barto, 2018). It could be that adapting the simulation to include only 30 iterations (corresponding to the 30 rounds in the human experiment) allowed more room for erroneous convergence.

Findings from Study 1 were used to eliminate previous methodological limitations to design empirical studies on human group behavior focusing on (a) the use of social information in group decision making (Study 2), and (b) emergent group processes guiding group decision making under uncertainty (Study 3). In both experimental studies, groups were able to identify the best option (Study 2: card stack, Study 3: reward field; *H1*) as was also found in previous research (Ritter *et al.*, 2021). However, no difference between conditions could be found in terms of decision quality (*H2*, *H4*): In both studies, groups that were rewarded for cohesion chose the best option about equally as often as groups who were not rewarded for cohesion. Learning rates (i.e., increasing probability of choosing the best option with increasing rounds) did not differ between conditions either. By extension, groups in both conditions performed equally well in terms of the overall decision quality (measured by the choice score), in both studies. It should be noted that the absence of a significant difference should not be interpreted as evidence for the absence of an effect. Instead this lack of effect should be investigated in the future or analyzed using Bayesian statistics to determine whether the evidence supports the null hypothesis.

Contrary to expectations, group cohesion did not shorten participants' exploration phases (*H3*). While participants in both conditions explored for an approximately equal length of time in Study 3, participants in the cohesion condition actually spent longer on exploration in Study 2. This difference in exploration was not found previously (Ritter *et al.*, 2021) and could originate in the design of the study: In order to get the cohesion reward in Study 2, participants had to choose the same cards as the other group members. As there was no possibility to communicate, this was no simple task: Participants could not simply follow the tendencies of other group members (as in Study 3) but had to take a chance by switching their card stack, hoping that the other group member will choose the same card in the next round as well. Due to the limitation of communication possibilities, participants might have "missed" each other, creating a need to switch choices again in the next round. With the chosen operationalization (half-change round), choice switches due to exploration motivations cannot be distinguished from choice switches serving cohesion purposes.

We predicted that a medium level of exploration will lead to the highest decision quality, while lower and higher exploration levels will decrease decision performance. Results of Study 3 show the opposite relationship with medium exploration rates being associated with the lowest choice scores, while low and high exploration rates were associated with higher choice scores (*H5*). In Study 2, no relationship between exploration and decision quality was found. Additionally, the hypothesized mediation of group cohesion on decision quality through exploration (*H6*) could not be shown in either Study 2 or 3. As the relationship between exploration and decision quality was so surprising and contradictory to previous findings (Sutton and Barto, 2018; Yahosseini *et al.*, 2018), we suspect that the task might have been too simple (i.e., a ceiling effect of decision performance). In adapting the paradigm by Ritter and colleagues (2021), care was taken to eliminate distracting information in

doi: 10.53846/goedoc-9589

order to gain as much insight as possible into the basic mechanism of group decision making under uncertainty. The main methodological limitation of the previous study (i.e., occlusion of information due to the cohesion reward) was successfully eliminated as could be shown by the high association of earned rewards and decision quality in both conditions. As an additional adaptation, the expected value of the profitable option was made more distinct from the expected value of the neutral options (Table 1). The clear distinction between options will have reduced uncertainty in Study 2 and 3. Additionally, the local visual radius in the previous study (Ritter *et al.*, 2021) allowed participants to observe the behavior of other group members only when they were close to them. With the global visual radius in Study 3 and the information about the choices of all group members in Study 2, participants had comparatively more information about the behavior of others. This means that groups in these studies could have made use of a global information transmission between members, even though previous findings mainly show local information transmission in collective information pooling (Helbing, Farkas and Vicsek, 2000; Couzin *et al.*, 2002; Conradt and Roper, 2009; Moussaïd *et al.*, 2009). With this large amount of information to go on in a less uncertain environment, participants needed only little exploration before being able to identify the most profitable option. Once participants had identified the best option, they could transition from exploration of options to exploitation of the best. This seems even more likely as the predicted probability of choosing the profitable field in early rounds (see Figure 3 and 5) is already higher (> 35%) than predicted by chance alone (25%).

In summary, Study 2 and 3 could replicate the previously found effect (Ritter *et al.*, 2021) that groups can identify the best option under uncertainty, while differences between cohesive groups and groups with independent members could not be found. It is for future research to decide whether this lack of differences is due to methodological limitations of the presented empirical studies or whether group cohesion simply does not significantly impact uncertainty reduction in human groups.

The main goal of Study 3 was to identify and disentangle the group processes that might emerge to reduce uncertainty in group decision making. To this end, we explored whether behavioral measurements of two specific processes, emerging leader-/followership patterns and entitativity, would correspond to self-reported participant experience and typical correlates of these group processes. Results showed that leader-/followership as operationalized by the L-F-score was positively associated with self-reported experience of leading or following. Yet, typical trait correlates of leadership behavior (self-confidence, achievement maximization, decisiveness, risk propensity) were not associated with leadership in this study. This corresponds to previous findings: Boos and colleagues (2014) found leadership behavior in the HoneyComb paradigm was not associated with the Big-Five personality factors and recent work showed that links between personality and leadership are highly conditioned on the group or team context (Mitchell, Lemoine and Lee, 2022). Notably, we could show that leadership and followership emerged in most groups in Study 3, regardless of experimental condition. A first analysis suggests that leaderless groups (i.e., groups in which leader-/followership did not emerge) performed worse in terms of decision quality. This is in line with findings that the emergence of leadership can have an advantageous effect in group movement and group decision making (Boos *et al.*, 2014; Ioannou, Singh and Couzin, 2015; Strandburg-Peshkin *et al.*, 2015; Sridhar *et al.*, 2021; von Ameln, 2021). However, as most groups in our study spontaneously exhibited leader-/followership, this result can be only preliminary in nature.

In terms of group cohesion, Study 3 suggests that behavioral cohesion as measured by spatial distribution on the HoneyComb playing field (field distribution) is closely associated with self-reported group cohesion measures, such as entitativity, interactivity, and shared goals. Manipulation of group cohesion through implementing a cohesion reward also proved to be successful.

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Importantly, participants in groups with higher behavioral cohesion (field distribution) were also more likely to make better decisions, regardless of condition. This finding is contrary to previous findings (Ritter *et al.*, 2021) and shows the importance of future research investigating the effect of cohesion on group decision making. Overall, these are encouraging findings as they indicate that behavioral measures of group cohesion and leader-/followership can be used to identify basic processes of group behavior and, perhaps, even predict group performance in decision making under uncertainty.

In summary, this paper contributes to the theoretical understanding of group decision processes under uncertainty by identifying key elements of the decision task as well as emergent group processes (i.e., group cohesion, leadership) that contribute to the decision outcome. While the theoretical relationship of cohesion and group decision outcomes could not be solved conclusively, this paper was able to identify nonstationarity of a decision problem (see Study 1) as an important determinant of decision outcomes. This has methodological implications as future group decision studies should be designed with this finding in mind. Additionally, this paper could show that emergent group processes such as leadership spontaneously emerge in a reductionist experimental group movement paradigm and that these processes might play a role in group decision making under uncertainty. Moreover, findings in this paper indicate that behavioral patterns of group cohesion and leadership correspond to subjective reports of participants, paving the way for the development of behavioral markers of these processes.

5.1 Limitations and Future Directions

The main limitation of this paper is the low difficulty of the group decision task used in Study 2 and 3. In choosing to adapt the task from a previous work (Ritter *et al.*, 2021), the uncertainty inherent in the task was reduced so much as to create a ceiling effect of performance in the task. Adaptations directed at reducing uncertainty in the current studies might have overshot their goal and future research should determine whether the expected relationships present themselves in a study with medium uncertainty. Future adaptations should adjust the expected values associated with the reward choices and, possibly, restrict the visual radius of the HoneyComb paradigm to a local visual radius again in which participants can only observe the behavior of group members in their close vicinity. In this way local information transmission between group members (e.g., Conradt and Roper, 2005) might be investigated more closely. In addition, future simulation studies might be used to determine a well-balanced design of different choice options so that experimental studies can be designed accordingly.

Additionally, the studies in this paper manipulated only two levels of group cohesion. While group cohesion was not incentivized in the independence condition, spontaneous group cohesion emerged (see Study 3), albeit it was lower than in the cohesion condition. Future studies might investigate three levels of group cohesion (e.g., none, medium, and high) in order to investigate the claim that "right balance of interdependence and independence" (Conradt, 2012, p. 1) might be crucial for group decision making.

While this paper was able to provide first insights into processes that groups might use while making decisions under uncertainty (i.e., cohesive behavior, leader-/followership, collective information pooling), the three presented studies were not able to clearly differentiate between these processes. Even more so, the experimental paradigm might not be able to clearly distinguish the contributions of environmental factors and social information (Mehlhorn *et al.*, 2015). Future studies might address this issue, for example, by using different operationalizations (e.g., centrality of group networks to

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classify leadership, Lusseau and Conradt, 2009; first-mover classification, Boos *et al.*, 2014) or analysis methods (testing differences between cohesion and their effect on decision making, Casey-Campbell and Martens, 2009; applying time-dependent cross-correlations, Lombardi, Warren and di Bernardo, 2020).

The samples recruited for Study 2 and 3 consisted mainly of German psychology students and are, therefore, not representative of the general population. We argue that the processes investigated in this paper are very basic and can also be observed in some primate groups (e.g., Conradt *et al.*, 2009). To the best of the authors' knowledge, there is little to no evidence suggesting that the observed processes might differ significantly across cultures. However, previous research should confirm this assumption by comparatively testing our results across representative samples from different backgrounds.

In order to design future studies, simulations of group decision making, as in Study 1, should be used to determine parameters or principles that might guide group decision making or group movement (e.g., Hornischer *et al.*, 2022). First, the basic ε-greedy algorithm that was used to model behavior in the experiment might be adapted to include (a) the "soft max decision rule" or (b) a combination of the soft max decision rule and an "uncertainty bonus" (Cohen, McClure and Yu, 2007). Using the soft max decision rule, options are chosen with a probability weighted by their estimated values. This means, as in the ε-greedy algorithm, agents preferentially choose the option with the highest value. However, this rule is "softened" by the relative value of other options and noise added to the decision rule (i.e., even when a decision rule would dictate exploitation of an option, agents might randomly choose another option to explore). Lastly, the uncertainty bonus expands the soft max decision rule by promoting exploration of previously unchosen options. This is implemented by increasing the probability of choosing options that have not been explored by the uncertainty bonus, thereby driving exploration. Another possibility is to include a function with which the exploration parameter ε decreases over time, in order to model findings on human exploration behavior (e.g., Bechara *et al.*, 1994) more closely. Using these adaptations of the ε-greedy algorithms has been shown to be more suited to predict behavior under unexpected uncertainty or volatility (i.e., when rewards might vary above and beyond the known uncertainty of an option; Bland and Schaefer, 2012; Cohen, McClure and Yu, 2007). In this way, these algorithms might be invaluable in investigating how exploration/exploitation decisions are made by groups. Second, future simulation studies should aim to model mechanisms that balance personal preferences and goal-orientation with social motivations (e.g., Sridhar *et al.*, 2021) in order to reflect different motivations guiding decisions of individual group members. Third, the refinement of the ε-greedy algorithm can be informed by studying or including other decision models, such as Bayesian SPRT, drift-diffusion, or adaptive gain models to determine stopping rules for exploration (Tickle *et al.*, 2021). Another possibility might be to use Bayesian network decision making models that incorporate agents holding private information and leveraging this for collective decisions (Hązła *et al.*, 2021).

In summary, we argue that future research investigating group decision making under uncertainty should start with simulations in order to pin-point key variables and parameters within this opaque process. In this way, empirical studies can be designed to specifically assess, manipulate, or control the effect of these variables in empirical investigations of human behavior. This approach has two advantages: First, simulations can include a wide range of variables, test boundary conditions, and reveal relationships that can generate new hypotheses. Second, using simulations first and designing targeted experiments based on them will direct researchers' resources at promising relationships, instead of running a series of costly experiments.

doi: 10.53846/goeduss-9589

6 Conclusion

In this paper, we replicate findings showing that groups are able to successfully cope with an uncertain environment. Contrary to previous findings (Ritter *et al.*, 2021), groups performed well in the decision task even when they were rewarded for cohesive behavior, and longer exploration times were not detrimental to group decision making. Future research will have to assess whether these findings hold when more uncertainty is introduced into the group decision task. We were able to provide first results that both behavioral (vs. manipulated) cohesion and leader-/followership might contribute to uncertainty reduction in groups and might be identified using behavioral markers. Future research might use methodological insights from this paper on the interchange of computer simulation and experimental design to further investigate the interrelations of group cohesion, exploration, and leadership in group decision making under uncertainty. For now, we conclude that when the environment is laid out in no uncertain terms, group cohesion will not deter groups from exploring their options and making profitable decisions.

7 Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

8 Author Contributions

MR, JP, and MB contributed to conception and design of all three studies. MR and LM were responsible for writing of the preregistration of Study 3. JP programmed the simulation study and the HoneyComb paradigm. EB programmed the online experiment in Study 2. JP was responsible for data collection in Study 1. EB and LM were responsible for data collection in Study 2 and 3, respectively. MR conducted all data analyses and wrote the first draft of this manuscript. MR and MB were responsible for scientific supervision. MR, JP, and MB contributed to revision of the manuscript. All authors read and approved the submitted version.

9 Funding

Data collection of Study 3 was partially funded by a grant of the Südniedersachsen Innovations Campus to Lara Morscheck. We acknowledge support by the Open Access Publication Funds of the Göttingen University.

10 Acknowledgments

We want to thank Paul Pritz for our discussions, his helpful ideas on and proof-reading of this manuscript. We thank Greta Heinemeyer and Phuong Anh Tran for their help with data collection.

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12 Data Availability Statement

The datasets analyzed for this study can be found in the OpenScienceFramework repository of this project: https://s.gwdg.de/y0cOIu.

doi: 10.53846/goedis-9589

13 Tables

Table 1.

	Ritter et al. (2021) / Study 1	Study 2	Study 3
Task	Movement paradigm (HoneyComb) / Simulation	Card-choice task	Movement paradigm (HoneyComb)
Response format	Follow pre-programmed leader	Choose card stack	Move to reward field
Social Information	Movement Local visual radius	Minimal Feedback of others' choices	Movement Global visual radius
Conditions	Single, Independence, Cohesion	Independence, Cohesion	Independence, Cohesion
Cohesion Reward	Multiplicative	Additive (3 cent)	Additive (3 cent)
Options		Option name Payout; Probability Expected Value	
Most profitable	Profitable leader 20 cent; 80% 480 cent	Profitable stack 30 cent; 80% 720 cent	Profitable field 30 cent; 80% 720 cent
Secure Neutral	Secure neutral leader 10 cent; 90% 270 cent	Secure neutral stack 10 cent; 90% 270 cent	Secure neutral field 10 cent; 90% 270 cent
Risky Neutral	Risky neutral leader 20 cent; 45% 270 cent	Risky neutral stack 30 cent; 30% 270 cent	Risky neutral field 30 cent; 30% 270 cent
Least profitable	Unprofitable leader 20 cent; 20% 120 cent	Unprofitable stack 10 cent; 20% 60 cent	Unprofitable field 10 cent; 20% 60 cent

doi: 10.53846/goedis-9589

Table 2.

	1	2	3	4	5	5.1	5.2	5.3	5.4	6	7
2	-0.199										
3	0.269*	0.219									
4	0.324**	-0.313**	0.501***								
5	0.018	-0.024	0.073	0.091							
5.1	0.037	0.033	0.048	0.066	0.882***						
5.2	0.053	-0.183	0.019	0.131	0.749***	0.610***					
5.3	-0.013	0.038	0.093	0.074	0.846***	0.623***	0.486***				
5.4	-0.007	-0.024	0.066	0.034	0.793***	0.652***	0.464***	0.543***			
6	0.094	-0.117	0.162	0.102	0.338***	0.371***	0.312**	0.111	0.380***		
7	0.054	0.217*	0.032	-0.145	-0.368***	-0.247*	-0.250*	-0.401***	-0.278**	0.05	
8	0.131	-0.15	0.218	0.142	0.174	0.127	0.193	0.189	0.05	0.206*	-0.035

Note. Pearson correlation coefficients (*r*) of associations between observed leadership behavior (1), self-reported leadership behavior (2-4), and typical leadership correlates (5-7). 1 – L-F-scores, 2 – self-reported followership, 3 – self-reported leadership, 4 – self-reported role (1 = follower, 7 = leader), 5 – self-confidence, 5.1 – emotional self-esteem, 5.2 – social self-esteem in contact with others, 5.3 – social self-esteem when critiqued, 5.4 – performance-related self-esteem, 6 – achievement motivation, 7 – decisiveness, 8 – risk propensity.

* $p < .05$, ** $p < .01$, *** $p < .001$

doi: 10.53846/goedss-9589

Table 3.

	1	2	3	4	5	6	7	8	9	10	11
2	0.866***										
3	-0.799***	-0.862***									
4	-0.842***	-0.915***	0.967***								
5	0.650***	0.656***	-0.608***	-0.655***							
6	0.153	0.189	-0.239*	-0.233*	-0.026						
7	-0.632***	-0.646***	0.660***	0.666***	-0.601***	-0.436***					
8	0.595***	0.590***	-0.589***	-0.616***	0.598***	0.113	-0.637***				
9	0.559***	0.583***	-0.591***	-0.597***	0.614***	0.239*	-0.653***	0.654***			
10	0.039	0.09	-0.153	-0.149	0.249*	0.082	-0.233*	0.280**	0.471***		
11	0.557***	0.590***	-0.548***	-0.585***	0.552***	0.281**	-0.673***	0.577***	0.719***	0.453***	
12	0.342***	0.362***	-0.359***	-0.372***	0.217*	0.19	-0.296**	0.443***	0.413***	0.261*	0.381***

Note. Person correlation coefficients (*r*) of associations between manipulated (1), observed (2-4), and self-reported cohesion and entitativity measures. 1 – condition, 2 – transitivity, 3 – field distribution, 4 – field distribution (move level), 5 – interaction rating (start of the game), 6 – interaction rating (during the game), 7 – interaction rating (none), 8 – entitativity, 9 – entitivity, 10 – similarity, 11 – interactivity, 12 – goals. All correlations are Pearson correlation coefficients (with all correlations with condition being point-biserial correlations).

* $p < .05$; ** $p < .01$; *** $p < .001$

doi: 10.53846/goedis-9589

14 Figure legends

Figure 1. Results of Study 1. (**A** – upper panel) shows how often each field was chosen (in percent) by 6 simulated agents (30 rounds, 1000 runs) with no group bonus ("None"), an additive bonus, and a multiplicative bonus. The lower panel (**A**-b) shows the predicted number of agents choosing the profitable or secure neutral field, depending on round and group bonus. (**B –** upper panel) shows how often each field was chosen (in percent) by 6 simulated agents (30 rounds, 1000 runs) with different exploration parameters (Epsilon). The lower panel (**B**-b) shows the predicted number of agents choosing the profitable or secure neutral field, depending on round and exploration length.

Figure 2. Screenshots from the experiment as seen by participants. The upper screenshot shows a screen in the independent condition when the participant received a pay-out for choosing a card (green bar). The lower screenshots show the cohesion condition in which participants received a group bonus (blue bar) and received payout (left, green bar) or did not receive payout (right, red bar). Card stacks were colored differently and colors were randomly assigned in the beginning of each game. Participants were naïve to the exact pay-out probabilities and amounts and had to infer the best stack through exploring the different card stacks.

Figure 3. (**H2**) Lower panel: Predicted probability of choosing the profitable card stack in each round. Lines represent the marginal effects, shaded areas represent the 95% C.I.. Upper panel: Raw frequency of profitable card stack choices over rounds, separate for cohesion and independent condition. (**H4.2**) Relative frequency (percentage) of card stack choices, separate for cohesion and independent condition.

Figure 4. Screenshot of the HoneyComb game environment. The colored circles are the reward fields. The colored avatars are moving across the field. The avatar of the participant (black) is larger than the avatar of the other participants. Small tails on the avatars are shown for 1000ms after each move to indicate from where the avatar had moved onto the current field. On the top-left, the remaining time in each round ("Time-Out"), the current account balance of the participant ("Kontostand"), and the remaining moves in the current round ("Restzüge") are shown. All colors are randomly assigned at the beginning of each game and remain the same during all 30 rounds of the game (1 game = 30 rounds). Colors were chosen to be easily discriminable. Participants were naïve to the exact pay-out probabilities and had to infer the best reward field through exploration.

Figure 5. (**H2**) Lower panel: Predicted probability of choosing the profitable field in each round. Lines represent the marginal effects, shaded areas represent the 95% C.I.. Upper panel: Raw frequency of profitable field choices over rounds, separate for cohesion and independent condition. (**H4.2**) Relative frequency (percentage) of reward field choices, separate for cohesion and independent condition.

Figure 6. Ratings of interactivity (retrospective self-report) during the first (round 1-10), second (11-20), and last third (21-30) of the game (7-point Likert scale). Violin plots show density distributions of ratings. Boxes represent the interquartile range, the thick line in the box represents the median, whiskers represent the range of data, dots represent raw data.

Figure 7. Cumulative L-F-score sums over rounds. Each panel shows data from one group. Each line represents the cumulative L-F-score sum of one individual participant. Higher scores represent leadership behavioral patterns, while lower scores represent followership behavioral patterns. More divergent cumulative L-F-score sums indicate spontaneous emergence of leader-/follower roles within a group.

doi: 10.53846/goediss-9589

Chapter 4: Reduction of personal uncertainty

Chapter 4.1: Measuring Collective Trust

Ritter, M., Kroll, C. F., Voigt, H., Pritz, J., and Boos, M. (2022). The Collective Trust Game: An online group adaptation of the Trust Game based on the HoneyComb paradigm. *Journal of Visualized Experiments, 188*, e63600. https://doi.org/10.3791/63600

Supplementary Material:
https://s.gwdg.de/w88YNL (DOI 10.17605/OSF.IO/U24PX)

doi: 10.53846/goediss-9589

The Collective Trust Game: An Online Group Adaptation of the Trust Game Based on the HoneyComb Paradigm

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Citation

Ritter, M., Kroll, C.F., Voigt, H., Pritz, J., Boos, M. The Collective Trust Game: An Online Group Adaptation of the Trust Game Based on the HoneyComb Paradigm. *J. Vis. Exp.* (188), e63600, doi:10.3791/63600 (2022).

Date Published

October 20, 2022

DOI

10.3791/63600

URL

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Abstract

The need to understand trust in groups holistically has led to a surge in new approaches to measuring collective trust. However, this construct is often not fully captured in its emergent qualities by the available research methods. In this paper, the Collective Trust Game (CTG) is presented, a computer-based, multi-agent trust game based on the HoneyComb paradigm, which enables researchers to assess the emergence of collective trust. The CTG builds on previous research on interpersonal trust and adapts the widely known Trust Game to a group setting in the HoneyComb paradigm. Participants take on the role of either an investor or trustee; both roles can be played by groups. Initially, investors and trustees are endowed with a sum of money. Then, the investors need to decide how much, if any, of their endowment they want to send to the trustees. They communicate their tendencies as well as their final decision by moving back and forth on a playfield displaying possible investment amounts. At the end of their decision time, the amount the investors have agreed upon is multiplied and sent to the trustees. The trustees have to communicate how much of that investment, if any, they want to return to the investors. Again, they do so by moving on the playfield. This procedure is repeated for multiple rounds so that collective trust can emerge as a shared construct through repeated interactions. With this procedure, the CTG provides the opportunity to follow the emergence of collective trust in real time through the recording of movement data. The CTG is highly customizable to specific research questions and can be run as an online experiment with little, low cost equipment. This paper shows that the CTG combines the richness of group interaction data with the high internal validity and time-effectiveness of economic games.

doi: 10.53846/goediss-9589

Introduction

The Collective Trust Game (CTG) provides the opportunity to measure collective trust online within a group of humans. It generalizes the original Trust Game by Berg, Dickhaut, and McCabe[1] (BDM) to the group level and can capture and quantify collective trust in its emergent qualities[2,3,4], as well as related concepts such as fairness, reciprocity, or forward-signaling.

Previous research mostly conceptualizes trust as a solely interpersonal construct, for example, between a leader and a follower[5,6], excluding higher levels of analysis. Especially in organizational contexts, this might not be enough to comprehend trust holistically, so there is great need to understand the processes by which trust builds (and diminishes) on a group level.

Recently, trust research has incorporated more multi-level thinking. Fulmer and Gelfand[7] reviewed a number of studies on trust and categorized them according to the level of analysis that is investigated in each study. The three different levels of analysis are interpersonal (dyadic), group, and organizational. Importantly, Fulmer and Gelfand[7] additionally distinguish between different referents. The referents are those entities at which trust is directed. This means that when "A trusts B to X", then A (the investor in economic games) is represented by the level (individual, group, organizational) and B (the trustee) is represented by the referent (individual, group, organizational). X represents a specific domain to which trust refers. This means that X can be anything such as a generally positive inclination, active support, reliability, or financial exchanges as in economic games[1].

Here, collective trust is defined based on Rousseau and colleagues' definition of interpersonal trust[8], and similar to previous studies on collective trust[9,10,11,12,13,14]; collective trust comprises a group's intention to accept vulnerability based upon positive expectations of the intentions or behavior of another individual, group, or organization. Collective trust is a psychological state shared among a group of humans and formed in interaction among this group. The crucial aspect of collective trust is therefore the sharedness within a group.

This means that research on collective trust needs to look beyond a simple average of individual processes and conceptualize collective trust as an emergent phenomenon[2,3,4], as new developments in group science show that group processes are fluid, dynamic, and emergent[2,15]. We define emergence as a "process by which lower level system elements interact and through those dynamics create phenomena that manifest at a higher level of the system"[16] (p. 335). Proposedly, this should also apply to collective trust.

Research that reflects the focus on emergence and dynamics of group processes should use appropriate methodologies[17] to capture these qualities. However, the current status of collective trust measurement seems to lag behind. Most studies have employed a simple averaging technique across the data of each individual in the group[9,10,12,13,18]. Arguably, this approach has only little predictive validity[2] as it disregards that groups are not simply aggregations of individuals but higher-level entities with unique processes. Some studies have tried to address these drawbacks: A study by Adams[19] employed a latent variable approach, while Kim and colleagues[10] used vignettes to estimate collective trust. These approaches are promising in that they recognize

doi: 10.53846/goediss-9589

collective trust as a higher-level construct. Yet, as Chetty and colleagues[20] note, survey-based measures lack incentives to answer truthfully, so research on trust has increasingly adopted behavioral or incentive-compatible measures[21,22].

This concern is addressed by a number of studies which have adapted a behavioral method, namely the BDM[1], to be played by groups[23,24,25,26]. In the BDM, two parties act as either investors (A) or trustees (B). In this sequential economic game, both A and B receive an initial endowment (e.g., 10 Euros). Then, A needs to decide how much, if any, of their endowment they would like to send to B (e.g., 5 Euros). This amount is then tripled by the experimenter, before B can decide how much, if any, of the received money (e.g., 15 Euros) they would like to send back to A (e.g., 7.5 Euros). The amount of money A sends to B is operationalized to be the level of trust of A toward B, while the amount that B sends back can be used to measure the trustworthiness of B or the degree of fairness in the dyad of A and B. A large body of research has investigated behavior in dyadic trust games[27]. The BDM can be played both as a so-called 'one-shot' game, in which participants play the game only once with a specific person, and in repeated rounds, in which aspects such as reciprocity[28,29] as well as forward-signaling might play a role.

In many studies that have adapted the BDM for groups[23,24,25,26], either the investor, the trustee, or both roles were played by groups. However, none of these studies recorded group processes. Simply substituting individuals with groups in study designs does not meet the standards Kolbe and Boos[17] or Kozlowski[15] set up for investigations of emergent phenomena. To fill this gap, the CTG was developed.

The aim of developing the CTG was to create a paradigm that would combine the widely used BDM[1] with an approach that captures collective trust as an emergent behavior-based construct that is shared among a group.

The CTG is based on the HoneyComb paradigm by Boos and colleagues[30], that has also been published in the Journal of Visualized Experiments[31] and has now been adapted for use in trust research. As described by Ritter and colleagues[32], the HoneyComb paradigm is "a multi-agent computer-based virtual game platform that was designed to eliminate all sensory and communication channels except the perception of participant-assigned avatar movements on the playfield" (p. 3). The HoneyComb paradigm is especially suitable to research group processes as it allows researchers to record the movement of members of a real group with spatio-temporal data. It could be argued that, next to group interaction analysis[17], HoneyComb is one of the few tools that allows researchers to follow group processes in great detail. In contrast to group interaction analysis, quantitative analysis of the spatio-temporal data of HoneyComb is less time-intensive. Additionally, the reductionist environment and possibility to exclude all interpersonal communication between participants except the movement on the playfield allows researchers to limit confounding factors (e.g., physical appearance, voice, facial expressions) and create experiments with high internal validity. While it is difficult to identify all influential aspects of a group process in studies employing group discussion designs[33], the focus on basic principles of group interaction in a movement paradigm allows researchers to quantify all aspects of the group process in this experiment. Additionally, previous research has used proxemic behavior[34]-so reducing space between oneself and another individual-to investigate trust[35,36].

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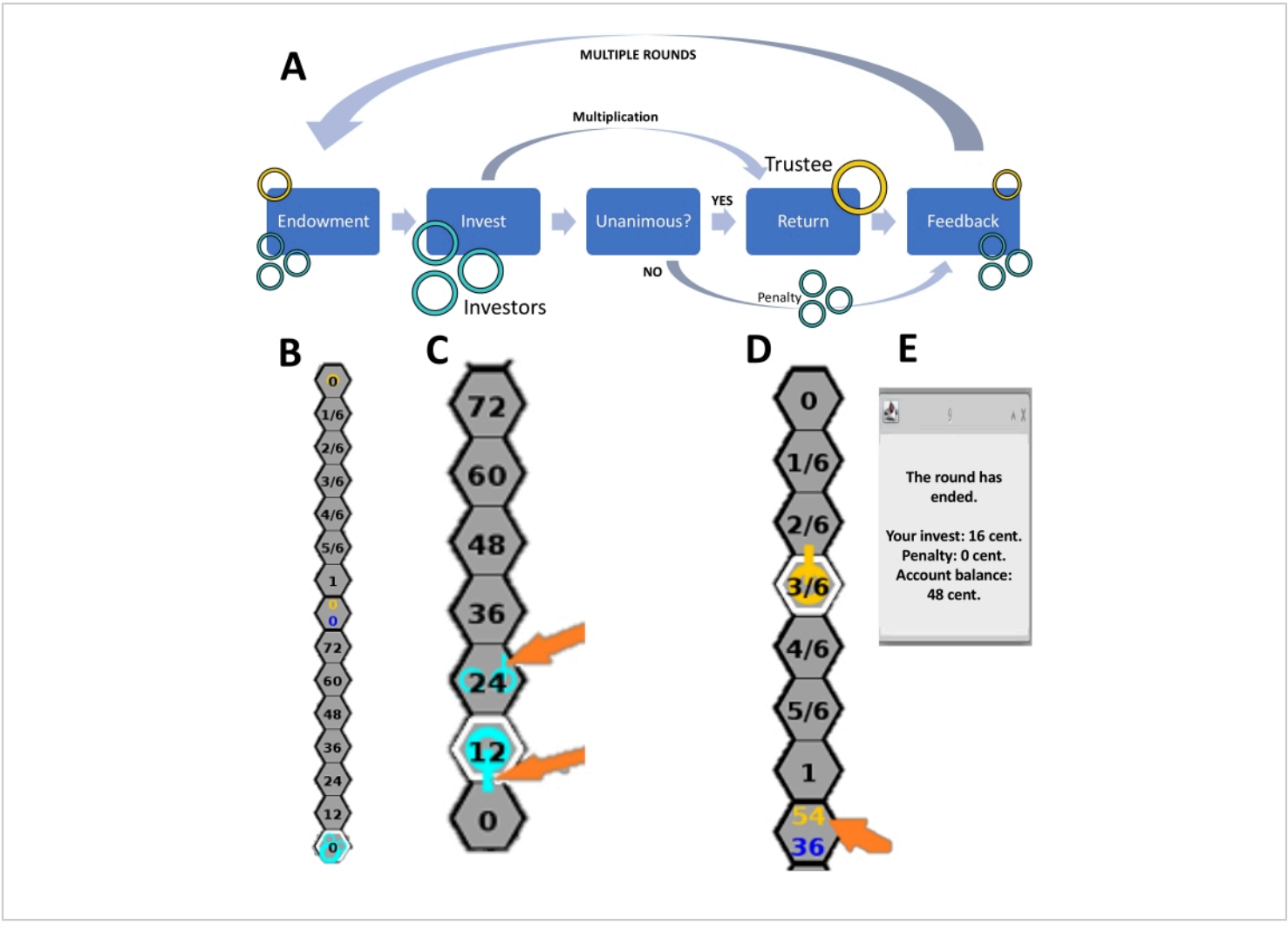

Figure 1: Schematic overview of the CTG. (**A**) Schematic procedure of one CTG round. (**B**) Initial placement of avatars at beginning of round. The three blue-colored investors are standing on the initial field "0". The yellow trustee is standing on the initial field "0". (**C**) Screenshot during the invest phase showing three investors (blue avatars) on the lower half of the playfield. One (big blue avatar) is currently standing on "12", two investors are currently standing on "24". Two avatars have tails (indicated by orange arrows). The tails are indicating from which direction they moved to their current field (e.g., one investor (big blue avatar) just moved from "0" to "12"). The avatar without a tail has been standing on this field for at least 4000 ms. (**D**) Screenshot during the return phase showing one trustee (yellow avatar) and the upper half of the playfield. The trustee is currently standing on "3/6" and has recently moved there from "2/6" as indicated by the tail. The blue number below (36) indicates the investment made by the investors. The yellow number, indicated by the arrow, is the current return (54) as depicted in the middle of the playfield. The return is calculated as follows: (invest (36 cents) x 3) x current return fraction (3/6) = 54 cent. (**E**) Pop-up window giving feedback to participants on how much they have earned during the round, displayed for 15 s after time-out of trustee expires. Please click here to view a larger version of this figure.

The main procedure of the CTG (**Figure 1A**) is closely based on the procedure of the BDM[1], in order to make results comparable to previous studies using this economic game. As the HoneyComb paradigm is based on the principle of movement, participants indicate the amount they would like to invest or return by moving their avatar onto the small hexagon field that indicates a certain amount of money or fraction to return (**Figure 1C,D**). Prior to each round, both the investors and trustees are endowed with a certain amount of money (e.g., 72 cents) with the investors being placed in the lower half of the playfield and the trustees being placed in the upper half of the playfield (**Figure 1B**). In the default setting, the investors are allowed to move first, while the trustees remain still. The investors move across the playfield to indicate how much, if any, of their endowment they would like to send to the trustee (**Figure 1C**). Through moving back and forth on the field, participants may also communicate to other investors how much they would like to send to the trustee. Depending on the configuration, participants need to reach a unanimous decision on how much they would like to invest by converging on one playfield when the time-out is reached. Unanimous decisions were required in order to enforce that investors need to interact with each other, instead of simply play alongside one another. If the investors do not reach a joint decision, a penalty (e.g., 24 cents) is deducted from their account. This was implemented to ensure that investors would be highly motivated to reach a shared level of collective trust. Once the investors' time is up, the invested money is multiplied and sent to the trustees who are then allowed to move while the investors remain still. The trustees indicate through movement how much they would like to return to the investors (**Figure 1D**). The available return options are displayed as fractions on the playfield to keep cognitive load on trustees comparatively low. The playfield on which trustees stand once their allocated time runs out indicates which fraction (e.g., 4/6) is returned to investors. The round ends with a pop-up (**Figure 1E**) that summarizes for each participant how much they earned during that round and what their current account balance is.

Rounds should be repeated multiple times. Researchers should have participants play the CTG for at least 10 or 15 rounds in the same roles. This is necessary as collective trust is an emergent construct and needs to develop during repeated interactions within a group. Similarly, other concepts such as forward-signaling (i.e., reciprocating high returns from trustees with high investments in the next round) will only emerge in repeated interactions. It is crucial, however, that participants are unaware of the exact number of rounds to be played as it has been shown that behavior can drastically change when participants are aware that they are playing the last round (i.e., more unfair behavior or deflections in economic games[37,38]).

In this way, the CTG provides information about the emergence of collective trust on multiple levels. First, the level of collective trust exhibited in the final round should be a close representation of the shared level of trust investors hold towards the trustee(s). Second, the amount invested in each round can serve as a proxy for the emergence of collective trust over repeated interactions. Third, movement data sheds light on the group process that determines how much money is invested in each round.

Protocol

Data collection and data analysis in this project have been approved by the Ethics Committee of the Georg-Elias-Müller Institute for Psychology of the University of Göttingen (proposal 289/2021); the protocol follows the guidelines on human research of the Ethics Committees of the Georg-Elias-

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Müller-Institute for Psychology. The CTG software can be downloaded from the OSF project (DOI 10.17605/OSF.IO/U24PX) under the link: https://s.gwdg.de/w88YNL.

1. Prepare technical setup

1. Prepare online consent forms and questionnaires
    1. Prepare an online consent form in an online questionnaire tool.
    2. If applicable, prepare an online questionnaire in an online questionnaire tool.
       NOTE: It is possible to include a short questionnaire within the HoneyComb program (see step 1.3.5). To use longer questionnaires, use a separate online questionnaire tool instead. Examples for online questionnaire tools are given in the **Table of Materials**.
2. Prepare remote desktop server
    1. Install a Linux-based operating system on a remote server. If possible, ask technical assistants about the available resources at the institution. Otherwise, follow an installation guideline[39].
    2. Create different users on this server[40].
        1. Create a user **admin** which has root permissions and is accessed solely by the technical lead in the experiment.
        2. Create a user **experimenter** which has permissions to create shared folders, import and export data, and can be accessed by all personnel collecting data (including students/research assistants, etc.).
        3. Create multiple users named **participant-1, participant-2**, etc.
           NOTE: Researchers will only be able to test as many participants in one experimental session as users that are created.
    3. Execute the command **java -version** on the admin user to ensure that a Java runtime environment is available on the server. If not, install the most recent Java version before continuing and make sure all users can access it.
    4. Install the program
        1. Download the program.
           NOTE: The program can be downloaded as a zip-file **HC_CTG.zip** containing 1) the runnable HC.jar, 2) three files for configuration (**hc_server.config, hc_panel.config**, and **hc_client.config**), and 3) two subfolders named **intro** and **rawdata**.
        2. Create a folder on the experimenter user and share it with the other users[41]. Extract the files from the compressed file **HC_CTG.zip** into this folder.
        3. For each participant user, access this shared folder and check that the user can access the files.
3. Open the three configuration files.
    1. Edit **hc_server.config** and save the edited file.
        1. Configure the number of players by setting **n_Pl** to the desired number. For example, enter **4** behind the **=**.

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2. Configure the number of rounds to play (**playOrder**) by repeating the game number **54a** (e.g., **54a, 54a, 54a, 54a** for four rounds).
   NOTE: **i54a** stands for the instructions and should not be deleted in the configuration file.
3. Configure whether a questionnaire should be shown in HoneyComb by including **200** at the end of **playOrder**. Delete **200** if a separate online questionnaire tool is used.
4. Configure the investment scale. To configure the scale for investors (**iscale**), enter which values should be available as investment steps (e.g., 0, 12, 24, 36, 48, 60, 72). Use integers that are multiples of three so that payouts are also integers.
   NOTE: These configured values are also displayed as possible investment steps to the investors.
   1. Configure the display scale for trustees (**tlabel**) by choosing which values should be displayed as possible returns on the playfield (e.g., 0, 1/6, 2/6, 3/6, 4/6, 5/6, 1).NOTE: This scale does not influence the calculation of payouts.
   2. Configure the scale for trustees (**tscala**) by choosing which return values should be possible as returns (e.g., 0, 0.166666, 0.3333, 0.5, 0.6666, 0.833331, 1). Use digital values only (i.e., no fractions).
      NOTE: These values are used to calculate payouts and are NOT displayed on the playfield.
   5. Configure the time-ins (**timeInI** for investors, **timeInT** for trustees) and time-outs (**timeOutI** for investors, **timeout** for trustees) in seconds. For example, timeInI = 0, timeOutI = 30, timeInT = 30, and timeout = 45.
   6. Configure the amount of money investors and trustees are endowed with in each round in cents (**r52**).
   7. Configure the factor with which the investment is multiplied before being sent to the trustee (**f52**).
   8. Configure whether the group has to reach a unanimous decision (set **bUnanimous** to **true**) or not (set **unanimous** to **false**)
   9. Configure whether the group is paid out in equal parts (set **bCommon** to **true**) or according to how much each investor has contributed to the investment (set **bCommon** to **false**).
   10. If **bUnanimous** is set to **true**, configure the penalty-the amount of money deducted from the investors if a unanimous decision is not reached (**p52**).
2. Edit **hc_client.config** if necessary. Make sure to set **ip_nr** to **localhost** so that the clients can connect to the experimenter.
3. Edit **hc_panel.config**.
   1. Adjust the size of the hexagons (**radius**) according to the screen resolution. Test the experiment on multiple different screens to ensure that the experiment will be visible on a wide variety of screens.

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2. Adjust the text that is displayed on the playfield under **labels** (e.g., **Your role is: investor, Account Balance**, etc.)

4. Adjust and/or translate the instructions, if necessary. To do so, edit and save the simple HTML-files (**Figure 2A**) in the "intro" folder within the HoneyComb program folder.

5. If you want to use the questionnaire within the HoneyComb program, adjust and/or translate the questionnaire in the file **qq.txt** and save the file.

6. Keep this setup constant across all experiment sessions (within one experiment condition). Document all configurations.

2. Participant recruitment

1. Online advertisement

    1. Recruit participants over available channels (e.g., social media, university blog, flyer with QR-code). Name important information about the experiment, such as its purpose, duration, and maximum payment calculated according to game behavior.
    NOTE: The sample presented here was recruited *via* an online blog for psychology students at the University of Göttingen as well as unpaid advertisements in social media groups. An example flyer can be seen in **Supplemental Figure 1**.

    2. Make potential participants aware that participation will require usage of personal laptops/PCs with a stable internet connection and in a quiet, secluded area. Make participants aware that they might need to install a program to establish the Remote Desktop connection.
    NOTE: Participation *via* mobile phones or tablets is not possible.

    3. Make sure the participants meet the experiment's inclusion criteria such as language requirements or color sightedness.

    4. Make sure the participants have not taken part in previous experiments on the CTG.

2. Book experimental sessions with the participants

    1. Ask the participants to book time-slots for their participation.

    2. Use a participant management software to send automated invitation or reminder e-mails.

    3. Overbook time-slots by at least one participant to ensure enough participants are present to run the experiment.

3. Send participants a confirmation e-mail with the following details: guide on computer setup, installation of Remote Desktop Connection Tool, and establishing connection to Remote Desktop. Make sure to NOT send any log in information yet, in order to avoid technical issues due to earlier log in.

4. Send participants reminder e-mails about 24 h prior to the experiment, including the link to the video conferencing platform. Include the information about installation that was sent in the confirmation e-mail.

3. Experimental setup (before each experimental session)

1. Prepare the video conferencing platform (**Figure 3**)

    1. Make sure the participants are blocked from sharing their microphone or camera. Make sure the participants cannot see each other's names.

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2. Share the experimenter's microphone and camera, and share the screen with minimal instructions on the video conferencing platform (**Figure 3**).

2. Prepare the remote desktop

1. User **experimenter**

1. Start a remote desktop connection with the experimenter user. Open the shared folder and start a terminal by right clicking in the directory and choosing **Open Terminal here**.

2. Start the server program HC_Gui.jar by typing the command **java -jar HC_Gui.jar** in the terminal and pressing **ENTER**.

2. Users **participant-1, participant-2**, etc.

1. Establish a remote desktop connection with users **participant-1**, **participant-2, ...**. Open the shared folder and start a terminal in this folder as before.

2. Start the client programs for each user by typing the command **java -jar HC.jar** in the terminal and pressing **ENTER**.

3. Check whether the connections are established correctly on all participant users.

NOTE: The participant users' screens should display the message **Please wait**. **The computer is connecting to the server.** It is recommended to have as many laptops present as users (**Figure 4**).

3. User experimenter

1. Check that a line appears in the server GUI, displaying the IP address of each of the participant users. When all participant users are connected, check that the server program displays the message **All Clients are connected. Ready to start?**. Click on **OK**.

2. Check that the screens of the participant users display the welcome screen of the experiment (first instructions page).

NOTE: The experimenter can prepare the session up to this point.

4. Experimental procedure

1. Admit participants to the video conference at the scheduled experiment time-slot. Welcome all participants using a standardized text. Explain the technical procedure to participants.

2. Share the link to the online consent form. Check that all participants have given written consent.

3. Guide participants to open the Remote Desktop Connection tool and send each participant their individual login data *via* personal chat in the video conference.

NOTE: When the participants log in to the participant users, the notebooks in the laboratory will lose connection to the participant users. From here on, the experiment runs automatically until the participants reach the final page, instructing them to return to the video conference.

4. Have participants confirm that they have read the first instructions page by clicking on **OK**. Once all participants have confirmed, wait until the participants have completed the game.

NOTE: The participants can page through the instructions at their preferred pace. Once all participants have confirmed that they have read the instructions, the CTG automatically commences. The game progresses

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automatically through as many rounds as indicated in the server.config file.

5. Testing phase

    1. Assign participants to one of two roles: investor or trustee.

       NOTE: Multiple participants can be assigned the same role.

    2. Have investors start on the bottom-most field (indicated investment of 0) and trustees on the upmost field (indicating return of 0) (**Figure 1B**).

    3. Instruct participants to move their avatar by **left-click into an adjacent hexagon field**. Instruct participants that only adjacent fields can be chosen and fields cannot be skipped. Instruct participants that their avatar will display a small tail for 4000 ms after each move that indicates the last direction from which they moved to the current field (**Figure 1C**).

    4. Allow investors to move from the beginning (time-in = 0) to indicate through movement how much they would like to invest. After a certain amount of time, prohibit the movement of investors (time-out).

       NOTE: The field on which they stand will then indicate how much is invested. In the middle of the playfield, a blue number will additionally show the amount sent to the trustee. If the experiment is set up to require unanimous invests, investments will only be made if all participants stand on the same field.

    5. Explain in the instructions that the invested amount is multiplied by a factor (e.g., three) and sent to the trustees. Restrict the trustees from moving for as long as the investors are moving by setting the trustee time-in to the length of the trustee time-out.

    6. Instruct the trustees to move to indicate the fraction they would like to return to the investors. Once the trustee time-out is reached, the field on which the trustees stand is taken to indicate the fraction that is returned to the investors. The amount returned is also indicated in the middle of the playfield by a yellow number (**Figure 1D**).

    7. Have the pop-up window display the amount of money the person has earned at the end of the round (**Figure 1E**).

    8. Repeat the game round as needed (i.e., as indicated in the server.config file).

    9. Once all rounds are completed, ask participants to generate a personal unique code so that the in-game earnings can be connected to their name while keeping the behavioral data anonymous.

    10. After participants have generated the code, display a screen which instructs participants to return to the video conference and close the Remote Desktop connection.

        NOTE: The experimental procedure (section 4 in this protocol with 15 game rounds) takes 35 min.

    11. If technical issues or failure of a participant require that the experiment session is aborted, refrain from restarting the experiment with the same participants.

6. Post-testing phase

    1. Once the game is completed, make sure that all participants have closed the Remote Desktop connection. Have the participants fill out questionnaires as seen fit for a specific research question.

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2. While the participants are filling out the questionnaires, close the server program on the experimenter user by clicking on **Stop & Exit**. This will also close the program on the participant users.
3. Thank participants for their time and explain how and when their earnings will be transferred to them. Make sure all participants have left the video conference, especially if another experiment time-slot is scheduled directly afterwards.

5. Finishing the experiment

1. Transfer and back up the data (e.g., in the cloud), in the form of one *.csv and one *.txt file per group and experiment time-slot, marked by a day- and time-stamp of the experiment.
2. Close all Remote Desktop connections.

Representative Results

This paper presents results of a pilot study conducted with the CTG with 16 participants (five men, 11 women; Age: M = 21, SD = 2.07). According to Johanson and Brooks[42], this sample size is sufficient in a pilot experiment, especially when paired with a qualitative approach to reach a high information density about participants' subjective experience during the experiment. It is recommended that whenever researchers intend to adapt the CTG to their specific research idea, for example, by customizing the number of participants within each group, a similar pilot study should be run prior to the main data collection in order to ensure high data quality.

On the basis of the pilot data, this paper provides both an illustration of possible analysis methods of CTG data as well as a first validation of the CTG setup. Results reported here include movement and investment data from the CTG pilot study (example output from one group can be seen in **Supplementary Data 1** and **Supplementary Data 2** and an example data preprocessing script can be seen in the OSF project: https://s.gwdg.de/Cwx3ex) as well as questionnaire data on participants' subjective experience during the experiment and remarks on the game.

For this publication, pilot data (N = 16) is used in order to demonstrate how scientific hypotheses might be tested with the CTG when a sufficient sample size has been reached. It should be noted that, usually, much larger sample sizes are needed in order to reach sufficient power for statistical analyses. The results reported here should merely serve as illustrations for possible analyses and visualizations (**Figure 5**). The CTG is especially suitable for investigating processes of collective trust, and how it emerges or wanes depending on the behavior of other group members or the trustee.

First, the qualities of collective trust as an emergent phenomenon were investigated. It is hypothesized that investments in the collective trust game change over time (i.e., emerge). This means that mean investments in the first, middle (i.e., seventh), and fifteenths round should be significantly different from each other. This hypothesis was tested with paired sample t-tests (Bonferroni corrected). Due to the small sample size (N = 16 in four groups), no significant differences could be found in the pilot data between the first (M = 27.0, SD = 20.49), seventh (M = 39, SD = 30.0; difference to round 1: $t(3) = -0.511$, $p = 1$), and fifteenth round (M = 42, SD = 31.75; difference to round 1: $t(3) = -0.678$, $p = 1$; difference to round 7: $t(3) = -0.397$, $p = 1$). The data were reanalyzed using only those invests that had been made unanimously. No significant differences were found between the rounds, probably due to the small sample as well (M_1 = 24, SD_1 = 24; M_7 = 52, SD_7 = 18.33; M_{15} = 56, SD_{15} =

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18.33). The accompanying data can be seen in **Figure 5A**. In studies with sufficient sample sizes, a significant difference between rounds and either a continuous increase or decrease in investments over rounds would indicate emergence of collective trust in the experiment as investors in the group can repeatedly interact and, therefore, establish a shared level of trust.

Additionally, the emergence of collective trust can also be investigated using movement data, as can be seen in **Figure 5B**, which shows three behavioral markers of the decision process: (a) decision time (red; time until last move of investors; M = 12.25, SD = 7.05) as an operationalization of process length, (b) move length (green; average time between two moves: M = 2.42, SD = 2.16) as an operationalization of deliberation, and (c) direction changes (blue; number of times a movement direction was changed; M = 0.25, SD = 0.66) as an operationalization of adjustment to other investors during a decision. If collective trust emerges over rounds, the process as quantified by the three behavioral markers should become less complex over time as collective trust should be the basis for the group investment decision. This means that if collective trust is an emergent construct, we should see groups take longer for investment decisions in earlier rounds as no shared level of trust (i.e., collective trust) has emerged yet. Over interactions, investment decisions should become shorter (as measured by decision time) and easier (as measured by move length and direction changes) as a shared level of collective trust has developed and less interaction or coordination is needed to determine a group investment. Therefore, researchers should use a larger sample to model the progression of behavioral markers over rounds. A negative slope might indicate the emergence of collective trust as a basis for group investment decisions.

Second, the behavior of the trustee and dependencies of the trustees' and investors' behavior were analyzed. It was hypothesized that trustees would return a non-zero amount of money to the investors, as has been found in research on individual trust games[1,43]. A one-sample t-test indeed showed that trustees returned significantly more than zero (M = 43.89, SD = 35.38) to investors; $t(59) = 9.608$, $p < .001$. This was even more pronounced when only those returns were included which were preceded by non-zero invests (M = 62.70, SD = 24.36; $t(46) = 16.677$, $p < .001$). **Figure 5C** shows that trustees most often chose to return 4/6 of the investment.

Additionally, it was investigated whether the trustees' returns are based on reciprocity, in that a higher investment in one round correlates with higher return fractions (i.e., 0/6, 1/6, 2/6, ...) in the same round. There seems to be a significant correlation between invests and returns as can be seen in **Figure 5D**, left panel; $t(58) = 9.446$, $p < .001$, $r = .78$. This indicates that trustees might have reciprocated high invests with high returns. However, this might be driven by the rounds in which investors invested either zero or did not reach a unanimous decision so that the trustee did not have an option to return anything. Lastly, it was analyzed whether higher return fractions are perceived as forward signals by investors, so that higher return fractions in round t are correlated with high invests in round t+1. As can be seen in **Figure 5D**, right panel, this was not corroborated by the data; $t(54) = 0.207$, $p = .837$, $r = .028$.

To summarize, the quantitative data from the CTG consists of both movement and investment data of each participant in each round. While investment data provides parallels to previous applications of the individual trust game, movement

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data allows researchers to observe the process of collective trust. It should be noted that data is collected in actual groups, which increases external validity, but necessitates that the nested data structure is considered. This was not done for the reported analyses as the small sample size of the pilot data restricts the application of mixed-effects linear models.

Additionally, data on subjective experience was gathered in the pilot sample with a post-experiment questionnaire (**Supplementary File 1**) that included 13 items in total, of which 11 were open-ended questions. Next to subjective experience during the experiment, the items asked about specific aspects of the CTG that might influence data quality, such as participants' subjective principles of behavior during the game, believed intention of the experiment, or clarity of instructions. Two closed-format questions assessed on a five-point Likert scale whether participants perceived the investment through movement to be intuitive (-2: "not at all" to +2: "very") and whether the time given to participants to move in the game seemed sufficient (-2: "much too short"; 0: "about right"; +2: "much too long").

Generally, participants reported subjective experiences in line with the intention of the experiment and ease of following instructions, while also showing sufficient naïveté of the study's intention. Participants on average reported the game to be "quite intuitive" (M = 0.69, SD = 0.79) and perceived the time to be "about right" (M = -0.31, SD = 0.79).

Participants' answers to the open-ended questions were analyzed qualitatively according to Mayring[44]. Overall, participants were satisfied with the recruitment process and online procedure, preservation of anonymity in the experiment, the clarity of instructions and information provided, and the logic of the game. Most participants were satisfied with the design of the avatars in that they could be distinguished easily. However, only half of the participants reported that they felt represented by their avatar and remarked that symbols or animal faces might have been more interesting. Due to these results, researchers should consider including a measure of participants' embodiment in applications of the CTG to control for this experience while still maintaining a minimalist experimental design.

Most participants remarked that they experienced the urge to converge in the middle of the playfield, (i. e., at the highest investment option). Participants who experienced this reported that the urge to converge in the middle coincided with their willingness to invest high amounts. Additionally, some participants reported that instead of feeling drawn to the middle they felt they had to pull co-players toward the middle. Because of practical constraints of the experiment and potential trade-offs with intuitiveness, the initial design was retained in which high investments and returns converge in the middle.

Participants reported a multitude of suppositions about the aim of the study, such as group influence on own decisions, trust, or behavior of trustees. While those suppositions are thematically close to the investigated emergence of trust, the participants reported behavioral strategies such as profit maximization or intentions to influence the behavior of co-players. These strategies fit well with the economic game character of the CTG and do not counteract behaviors the study aimed to observe.

On the basis of results on subjective experience, it could be concluded that the CTG satisfies criteria of internal validity. The quantitative data analysis reported here should merely serve as an illustration of how data collected with the CTG can be statistically analyzed.

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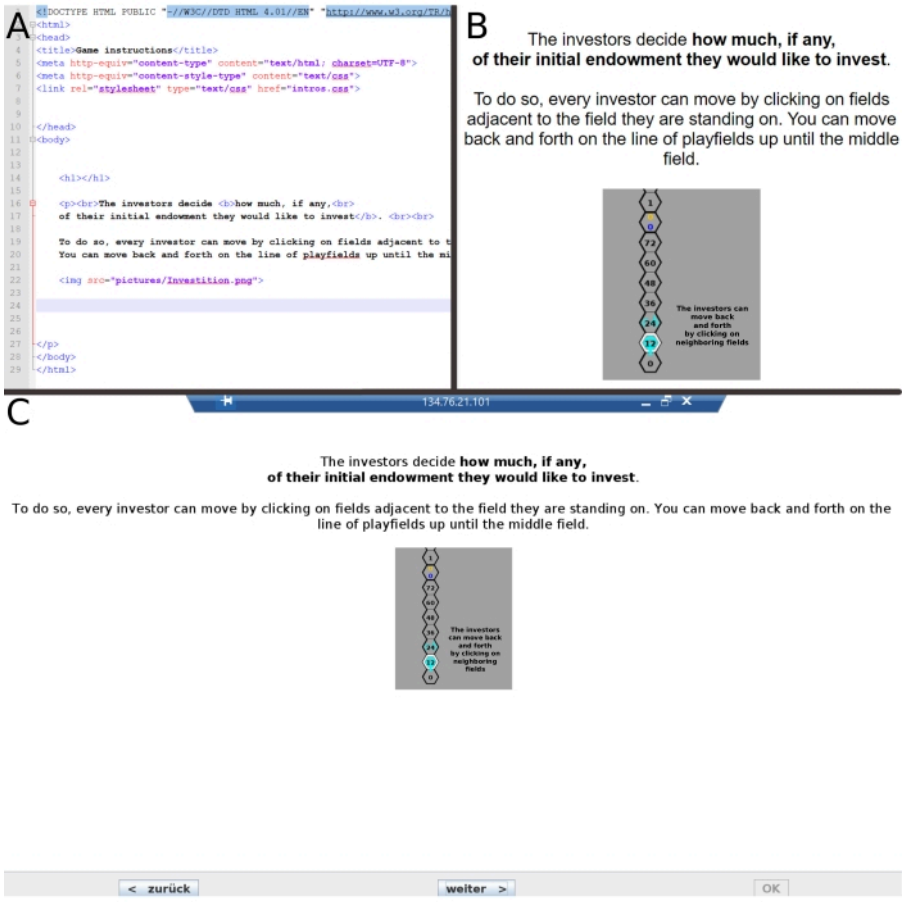

Figure 2: Example of game instructions. (**A**) HTML code prepared by experimenter. (**B**) HTML file displayed in browser. (**C**) Instructions as shown to participants during the experiment. Note the buttons on the bottom to navigate through instructions. Please click here to view a larger version of this figure.

doi: 10.53846/goediss-9589

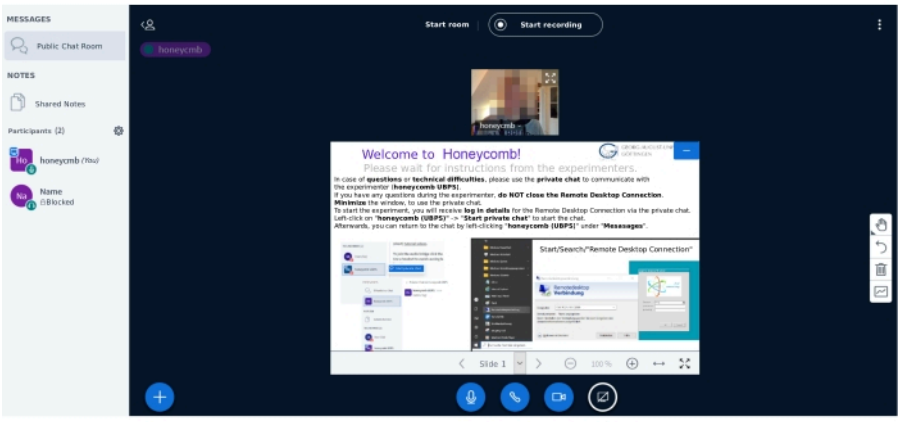

Figure 3: Screenshot of video conference platform. The experimenter has shared their camera, microphone, and presentation with basic information on the video conferencing platform and Remote Desktop connection. One participant has already joined the conference but is prohibited from sharing their microphone, screen, or camera in order to keep anonymity. Please click here to view a larger version of this figure.

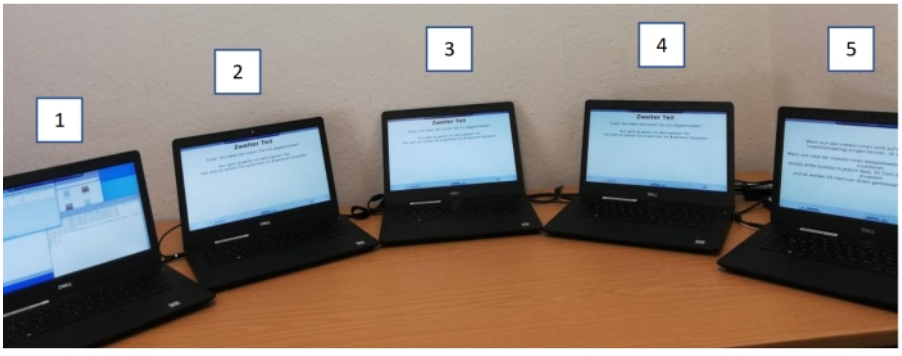

Figure 4: Setup in laboratory. Before the experiment starts, the experimenter will start a Remote Desktop connection with all laptops. Notebook 1 is connected with the experiment user and remains connected throughout the experiment. Notebooks 2 through 5 are used to establish and check connection with participant users ("participant-1" through "participant-4"). When participants establish connection to participant users *via* Remote Desktop Connection tool, notebooks in laboratory will lose the connection. Please click here to view a larger version of this figure.

doi: 10.53846/goediss-9589

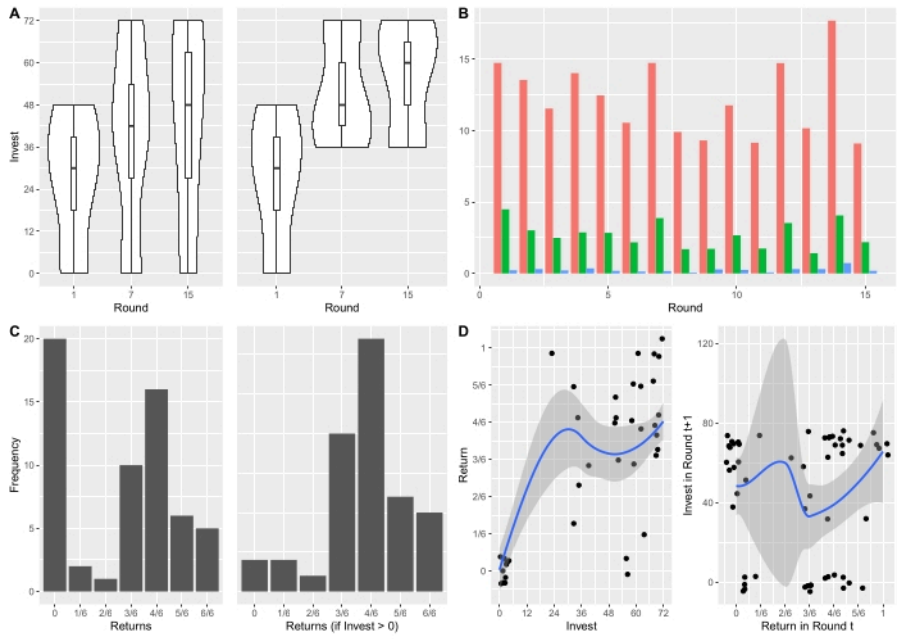

Figure 5: Results based on pilot data (N = 16 in four groups). (**A**) Violin plots of group investments (cents) in rounds 1, 7, and 15. Violin shapes indicate probability density of invests, bold lines indicate median, boxes in violins indicate interquartile range, and whiskers indicate 1.5 times interquartile range. Left; all invests. Right; unanimous invests. (**B**) Three different markers of movement data that can be used to quantify aspects of investment decision process in group. Red; decision time (time until last move in seconds). Green; mean of move lengths (time from one move to the next in seconds). Blue; number of direction changes in movement pattern (count). (**C**) Frequency (count) plot of returns. Left; all returns (as return fractions) across rounds are counted. Right; only those returns (as return fractions) are counted prior to which trustees received an investment. (**D**) Scatterplots of investments (cents) and returns (as return fractions). Blue line indicates predicted values (using a linear model with formula: y ~ x), grey ribbon indicates standard error of predictions. Left; reciprocity correlation. Do high invests correlate with high returns in same round? Right; forward-signaling correlation. Do high returns correlate with high invests in subsequent round? Please click here to view a larger version of this figure.

Supplementary Figure 1: Example of online advertisement through flyer that was posted on an online blog. This flyer is an example of what information should be included in the advertisement of the participant recruitment flyer and in which way it could be presented. Please click here to download this File.

Supplementary File 1: Full questionnaire of pilot study. The full questionnaire used in the pilot study can be found here. Please click here to download this File.

Supplementary Data1: Example data output containing investment data of one group (i.e., four participants: three investors (pid 0-2) and one trustee (pid 4). This is an example of a raw data file containing a) information of

doi: 10.53846/goediss-9589

play order, b) the list of players, c) the starting ("StartSicht") and final positions ("last common playground") of all players, as well as d) their investment, earnings, and account balance ("Balances: cost reward saldo"). Please click here to download this File.

Supplementary Data 2: Example data output containing movement data of one group (i.e., four participants: three investors (pid 0-2) and one trustee (pid 4). This is an example of a raw data file containing coordinated ("sj") of each player ("pid") at any given time in the experiment. The start of a new round is indicated by a "-1" as the "pid". Please click here to download this File.

Discussion

The CTG provides researchers with the opportunity to adapt the classic BDM[1] for groups and observe emergent processes within the groups in depth. While other work[23,24,25,26] has already attempted to adapt the BDM[1] to group settings, the only way to access group processes in these studies are laborious group interaction analyses of video-taped discussions. As this is often a tedious and time-consuming task[17], studies regularly do not report these aspects. With respect to these existing methods, the CTG is, to the authors' knowledge, the first paradigm that allows researchers to follow collective trust as an emergent phenomenon in real time through movement data. The CTG is, therefore, more time-efficient. Additionally, using quantitative analyses to capture group processes allows researchers to preregister process analyses, which is often difficult with more qualitative approaches.

For the paradigm to produce high-quality data, it is crucial to closely follow the protocol. The following five critical steps warrant researchers' special attention. First, the configurations made in the game are to be held constant across all experiment sessions and should be documented. Second, participants that have already participated in similar studies (i.e., studies using any trust game version) should be excluded at the recruitment stage as this might create biases in behavior and reduce effect sizes[45]. Third, researchers need to ensure that participants are anonymous by prohibiting participants to share their microphone, camera, and full name during the video conference, as the level of anonymity has been shown to affect behavior in economic games[27]. Fourth, during start-up of the game, researchers need to check thoroughly that a correct connection between the participant user and the experiment user is established by making sure that the participant user is listed in the experimenter GUI. Fifth, research assistants who collect the data need to be trained extensively to be able to troubleshoot technical challenges with participants. In case participants experience problems establishing the Remote Desktop connection, research assistants need to be able to provide support in order to retain participants in the group. If a person drops out due to technical difficulties, all participants within the experiment time-slot might have to be rescheduled, resulting in additional monetary costs and time-loss.

If technical difficulties occur during start-up of the game, make sure that (a) a current Java runtime environment is installed on your Remote Desktop machine, (b) all users can access and execute the files in the shared folders, (c) all users are executing the commands in the same directory, and (d) all PCs/laptops accessing the Remote Desktop connection have a stable internet connection. For troubleshooting during the experimental session, check that (a) all participants and the researchers have a stable internet connection, (b) participants received the correct log in information for the Remote Desktop Connection, and (c) the server running the

doi: 10.53846/goediss-9589

Remote Desktop Connection has sufficient resources (e.g., check CPU utilization) during the experimental session.

The CTG is highly adaptable to different research questions which allows for a breadth of possible applications in research. Depending on the aim of a study, a multitude of parameters can be customized, such as the number of players, requirement of unanimous decisions, visual appearance, timing, and monetary parameters of the BDM. While the flexibility of this paradigm is an advantage, it is important to keep in mind that adaptations of the paradigm should always be rigorously founded in theory and piloted. Beyond the configurations that researchers can make in the *.config files, the game can be adjusted only through the source code programmed by Johannes Pritz, which is not available online yet. While many adaptations are possible, the framework of the HoneyComb platform restricts possible applications to movement tasks and to discrete investment options.

In future applications of the CTG, the amount of return fractions could be increased (e.g., 1/10, 2/10, 3/10, ...) in order to provide higher resolution on return behavior. In this way, both the side of investors as well as trustees can be played by individuals or groups, allowing investigation of different levels and referents of trust as was proposed by Fulmer and Gelfand[7]. Future applications of this protocol might also combine the online procedure of this method with other experiments from the HoneyComb platform[30,32,46,47] or include other forms of communication such as a chat or even face-to-face interaction between investors and/or trustees in an on-site experiment as presented by Boos and colleagues[31]. In this way, other cues influencing the emergence of collective trust, such as nonverbal communication, could also be studied using this paradigm.

Overall, the CTG combines the advantages of economic games-high internal validity and simplicity-with rich group process data. By this means, the CTG can serve as a stepping stone in group research on trust and fairness processes.

Disclosures

The authors have nothing to disclose.

Acknowledgments

This research did not receive any external funding.

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 doi: 10.53846/goediss-9589

Chapter 4.2: Collective Trust as an Emergent Construct

Ritter, M., Fritsch, M., Komes, H., Komes, M., Pritz, J., and Boos, M. (2022). Collective trust as an emergent construct: An investigation using the Collective Trust Game (CTG). Under review at *Journal of Experimental Social Psychology*.

Supplementary Material:
https://s.gwdg.de/t7MqkB (DOI 10.17605/OSF.IO/HNDU6)

 doi: 10.53846/goediss-9589

Collective trust as an emergent construct:

An investigation using the Collective Trust Game (CTG)

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Manuscript submitted to the *Journal of Experimental Social Psychology*

(revised for publication of dissertation).

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Funding for Study 2 was provided by the Fachgruppe Psychologie of the Georg-Elias-Müller-Institute for Psychology, University of Goettingen, Germany.

doi: 10.53846/goediss-9589

Abstract

Collective trust as an emergent group-level construct is distinct from dyadic trust. We define collective trust as a group-level emergent phenomenon, relying on repeated interactions among group members. To measure collective trust, we use the Collective Trust Game (CTG) that supersedes simple averaging of dyadic trust to gain insight into the emergence of collective trust. The CTG as a computer-based adaptation of the original Trust Game (OTG; Berg et al., 1995), implemented within the HoneyComb paradigm (Boos et al., 2019), addresses drawbacks of previous measures of collective trust and combines the advantages of a controlled economic game and movement-based process analysis. Participants are represented by colored avatars that can move around a playing field while observing the movements of other participants' avatars. All other communication is blocked. In Study 1, 136 participants in groups of 4 play the CTG two conditions (single vs. group). Results suggest that the adaptation of the OTG was successful and that collective trust emerges over repeated interactions. Exploratory analyses suggest that emergence of collective trust can also be measured via movement parameters. In Study 2, 144 participants in groups of four play a variant of the CTG to determine the influence of interaction on the emergence of collective trust. Results suggest that restricting interaction to a minimum might hinder the emergence of collective trust. While some differences between the two studies exist, we conclude that collective trust differs from the average of individual trust which should be accounted for in research and practice.

Keywords: trust, collective trust, collective trust game, emergence, HoneyComb

doi: 10.53846/goediss-9589

Collective trust as an emergent construct: An investigation using the Collective Trust Game (CTG)

Do you trust strangers? Most people would answer „no". We trust friends, family, and good acquaintances. However, if we closely inspect our everyday life, trust is ubiquitous. We trust the cab driver to drive safely to our destination and we trust the delivery person to handle our ordered goods carefully. With pervasive digitalization, trusting strangers becomes ever more important (Thielmann & Hilbig, 2015). While trust has been researched extensively on the individual level, humans in fact frequently interact in groups and, therefore, trust on a group level (Shamir & Lapidot, 2003).

In this paper, we define and describe the concept of collective trust and propose a method to measure collective trust in its emergent qualities: the Collective Trust Game (CTG). We describe two studies that investigated collective trust and its emergence and discuss possible applications of collective trust and the CTG in research and practice.

What is (individual) trust?

A majority of scientists seem to have agreed on two key elements of trust: The willingness to accept *vulnerability* and the presence of *positive expectations* regarding the result (Dietz & Den Hartog, 2006; Dirks & Ferrin, 2002; Edwards & Cable, 2009; Evans & Krueger, 2009; Fulmer & Gelfand, 2012; Kim et al., n.d.; Simpson, 2007).

Vulnerability in this context means accepting the possibility of losing something important (Boss, 1978; Zand, 1972). Trust, therefore, incorporates a certain acceptance of uncertainty and risk that the trusting party needs to be aware of (Schoorman et al., 2007).

Positive expectations in terms of trust mean that the trusting party expects the trusted party to be trustworthy (Li, 2007). This tendency is often dependent on previous experience

doi: 10.53846/goediss-9589

in trust situations (Glaeser et al., 2000). At the same time, trust is based on a certain interdependence between the two involved parties (e.g., Edwards & Cable, 2009).

Measuring Individual Trust.

In a comprehensive review, Dietz and Den Hartog (2006) emphasize that, as its definition, measurement of trust is diverse (McEvily & Tortoriello, 2011). While the majority of measures focus on trust as a belief, a smaller fraction measures trust-inspired behavior. Trust can be measured directly (self-report: Davis et al., 2000; think aloud method: Kramer, 2010) and indirectly through the observation of behaviors or decisions (Buskens & Weesie, 2000; Dietz & Den Hartog, 2006).

Berg, Dickhaut, and McCabe (1995) introduced another tool to measure trust: the original Trust Game (OTG). In order to observe and examine trust in a behavioral context, the authors proposed an economic game which has since been established as one of the most prominent measurements of trust and was used in numerous experiments (e.g., Charness & Sutter, 2012; Kleinert et al., 2020; Kugler et al., 2007; Rojas et al., 2017; Song, 2009; Thielmann et al., 2016) across 35 countries (Johnson & Mislin, 2011).

The structure and procedure of the OTG (Berg et al., 1995) can be outlined as follows. The trusting party (A) is the investor, the trusted party (B) is the trustee. A and B receive a $10 show-up fee at the beginning of the experiment. A moves first and decides if they want to trust B, specifically how much of their show-up fee they want to transfer to B. The amount A sends is usually the operationalization of trust. If A sends no money (0$), the game is over. If A decides to send an investment (e.g., 5$), this amount is tripled by the experimenter before being given to B. B has now received 15$ and must decide how much of this to send back. B can decide to exploit A’s trust and send back 0$, thereby, keeping all money for themselves. A would end up with 5$ (10$ show up fee – 5$ investment) and B with 25$ (10$ show up fee

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+ 3 x 5$ investment). Assuming B is trustworthy and wants to ensure that both A and B earn money in the game, B sends back 10$, so 2/3 of the money they received. The fraction B sends back is usually the operationalization of trustworthiness. At the end of the game, A's earnings are: 10$ show up fee – 5 $ investment + 2/3 x (3 x 5$ investment) = 15$. And B's earnings are: 10$ show up fee + 3 x 5$ investment – 2/3 x 3 x 5$ investment = 15$.

In this example, A showed trust and B proved to be trustworthy. However, their behavior contradicts expectations of rational behavior (Morgenstern & Von Neumann, 1953; Osborne, 2004). According to game theory, B should have kept all they received to themselves (y = 0). A in turn would have anticipated this behavior and not sent any money in the first place (X = 0$). However, as A trusts B, A accepts this vulnerability and takes on the subjective risk (Mayer et al 1995) with the positive expectation that B will prove to be trustworthy. In the original paper by Berg et al. (1995) and many following adaptations, behavior contradicts assumptions of self-interested humans prevailing in classical game theory (Johnson & Mislin, 2011).

In studies employing the OTG, it was observed that there is a certain reciprocity of trustworthiness (Bacharach et al., 2007; Cox, 2007; Guerra & John Zizzo, 2004; Malhotra, 2004). Reciprocity in this regard means that even though the personal interest of maximizing profits would dictate the exploitation of the others' trust, one behaves in a trustworthy way because one was trusted (Gunnthorsdottir et al., 2002).

While trustees can reciprocate trusting behavior with trustworthiness, investors can reciprocate trustworthiness with trust in the next interaction. We call this reciprocity forward-signaling in which previous experiences with a trustee will influence future trust (Dunn & Schweitzer, 2005; Rosanas & Velilla, 2003; Serva et al., 2005).

The original OTG was mostly used to assess trust in dyads. However, important decisions are often made by groups rather than individuals (Kocher & Sutter, 2005) and trust

doi: 10.53846/goediss-9589

can play a role in health care groups (Wong & Cummings, 2009), sports teams (Dirks, 2000), and even on a societal level (e.g., political voting behavior: Holm & Nystedt, 2010). In these contexts, trust between more than two individuals can affect outcomes such as successful negotiations (Olekalns & Smith, 2007), entrepreneurship (Blatt, 2009), team performance (De Jong & Dirks, 2012; Dirks, 2000; Dirks & Ferrin, 2002), job satisfaction (Braun et al., 2013), or successful collaboration (Reiter et al., 2018). Hence, the extension of interpersonal or dyadic trust to the collective level is important (Bornstein & Tomkins, 2015).

What is collective trust?

Recently, research has recognized that conceptualizing trust as a solely interpersonal construct is not sufficient and more multi-level thinking is needed (Schoorman et al., 2007; Shamir & Lapidot, 2003). In their comprehensive review, Fulmer and Gelfand (2012) review and categorize studies on trust according to the level at which trust is analyzed. The three different levels of analysis are: interpersonal (dyadic), group, and organizational. They additionally distinguish between different referents (Fulmer & Gelfand, 2012). The referents, or trustees, are those entities at which trust is directed. This means that when “A trusts B to X”, then A represents the level (individual, group, organizational) and B represents the trustee (individual, group, organizational). When “A trusts B to X”, then X represents a specific domain to which trust refers, the trust domain. As trust was defined as a mental state of accepting vulnerability and expecting positive intentions or behaviors (Rousseau et al., 1998), the trust domain would comprise these positive intentions or behaviors. This means that the trust domain can be anything such as a generally positive inclination, reliability in work procedures, or financial exchanges.

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Collective trust as an emergent construct

Fulmer and Gelfand (Fulmer & Gelfand, 2012) report on a multitude of studies on the individual level; yet, studies investigating the effects of trust on the group and organizational level were comparatively scarce at that point.

There are at least four different definitions of the term collective trust, using a variety of different trustees and operating not only on the group, but also the individual level, contrary to what the term might imply. In the first definition, collective trust is defined on the individual level towards a trustee that is a team, group, or organization (Campos-Castillo et al., 2016; McEvily et al., 2002; Ross, 2004; Salamon & Robinson, 2008; Smith & Rotolo, 2010). This means that the trusting party is an individual that extends his/her trust towards a collective entity. In spite of the fact that most publications use this definition of collective trust, we argue that this form of trust (individual level, group trustee) does not warrant the term collective trust as the term implies analysis at the group or organizational level.

The second definition of collective trust defines collective trust on the group level directed at individuals as the trustee, such as a team trusting their coach (Dirks, 2000; Kim et al., 2013). The third definition changes the trustee to be either another group or the organization (Forsyth et al., 2006; Gray, 2016; Kramer, 1994, 2010). The fourth definition locates collective trust on the organizational level with the trustee being an organization as well (e.g., Holm & Nystedt, 2010).

Taking all these different definitions into account, we propose the following definition: “Collective trust is a psychological state *shared among a team or group of humans* and *formed in interaction* among this group. Collective trust comprises the group’s intention to accept *vulnerability* based upon *positive expectations* of the intentions or behavior of *another individual, group or organization.*” (see also Ritter et al., 2022; based on Rousseau et al., 1998). This definition clarifies that collective trust should encompass a certain sharedness among the group which makes it a truly collective phenomenon (Holm & Nystedt, 2010;

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McEvily et al., 2002; Puusa & Tolvanen, 2006; Shamir & Lapidot, 2003). With this addition, we incorporate that the analysis of group processes should look beyond a simple averaging of individual processes in a group (Kocher & Sutter, 2005, 2007; McEvily et al., 2002). Further, collective trust should emerge through repeated interactions within a group (Costa et al., 2018; Kiffin-Petersen, 2004).

Emergence and sharedness of collective trust are key elements of this definition (Fulmer & Gelfand, 2012) and a key distinction from individual trust. There are, however, shared characteristics between those two concepts. The two essential components of individual trust, positive expectations and willingness to accept vulnerability (Rousseau et al., 1998) equally apply for the collective definition as well.

Previous measures of collective trust

To measure collective trust, most studies employ a simple averaging technique across the data of each individual in the group (Dirks, 2000; Gray, 2016; Kim et al., 2013; Kramer, 2010; McEvily et al., 2002). While this approach might capture the trust of each separate individual, it does not adequately capture collective trust and probably has little predictive value for actual group behavior (Costa et al., 2018). Crucially, the tested construct does not match the definition we put forward. A study by Adams (2013) uses a latent variable approach that addresses the limitation that averaging of individual trust does not adequately reflect collective trust as an emergent construct. Another line of research on collective trust uses behavioral measures and/or experimental designs (Holm & Nystedt, 2008, 2010; Kim et al., 2013). For example, Holm and Nystedt (2010) developed an economic game in order to compare trust behavior in dyads and large groups. Investors in the group trust games were not allowed to communicate with each other prior to the investment. It was found that large group investors are less likely to invest money, compared to individual investors. However,

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no difference in trustee behavior was found. Finally, some studies (e.g., Charness & Sutter, 2012; Cox, 2002; Kocher & Sutter, 2007; Kugler et al., 2007; McEvily et al., 2002; Song, 2009) have attempted to measure collective trust with modified group variants of the OTG by Berg et al. (1995).

While some of the aforementioned measurements address the fact that collective trust cannot be measured by averaging individual trust, these measurements are still focused on input-output relations and can only provide limited data on the process of collective trust emergence (e.g., Comer et al., 1999; Coote et al., 2003; Möllering, 2005). While some studies have attempted to analyze decision processes in economic games (audio recording: Schopler et al., 1995; Gummerum et al., 2008; Takezawa et al., 2006; group chat protocol: Franzen & Pointner, 2014; Ito et al., 2016; Luhan et al., 2009; behavioral observation: Orbell et al., 1988), these tend to be the exception.

To properly examine collective trust processes, an analysis tool that does without simple averaging techniques is needed, which can provide insight into the emergence and dynamics of collective trust, while being cost-effective.

The Collective Trust Game

One tool that seems to meet these requirements is the computer-based, multi-client game HoneyComb (Boos et al., 2014, 2019). The HoneyComb paradigm allows researchers to observe human coordination behavior in real time, while providing a cost-effective and systematic way of quantifying the behavior of both individual group members and the whole group (Boos et al., 2019). HoneyComb allows players to move on a virtual playing field and communicate with other players through their movement behavior.

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Collective trust as an emergent construct

In order to measure collective trust, we used a new HoneyComb variant: the Collective Trust Game (CTG; Ritter et al., 2022). The CTG adapts the widely known Trust Game (Berg et al., 1995) to a group setting.

Participants play the role of an investor or trustee; both roles can be played by groups. The game follows the general principle of the OTG (Berg et al., 1995) with investors and trustees communicating their investment or return decisions and tendencies by moving back and forth on a virtual playing field. Both investors and trustees can move as often as they would like during the allotted investment or return time and no restrictions on moving order are applied. As collective trust relies on repeated interaction, this procedure is repeated for multiple rounds. Movement data (e.g., decision latencies) is recorded to investigate decision processes. Participants are represented as avatars and can only communicate through movement. This way, confounding cues are excluded, such as outer appearance, voice tones, or communication styles of other participants (R. K. Wilson & Eckel, 2006). Participants' avatars provide a sense of social presence between participants, even when they cannot interact face-to-face (Knudsen, 2004). More information on the paradigm can be found in the CTG protocol publication (Ritter et al., 2022).

The CTG allows for online data collection, ensuring that participants remain completely anonymous towards each other. While interaction in a computerized manner might affect trust building (e.g., Hill et al., 2014), it has been shown that virtual teams can recover from this initial hindrance (J. M. Wilson et al., 2006). Additionally, with increasing virtualization, especially during the Covid-19 pandemic (Holton, 2001), virtual interactions have become increasingly common.

We argue that this tool combines the advantages of rich group interaction experiments with the high internal validity and time-effectiveness of economic games.

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Research Objectives

This investigation had several objectives. First, we aimed to adapt the OTG to the group level (OTGA). It was tested whether the adaptation of the OTG into the HoneyComb paradigm was successful by means of a conceptual replication (Erdfelder & Ulrich, 2018). If the CTG confirmed observations on the individual level that had been made using the Trust Game, conclusions could be drawn about collective trust on the group level. To this end, a single condition was implemented next to the group condition. During the single condition, individual trust was measured in order to compare those results to results of the OTG (Berg et al., 1995; Johnson & Mislin, 2011). Additionally, the individual level trust served as a baseline for our second research objective.

Second, we wanted to investigate whether collective trust would display emergent characteristics (EM) as we would expect theoretically. If collective trust is an emergent phenomenon, it should develop through interaction within the investor group (Costa et al., 2018; Grossman & Feitosa, 2018; Kiffin-Petersen, 2004; J. M. Wilson et al., 2006). As we argue that averaging individual trust is inadequate for measuring collective trust, the average of individual trust and the developed collective trust should differ.

Third, related constructs (i.e., reciprocity and forward-signaling) of trust should be explored and whether they could also be found in relation to collective trust. Both reciprocity and forward-signaling have been found in repeated applications of the OTG (Cox, 2002; Malhotra, 2004) and are strategies that could be used by investors and/or trustees to determine their next investment or return behavior. Moreover, we wanted to investigate whether embodiment would affect behavior in the CTG. As participants are represented by avatars, subjective feelings of embodiment might impact investment decisions. We define embodiment as the subjective feeling to act corporally within a virtual room (Hayes & Johnson, 2019), so how well participants feel represented within the CTG.

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Lastly, the implementation of a group version of the OTG in the HoneyComb paradigm allows systematic research into the process of collective trust emergence. We wanted to reap the benefits of this experimental paradigm by exploring the emergence process of collective trust through movement patterns.

With these objectives in mind, we designed two studies that differ only in terms of the answering format with which participants interacted and communicated their investment and return decisions. Study 1 employs the CTG paradigm as outlined by Ritter and colleagues (2022) and Study 2 used a less interactive and restricted format, comparable to the proposal format employed by Kocher and Sutter (2007). All measures, manipulations, and exclusions in the studies are disclosed.

Study 1

In Study 1, the Collective Trust Game was used to investigate the following hypotheses:

OTGA 1: Participants will invest significantly more than 0 cent in the single condition

OTGA 2: Trustees will choose to return more than 0/6 of the received money to investors.

EM 1: The group investments made in the group condition would significantly differ from the average of individual investments made during the single condition. Specifically, the average of the individual investments from three investors would significantly differ from the group investment during the first and fifteenth round of the group condition.

EM 2.1: The investor group should exhibit less collective trust, as measured by the number of unanimous investment decisions, during the first rounds of the group condition, compared to the later rounds of the group condition.

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EM 2.2: Due to the emergence of collective trust, the probability that investors reach a unanimous investment decision should increase with increasing rounds.

EM 3: As collective trust emerges with repeated interactions, the level of collective trust, as measured by group investments, should change over time. Specifically, how much investors invested in the first round should significantly differ from the amount invested in the fifteenth round.

Additionally, we wanted to use the movement data recorded by the CTG to investigate the decision process.

Method

Sample

Data was collected between March 29 and April 19, 2021. Data collection and data analysis procedures in this study were approved by the Ethics Committee of the institute (additional information removed for blind-review). In total, 136 participants (75% women, 25% men) were tested in groups of four (one person was not able to complete the post-experiment questionnaire due to technical difficulties and was excluded from analyses pertaining to questionnaire data). Additional demographic information can be found in Table 1. This sample size was considered sufficient according to an a-priori power analysis ran before data collection (Supplementary Material 1).

Table 1

Sample Descriptives

	Category	Percentage
Age	18 – 20 years	21%
	21 – 25 years	46%
	26 – 30 years	21%
	> 30 years	12%
Occupation	University student	85 %
	Employed	13 %
	Miscellaneous	2 %

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In the single condition, all participants played in the role of the investor. In the group condition, 102 participants were quasi-randomly assigned the role of the investor; the 34 remaining participants played the role of the trustees. Random assignment to the roles was done prior to the experiment. Once enough participants were scheduled for one time slot, an experimenter randomly determined one out of the four participants to be the trustee using a random draw function in R . The other participants were assigned to be investors.

Participants were compensated with 1,5 participation credits. Additionally, they received a minimum of 3 Euros and a maximum of 12 Euros as a reimbursement, depending on their performance during the game. In this way, behavior during the game had real-life consequences which should increase ecological validity of the game. The earned money was transferred to participants' bank accounts after data collection concluded.

Procedure

A schematic overview of the procedure of the CTG can be seen in Figure 1A. Supplementary Material 2 provides a detailed description of the procedure, while only essential characteristics shall be described here. For a detailed account of the technical set-up and experimental protocol, please refer to Ritter et al. (2022).

The experiment was run online. The experimenter welcomed all four participants of the experiment session in an online conference to create a sense of social co-presence and send the participants the log-in information to the CTG platform. To preclude any confounding interaction, participants were prohibited from sharing their microphone, camera, or their name in order to ensure anonymity. Participants were required to give written consent before starting the CTG.

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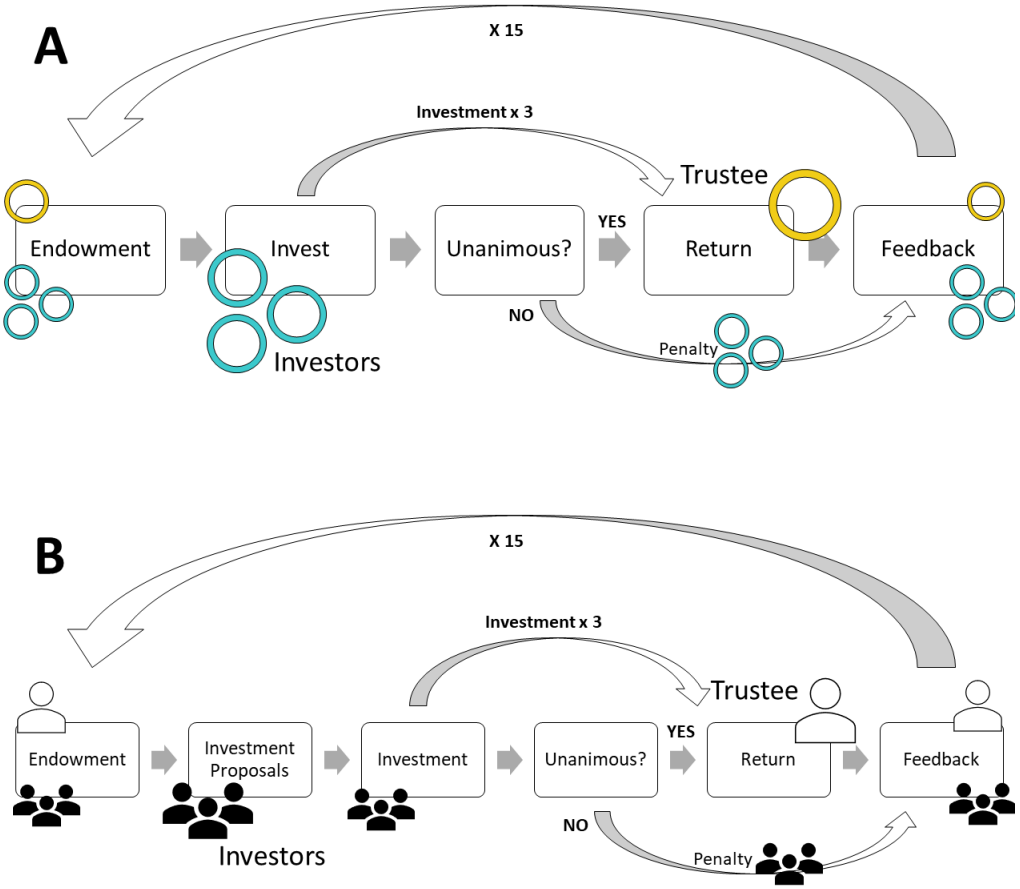
Figure 1

Schematic Overview of CTG procedure in Study 1 and Study 2



Note. **A** – Schematic procedure of the CTG procedure implemented in Study 1. **B** – Schematic procedure of the CTG adaptation using Labvanced used in Study 2. A and B differ in that B includes a proposal stage before the final investments are made.

Instructions on the game were standardized and given via the CTG program once participants were logged on and confirmed that they read and understood the instructions before continuing with the game.

Single condition. All participants played the role of the investor during the single condition. Unbeknownst to the participants, the trustees were simulated during the single condition to control carry-over effects from the single to the group condition. Participants in

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the single condition were represented by an avatar, a blue ring, on the playing field. The playing field was consistent across the single and group conditions. Figure 2 (left) shows a screenshot of the group condition.

Investors were represented by blue ring avatars and trustees by yellow ring avatars. At the beginning of the single condition, investors were placed on the “0” field. Both the investor and trustee received an endowment of 72 cent. To invest part of their endowment participants had to move their avatar on the investment fields (lower half of the playing field) to a field indicating the chosen investment amount (0 – 71 cent in steps of 12 cent). Investors had 30 seconds to move and the field they were standing on at time-out was taken to be their investment decision. After time-out investors could not move anymore and the investment was tripled by the program and sent to the trustee (as in Berg et al., 1995). The trustee had 15 seconds to indicate their preferred return on the upper half of the playing field (0 – 1 in steps of 1/6 of the received amount) by moving onto the respective field and remaining there until time-out. In the single condition, simulated trustees always returned 4/6 of the received sum.

The returned amount was sent back to the investors’ account. At the end of the round, all parties received feedback about their current account balance before continuing with the next condition.

Group condition. In the group condition, participants were playing on the same playing field as before. The only difference being that instead of just one, three investors represented by blue avatars were placed on the bottom most field, while one trustee represented by a yellow avatar was placed on the top most field (Figure 2; left). The trustees were played by participants.

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Figure 2

Comparison of response formats in Study 1 and Study 2

Note. Screenshots of the CTG (1) and the CTG adaptation in Labvanced (2) for investors (I) and trustees (T). The playing field of the CTG (**left**) is structured as follows: the lower fields ("0" to "72" in steps of 12) are the investment fields and investors indicate how much they want to invest by moving onto a specific field and remaining there until the investment time-out elapses (30s); the upper fields ("0" to "1" in steps of "1/6") are the return fields on which trustees indicate the return by moving to and remaining on a specific field until the return time-out elapses; the middle field shows the current investment (blue number) and the current return (yellow number). Investors are represented by blue ring avatars, trustees are represented by yellow ring avatars. The **blue arrows** indicate the movement direction with which higher investments would be selected. In the CTG, this corresponds to the movement direction of the avatar; in Labvanced, this corresponds to the movement direction of participants' mouse movements. Both the movement directions in the CTG (**1 I**) and Labvanced adaptation (**2 I**) start from the lowest investment (0) to the highest investment (72). The same is true for direction of returns (**yellow arrows**: **1 T** & **2 T**). A screenshot of the proposal phase of investors in Study 2 (**2 P**). The three investors are printed in bold. Below the investors, their respective reaction times ("Reaktionszeit") are shown.

Each round started with an initial endowment of 72 cents for the trustee and the investor group. The investor group had 30 seconds to indicate their investment by converging

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on one field and remaining there until time-out. Importantly, in the group condition, participants had to reach a unanimous decision among all three investors: all three investors had to stand on the same field in order for an investment to be made. If investors could not reach a unanimous decision, a penalty of 24 cent (a third of the endowment in one round) was deducted from the investors' account balance. This rule was implemented in order to ensure that collective trust could emerge as a group level construct. Had participants been able to invest independently, there might have been little incentive to interact with the other investors and form a shared trust towards the trustee. In fact, reaching a unanimous decision required participants to closely pay attention to the movement behavior of the other investors and communicate one's own investment preferences via movement.

If investors were able to reach a unanimous decision, the investment was tripled by the program and sent to the trustee. The trustee then had 15 seconds to indicate the amount they wanted to return. This procedure was repeated for 15 rounds.

Questionnaire and debriefing. Participants were asked to complete a post-experiment questionnaire, including a 3-item embodiment questionnaire (Heemeyer, 2006), demographics, and generation of a personal code.

Operationalization

Individual & collective trust. Individual trust was operationalized as the amount of money participants invested during the single condition. Collective trust was operationalized as the amount of money the investors invested in the fifteenth round during the group condition. As collective trust is an emergent construct and needs to form through repeated interaction, the level of collective trust within the group of investors was only measured in the last round. The investments that were made in the earlier rounds of the group condition are taken as indicators to show if and in what way collective trust is formed over time. Additionally, we measured the frequency with which a unanimous investment decision was

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reached in order to show the progression of collective trust emergence. With repeated interactions, collective trust should emerge as a group level construct that simplifies the investment decision: Once collective trust has formed, all group members should have a shared sense of how much the group would trust the other party and come to an investment decision more easily.

Trustworthiness. Trustworthiness is operationalized as the fraction of the investment, trustees returned during the group condition.

Embodiment. Embodiment was measured in order to compare investment modes in this study and Study 2. To measure embodiment three items were included in a post-game questionnaire (Heemeyer, 2006), assessing the degree to which (a) participants felt represented by their own avatar, (b) participants felt that the other avatars were controlled by human players, and (c) participants felt they were perceived as a real person by the other players. We used both the scores of the individual items, as well as a composite score (the average of all three items) to explore the effects of embodiment on collective trust, investment, and movement behavior.

Reciprocity. We explored whether trustees reciprocated high investments with high returns by calculating a correlation between investments and returns in the same round.

Forward signaling. We operationalized forward signaling as the correlation between the return in round t and the investment in round t+1.

Decision process. If collective trust is an emergent construct, the group decision making process within the investor group should become easier with repeated interactions. If the group has a shared understanding of how much they trust, the decision process should be quicker and more streamlined. We explored the decision process during individual and group investments using movement parameters, comparable to studies using mouse tracking as "real-time motor traces of the mind" (Freeman et al., 2011, p. 1). Specifically, we measured

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the length of the first move (*first move*), the average move length (*average move*), the average move length after the first move (i.e., excluding the first move; *second+ move*), the overall decision time (i.e., the time elapsed until the last move was made; *last move*), as well as the *directional changes* (i.e., number of times an avatar changed the movement direction on the playing field). Importantly, the length of one movement is a measurement of time (in seconds) and not distance; each move is defined as exactly one step from one field to an adjacent field.

Materials

All data reported here was collected using the Collective Trust Game (CTG). We direct interested readers to the publication by Ritter et al. (2022) in which the technical details of the CTG are presented. While the CTG program provides the possibility to customize the game in a multitude of ways, we draw attention to some important configurations that were chosen for this study.

Number of rounds. Using data of a pilot study (Ritter et al., 2022), we estimated that 15 rounds provide a sufficient number of interactions for collective trust to emerge.

Investment and return options. First, we had to ensure that the investment scale would only include multiples of three as discrete options so that the investor group could divide their account evenly among them and not produce split cent amounts. Second, due to the principle design of HoneyComb the return scale of trustees was also restricted to discrete options. We calculated the normatively “fair” returns for both individual (2/3) and group investors (5/6), following the equality norm (Bierhoff, 2021). This means that a return of 2/3 or 5/6 in the single and group condition, respectively, would ensure that both the trustee and all individual investors would receive equal absolute amounts of money.

Unanimity. The CTG was configured to require a unanimous decision to invest in the game, otherwise investors would be penalized by deducting 24 cents from the investors’

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group account. This was implemented in order to ensure that participants would not play "alongside" one another but were motivated to interact with each other through movement. Following our working definition of collective trust, interaction is an important predecessor to the emergence of collective trust. The penalty was introduced to ensure that participants with a tendency to invest 0 cent would not receive an unfair decision weight.

Data preparation and analysis

All data preparation and analyses were conducted with R (version: version 4.0.5; R Core Team, 2020) using RStudio (version 2022.2.3 .492; RStudio Team, 2020). The used R packages can be found in the Supplementary Material 3.

Data was first transformed from the raw state (TXT for investment data and CSV for movement data) into two analyzable data sets (investment and movement data). The transformed data sets and analysis script can be downloaded from the OSF project: https://s.gwdg.de/3lMe9s (anonymous peer-review link).

Results

OTG Adaptation (OTGA)

In order to test, whether the adaptation of the OTG with the HoneyComb paradigm was successful, we tested whether individual investments in the single condition, 31.76 cent on average (SD = 23.58, Mdn = 36), exceeded zero. We conducted a one-sample t-test against $\mu = 0$, showing that participants indeed invested significantly more than 0 cent (OTGA 1); $t(135) = 15.713$, $p < .001$; *95 % CI* [27.77, 35.76].

Additionally, a one-sample t-test of the absolute returns (M = 90.75 cent, SD = 68.77) was conducted, showing that in absolute numbers trustees returned significantly more than 0 cent (OTGA 2); $t(509) = 29.80$, $p < .001$; *95% CI* [84.77, 96.74]. It could also be shown, using a Wilcoxon Signed-Rank test, that trustees returned significantly more than 0 in terms

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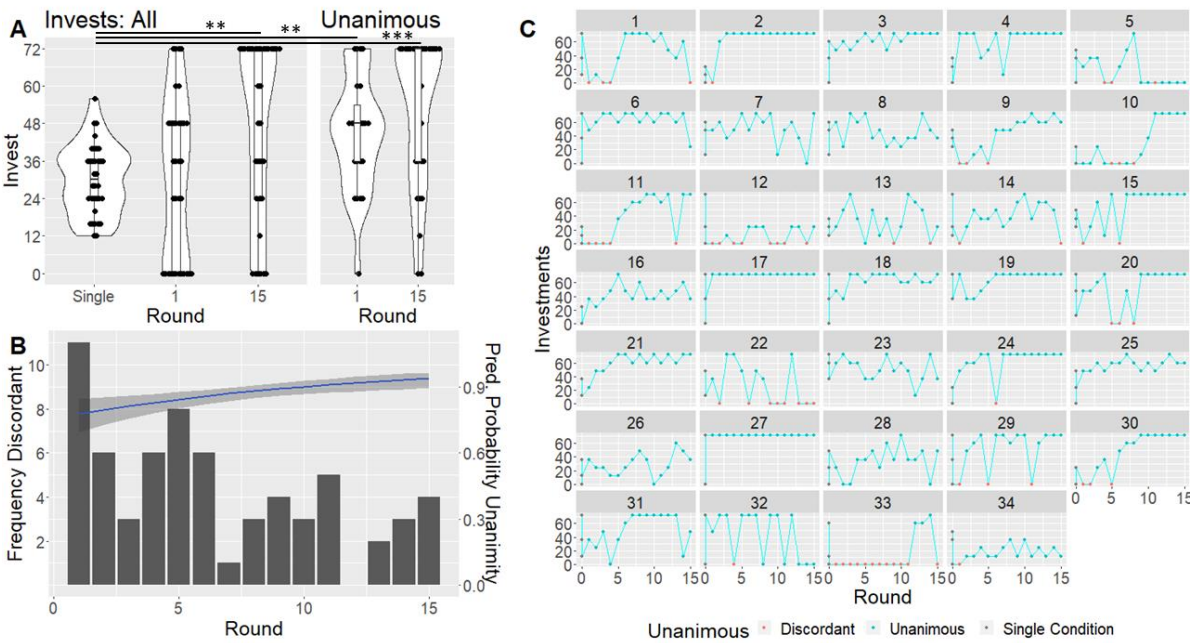
of return fractions (*Mdn* = 66. 67 ~ 4/6); *V* = 83436, *p* < .001. As in some trials no investments were sent to the trustee either due to failure to find a unanimous investment decision or investment of 0 cents, trustees did not have the possibility to return more than 0 cent, these analyses were rerun using only those trials which were preceded by a non-zero investment. Both in absolute returns (*M* = 109.41 cent, *SD* = 60.48) and return fractions (*Mdn* = 66. 67 ~ 4/6) the returns exceeded 0; *t*(422) = 37.21, *p* < .001, *95% CI* [103.63, 115.20], *V* = 83436, *p* < .001.

Figure 3

Investment data in Study 1



Note. **A** – Investments during the Single Condition (averaged within groups), Round 1, and Round 15. Violin plots represent density distributions, boxes represent interquartile ranges, dots represent raw data points. For Round 1 and 15 (group condition), separate data is shown for only unanimous investments. **B** – Bars represent the number of discordant decisions in each round. The blue line represents the predicted probability of reaching a unanimous decision. The shaded area around the line represents the 95% confidence interval for predictions. **C** – Investment decisions in each round for each group separately. Each panel represents one group, lines and dots represent investments.

** p < .01; *** p < .001

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Emergence of Collective Trust (EM)

In order to test the first emergence hypothesis (EM1, Figure 3A), the individual investments during the single round were averaged within the group. A paired t-test, testing the difference between average investments made during the single condition (*M* = 30.12 cent, *SD* = 11.19) and investments made during the first round (*M* = 30.35 cent, *SD* = 35; mean of the differences = -0.24), suggests no statistically different investment between the single condition and the first round of the group condition; $t(33) = -0.05$, $p = 0.961$; *95% CI* [-0.35, 0.33]. Additionally, a paired t-test was conducted suggesting that the average individual investments were lower than the group investments in the fifteenth round (*M* = 46.94 cent, *SD* = 28.55) with a medium effect size; difference = -16.82, *95% CI* [-27.31, -6.34], $t(33) = -3.26$, $p = 0.003$; Cohen's $d = -0.56$, *95% CI* [-0.93, -0.20]. This effect was even stronger when only considering the unanimous investments in the fifteenth round (*M* = 52.57 cent, *SD* = 24.14); difference = -22.10, *95% CI* [-32.23, -11.96], $t(20) = -4.55$, $p < .001$; Cohen's $d = -0.99$, *95% CI* [-1.55, -0.47]).

However, there was a high number of disagreements ($n = 11$) during the first group round. We reanalyzed only the groups in which a unanimous investment decision was made during the first round: The paired t-test testing the difference between the average of individual investments during the single condition and unanimous group investments in the first round (*M* = 44.86 cent, *SD* = 18.53) suggests that the effect is positive, statistically significant, and medium (difference = 14.78, *95% CI* [5.80, 23.76], $t(22) = 3.41$, $p = 0.002$; Cohen's $d = 0.71$, *95% CI* [0.25, 1.19]).

To test the second hypothesis regarding emergence (EM 2.1), we compared the number of unanimous and discordant decisions in the first and fifteenth group round, using Pearson's Chi-squared test. While the overall test was not significant ($\chi^2(1) = 3.079$, $p =$

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0.079), post-hoc comparisons (adjusted with the Bonferroni method) showed that during the fifteenth round, groups decided unanimously significantly more often (n = 30) than discordantly (n = 4; $p < .001$). Groups were increasingly more likely to decide unanimously in later rounds (Figure 3B), supporting EM 2.2. We fitted a logistic model, estimated using maximum likelihood (ML), to predict the occurrence of a unanimous decision depending on the round (formula: unanimous ~ round). The model's explanatory power is weak (Tjur's R^2 = 0.02). Within this model, the effect of round is statistically significant and positive (β = 0.11, *95% CI* [0.04, 0.17], p = 0.001; std. β = 0.46, *95% CI* [0.19, 0.74])[1].

Lastly, we tested the third emergence hypothesis (EM 3). There was considerable variation between groups in terms of the emergence process (Figure 3C). We fit a linear mixed effect model[2] (estimated using ML and Nelder-Mead optimizer) predicting investments with round (formula: investments ~ round). The model included round and group as random effects (formula: ~ round | group). The model's total explanatory power is substantial (*cond.* R^2 = 0.50) and the part related to the fixed effects alone (*marg.* R^2) is of 0.06. The model's intercept, corresponding to round = 0, is at 34.64 (*95% CI* [27.87, 41.41], $t(1626) = 10.04$, $p < .001$). Within this model, the effect of round is statistically significant and positive (β = 1.42, *95% CI* [0.74, 2.11], $t(1626) = 4.09$, $p < .001$; std. β = 0.24, *95% CI* [0.13, 0.36]), showing that investors significantly increased their investments with increasing rounds. This model outperformed both the model including only the random intercept ($\chi^2(2) = 239.35$, $p < .001$) and the model including only the random slope ($\chi^2(2) = 318.93$, $p < .001$). This suggests that the investors changed their investment behavior over time. Qualitative visual inspection of Figure 3C provides additional support for the emergence of collective

[1] Models including random effects for the group, returned singular fits, so the less complex model was fit.

[2] The model including participants as grouping factors produced a singular fit.

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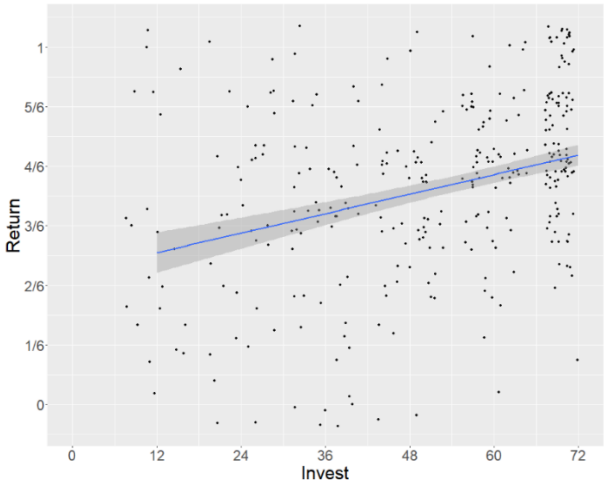
trust: While there was considerable variation between investors within the same group during the single condition, most groups were able to establish a level of collective trust around which investments in the later rounds varied. Note that, with a few exceptions, discordant decisions were mostly made during earlier rounds and that the emergent collective trust level did not necessarily increase but could also decrease over time.

Exploratory results

Reciprocity and Forward-signaling.

Figure 4

Correlation between investments and return (Study 1).



Note. Dots represent raw data points, the blue line represents the slope of the association between investments and returns. The shaded area represents the 95% confidence interval for predictions.

To check for reciprocity and forward-signaling, we calculated Kendall's rank correlation τ. For all investment and return data, Kendall's rank correlation τ between investments and return in the same round is positive, statistically significant, and very large ($\tau = 0.53$, $z = 15.00$, $p < .001$). As there might have been differences between groups in reciprocity between investors and trustees, a repeated measures correlations (Bakdash & Marusich, 2017) was calculated, confirming the positive, statistically significant, and large correlation ($r = 0.713$, $p < .001$, *95% CI* [0.66, 0.75]). However, this relationship could be

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driven by discordant investments of zero. In these cases, trustees could not return anything else than zero as they had not been sent any money. Hence, we repeated this calculation on data including only the unanimous investments: Kendall's rank correlation τ remained positive, statistically significant, and medium ($\tau = 0.28$, $z = 7.19$, $p < .001$), as well as the repeated measures correlation ($r = 0.33$, $p < .001$, *95% CI* [0.24, 0.42]) albeit only showing medium effects. However, visual inspection of Figure 4 shows that conclusions based on these statistical results should be interpreted with caution.

Additionally, we explored whether trustees might have used forward-signaling to communicate trustworthiness to investors. We calculated correlations between the returns in round t and investments in round t+1. Kendall's rank correlation τ was nonsignificant both when considering all data ($\tau < .001$, $z = 0.12$, $p = 0.905$) and when considering unanimous investments only ($\tau = 0.06$, $z = 1.50$, $p = 0.133$). The repeated measures calculations also remained nonsignificant (all data: $r = -0.07$, $p = .151$, *95% CI* [-0.16, 0.025], unanimous investments only: $r = -0.02$, $p = .674$, *95% CI* [-0.12, 0.07]). These results do not suggest forward-signaling.

Decision process.

Individual. Descriptive data of movement during the single condition can be seen in Table 2.

Group processes. Descriptive data of movement during the group condition can be found in Table 2 and Supplementary Table 1.

We further explored the decision process by contrasting the length of the first move with the average move length and the second+ move length (i.e., mean of all moves excluding the first move). A paired t-test suggests that participants took significantly longer to take their first move, compared to the average moves (difference = 1.44, *95% CI* [1.29, 1.58], $t(1419) = 19.41$, $p < .001$; Cohen's $d = 0.52$, *95% CI* [0.46, 0.57]) and the average

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moves, excluding the first move (difference = 1.86, *95% CI* [1.67, 2.05], $t(1327) = 19.14$, $p < .001$; Cohen's $d = 0.53$, *95% CI* [0.47, 0.58]).

Table 2

Descriptives of movement parameters

	Single N = 136	**Investors** N = 1,530	**Trustees** N = 510
Number of moves	3 (1, 4)	6 (4, 6)	4 (3, 5)
First Move	10.4 (6.8, 14.0)	3.5 (2.3, 5.7)	2.1 (1.4, 3.3)
Decision Time	18 (13, 24)	12 (8, 19)	6 (5, 10)
Mean length of moves	4.71 (3.39, 7.30)	2.50 (1.54, 3.82)	1.61 (1.21, 2.16)
Mean length of moves (excl. first move)	2.23 (1.03, 3.73)	1.78 (1.04, 3.18)	1.23 (0.90, 1.83)

Note. This table reports descriptives of movement parameters in both single and group condition. Each data point refers to one round. Participants were split up into investors and trustees in the group condition. We report the median and IQR.

Additionally, we explored how the decision process changed over time as the emergence of collective trust should simplify the decision. There seems to be a general trend for the decision process to become shorter (Figure 5). This was confirmed with a linear mixed model (estimated using REML and nloptwrap optimizer) to predict the length of the first move depending on round (formula: first move ~ round). The model included group as a random effect. The model's total explanatory power is moderate (*cond.* $R^2 = 0.19$) and the part related to the fixed effects alone (*marg.* R^2) is of 0.10. Within this model, the effect of round is statistically significant and negative ($\beta = -0.27$, *95% CI* [-0.30, -0.23], $t(2052) = -15.59$, $p < .001$; std. $\beta = -0.31$, *95% CI* [-0.35, -0.27]). A similar model was fitted for the

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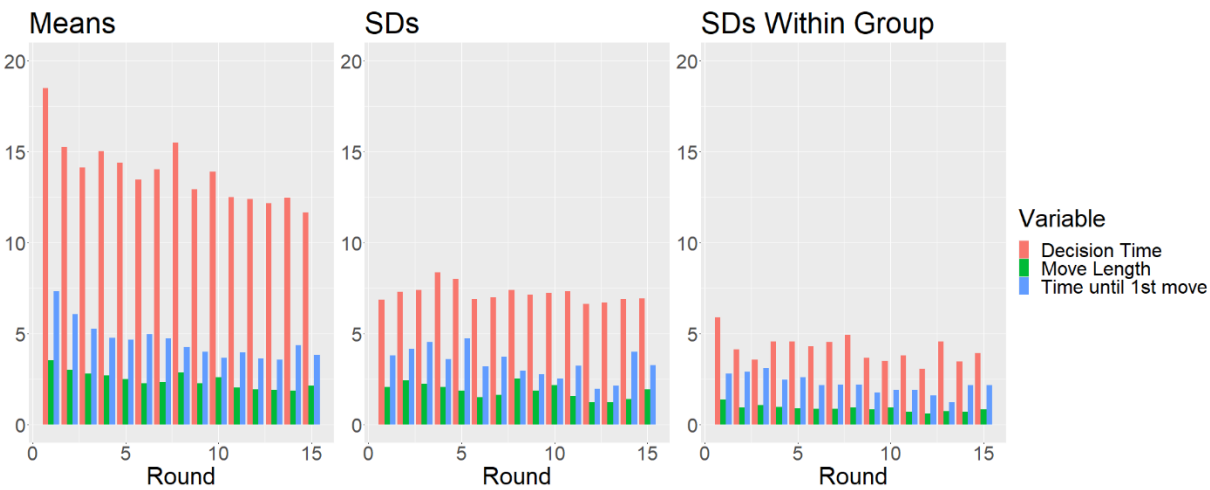
second+ average move length and the decision time (last move). For the second+ average move model, explanatory power is moderate (*cond.* R^2 = 0.16) and the part related to the fixed effects alone (*marg.* R^2) is of 0.03. The effect of round is statistically significant and negative (β = -0.07, *95% CI* [-0.09, -0.06], *t*(1797) = -8.50, *p* < .001; std. β = -0.19, *95% CI* [-0.23, -0.14]). Lastly for the decision time model, explanatory power is weak (*cond.* R^2 = 0.12) and the part related to the fixed effects alone (*marg.* R^2) is of 0.04. The effect of round is statistically significant and negative (β = -0.33, *95% CI* [-0.39, -0.26], *t*(2052) = -9.92, *p* < .001; std. β = -0.21, *95% CI* [-0.25, -0.16]).

Figure 5

Development of movement parameter means, SDs, and SDs within groups over rounds



Note. Means, SDs, and SDs within groups are shown for each round.

The overall standard deviations of the movement parameters (Figure 5) indicate the variance of movement parameters across all participants. The within-group standard deviations correspond to the variance of movement parameters within each group, so that a group with low within-group standard deviation moved more uniformly or coordinated, compared to a group with a high within-group standard deviation. This observation was confirmed analytically: We fitted a linear model, estimated using ordinary least squares

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(OLS), to predict within-group standard deviations depending on the round. The model explains a statistically significant and weak proportion of variance (R^2 = 0.03, F(1, 500) = 16.13, p < .001, *adj*. R^2 = 0.03). The effect of round is statistically significant and negative (β = -0.09, *95% CI* [-0.13, -0.05], t(500) = -4.02, p < .001; std. β = -0.18, *95% CI* [-0.26, -0.09]). Similar models were fitted for the within-group standard deviation of the average second+ move length and the within-group standard deviation of the decision time (last move). The second+ move length model explains a statistically significant and weak proportion of variance (R^2 = 0.02, F(1, 450) = 10.85, p = 0.001, *adj*. R^2 = 0.02). The effect of round is statistically significant and negative (β = -0.03, *95% CI* [-0.05, -0.01], t(450) = -3.29, p = 0.001; std. β = -0.15, *95% CI* [-0.25, -0.06]). Lastly, the decision time (last move) model explains a statistically significant and very weak proportion of variance (R^2 = 0.01, F(1, 500) = 5.91, p = 0.015, *adj*. R^2 < .001). The effect of round is statistically significant and negative (β = -0.08, *95% CI* [-0.15, -0.02], t(500) = -2.43, p = 0.015; std. β = -0.11, *95% CI* [-0.20, -0.02]).

Embodiment. Overall, participants felt moderate embodiment (average score: M = 3.65, SD = .82). Correlations with movement parameters and investments were explored with Spearman's rank correlations but no significant association could be found (first move: ρ = -.14, p = .14; second+ move: ρ = .10, p = .36; number of direction changes: ρ = .04, p = .68; single investment: ρ = .05, p = .54).

Discussion

First, we regard the adaptation of the OTG into the HoneyComb paradigm to be successful. Even though the response format was very different from the original trust game, we observed that investors would still exhibit trust during the single condition, even though game theory would predict a zero investment.

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Collective trust as an emergent construct

Second, the data suggests that collective trust can be conceptualized as an emergent construct: The collective trust level that was established during the group rounds (as measured by the investment in the fifteenth round) differed significantly from the investments made during the single condition. Additionally, the investments during the first round of the group condition also differed from investments made in the single condition when excluding those groups that did not reach a unanimous decision. These results at least partly support the first emergence hypothesis (EM1). Further, we hypothesized that there would be more unanimous investment decisions during the later rounds, compared to earlier rounds (EM 2.1), as the emergence of collective trust would allow investor groups to reach a decision more easily. We further hypothesized (EM 2.2) that the probability of reaching a unanimous decision would increase over rounds. This seems to be supported by the data. Investment groups were indeed more likely to find a unanimous decision during later rounds of the game. This is in line with the expectation that collective trust needs to emerge through repeated interactions among a group. Once the group shares this trust level, unanimous decisions can be reached more easily.

Our last emergence hypothesis (EM 3) stated that the level of collective trust, as measured by group investments, should change over time. Specifically, how much investors invested in the first round should significantly differ from the amount invested in the fifteenth round. This corresponds to our data, suggesting that through interaction, a shared level of trust is built over time. These results suggest that collective trust can indeed be conceptualized as an emergent construct and needs to be given time to develop before it can be measured. Hence, simple averaging of individual trust does not suffice to get a clear idea of how much a group trusts another entity.

It should be noted that there was considerable between-group variation in how collective trust developed. This is in line with the concept of an emergent construct

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(Kozlowski & Chao, 2012): The development of collective trust does not follow a “one size fits all” procedure but develops differently within each group. Within a group, the individual trust levels, interactions among group members, experience of trustee behavior, as well as decision procedures are likely determinants of how collective trust developed within each group. However, the design of this study makes it difficult to determine these effects separately. It should be noted that this study did not include any counterbalancing between the single and group condition. This design choice was made as we needed a baseline of individual trust that would not be influenced by the experience during the group condition. In order to minimize carry-over effects from the single to the group condition, participants were explicitly told that they would not play with the same person they had played with in the first round. While we cannot fully rule out any carry-over effects from the experience during the single condition, we argue that the interaction within the investor group and with the trustee should have a much larger influence on behavior in the CTG.

Furthermore, we explored whether investors and trustees might have used strategies such as reciprocity and forward-signaling in determining their investment or return behavior: Analytically, trustees seemed to reciprocate high investments with high returns. However, this evidence should be interpreted with caution as visual inspection of the data shows only limited support of this finding. Based on our data, forward-signaling was not employed by trustees and investors.

Lastly, we explored the decision process by investigating movement parameters. In general, we found that participants took longer to make an initial move, compared to the average length of following moves. This could indicate that participants deliberated on their final investment before starting to move onto the corresponding field. This is in line with the finding that participants usually moved only forward and did not change direction. This could suggest that the decision process itself is not an embodied process, rather than a means of

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communicating the investment decision to the trustee as well as other investors. Additionally, this could indicate that as soon as collective trust emerges, group members have a shared sense of its level and can simply move their avatar directly onto the corresponding field; there seems to be no need to "negotiate" the trust level by moving back and forth on the playing field. The movement parameters also suggest that the decision process within a group becomes faster, more uniform, and possibly easier with increasing rounds. The variance of movement within each group also decreased over rounds, suggesting that groups might have developed both a shared level of collective trust and a shared decision process.

It is important to keep in mind that participants only communicated through avatar movements and did not have the possibility to employ further verbal or nonverbal communication. Therefore, it seems that the interaction needed to form a shared level of collective trust can be rather minimal.

Study 2

Study 2 was conducted as a conceptual replication of Study 1, using a different response format and excluding movement as means of communication and interaction between participants. As such, it was expected that results would be comparable to those of Study 1 in terms of OTG adaptation (OTGA) and collective trust emergence (EM). We explore whether collective trust can emerge with only minimal interaction. Further, aspects of reciprocity and forward-signaling are be explored.

Method

Sample

For this study, 144 participants were tested in 36 groups of four. Due to technical difficulties only 138 participants were able to fill out the post-experiment questionnaire and

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the data of three groups was incomplete. The 138 participants (58.7 % women, 39.9 % men, 1.4 % diverse) were 29.8 years old on average (*SD* = 12.5) and the majority were university students (*n* = 84).

The same selection criteria and participation compensations were used as in Study 1. People who had participated in data collection for Study 1 were excluded from this data collection in order to prevent familiarity effects. Data collection and data analysis procedures in this study were approved by the Ethics Committee of the psychology institute (additional information removed for blind review).

While we were able to test 36 groups, exceeding the necessary sample size of 34 groups that was determined by a power analysis (Supplementary Material 1). Unfortunately, only 33 complete group data sets could be collected due to technical difficulties. As this was only discovered after data collection was complete, no additional group data was collected. However, for most of the reported analyses the sample should provide sufficient power as they were conducted on individual data.

Procedure

A schematic overview of the procedure can be seen in Figure 1B and a more detailed description can be found in Supplementary Material 2.

As in Study 1, a video conference platform enabled communication between the experimenter and participants and should create a sense of social presence. Instructions were kept as close to standardized instructions in Study 1 as possible. Written consent was collected from all participants before starting the study. Instructions on the game were given within the experiment program. As in Study 1, participants first played the single condition as an investor and were then randomly assigned to be either an investor or trustee during the group condition.

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Single condition. The instructions differed from the instructions in Study 1 only to the extent that the differing response options had to be made clear. Explanations on the principles of the (collective) trust game remained the same.

After receiving the endowment (72 cents), participants were presented with a single-choice question to indicate their investment preferences (0 – 72 cents in steps of 12); Figure 2 2 I). In the single condition, participants had 30 seconds to indicate their choice before the investment was tripled and sent to the trustee. Afterwards, simulated trustees had 15 seconds to decide on the amount to return. All simulated trustees returned 4/6 of the tripled investment as in Study 1.

Group condition. As in Study 1, both the trustee and the investor group received an endowment of 72 cents (i.e., 24 cents per individual investor). In order to send part or all of their endowment to the trustee, the investors had to reach a unanimous investment decision. Piloting of the study showed that unanimous decisions among the investors were too hard in this minimal response format so a proposal stage was implemented: Participants were given 15 seconds to indicate their investment preferences. Subsequently, investors were shown the proposals of all investors and their respective response times (Figure 2 - 2 P) to provide additional information for the final decision. Afterwards, investors were asked to provide their final investment decision within 15 seconds. In case no unanimous decision was reached, a penalty of 24 cents was deducted from the investors account. In case of a unanimous decision, the investment was tripled by the program and sent to the trustee. The trustee indicated the preferred return fraction (0 – 1 in steps of 1/6; Figure 2 2 T). The return was then sent back to the investors and the round ended. This procedure was repeated for 15 rounds.

Questionnaire and debriefing. Participants were asked to answer the same post-experiment questionnaire as in Study 1.

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Operationalization

As Study 1 and Study 2 are similar in every regard, except presentation and response mode of participants, operationalizations were also kept consistent across both studies. Please refer to Study 1 for details on operationalization of trust, trustworthiness, embodiment, reciprocity, and forward-signaling.

Materials

The experiment was programmed using the online platform LabVanced (Finger et al., 2017). During construction of the experiment, it was ensured that instructions, procedure, as well as game logic and monetary rewards were kept as close as possible to Study 1 in order to ensure comparability of results. The goal was to solely alter the response mode and communication style in comparison to Study 1.

While LabVanced does not provide any functionality to record movement (e.g., via mousetrack), a decision latency measure was introduced. As described in the procedure, this was included to enrich the information participants could exchange during the proposal phase of the investment. The post-game questionnaire was replicated from Study 1.

Data preparation and analysis

Data was downloaded from the LabVanced (Finger et al., 2017) platform and transformed into one analyzable data set. Analysis strategies from Study 1 apply. The transformed data set can be downloaded from the OSF project: https://s.gwdg.de/3lMe9s (anonymous peer-review link).

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Results

OTG Adaptation (OTGA)

First, we analyzed whether the investments during the single condition (M = 38.94 cent, SD = 21.04, Mdn = 36) exceeded zero, as expected (OTGA 1). The one Sample t-test testing the difference between single investments and $\mu = 0$ supports our expectations; the effect is positive, statistically significant, and large (difference = 38.94, *95% CI* [35.46, 42.41], $t(142) = 22.13$, $p < .001$; Cohen's $d = 1.85$, *95% CI* [1.58, 2.13]).

We further investigated whether trustees return more than 0 as expected (OTGA 2). In terms of absolute returns, trustees returned significantly more (M = 101.36 cent, SD = 64.51) than $\mu = 0$, with a positive and large effect (difference = 101.36, *95% CI* [95.21, 107.52], $t(423) = 32.35$, $p < .001$; Cohen's $d = 1.57$, *95% CI* [1.43, 1.72]). This was also true for returns in terms of return fractions (Mdn = 0.5): The Wilcoxon signed rank test with continuity correction suggests that the effect is positive, statistically significant, and very large ($W = 65341.00$, $p < .001$).

These effects persisted when excluding those returns that followed a zero investment or a discordant investment: Absolute returns (M = 106.64 cents, SD = 61.76) differed significantly from $\mu = 0$ with a positive and large effect (difference = 106.65, *95% CI* [100.60, 112.69], $t(402) = 34.66$, $p < .001$; Cohen's $d = 1.73$, *95% CI* [1.57, 1.88]). Return fractions (Mdn = 0.66) also significantly differed from the true location of zero with a positive and very large effect ($W = 65341.00$, $p < .001$).

Emergence of Collective Trust (EM)

We investigated whether the investors in the group condition would invest differently compared to investments during the single condition, as predicted by the first emergence hypothesis (EM 1; Figure 6A). A paired t-test showed that participants invested significantly

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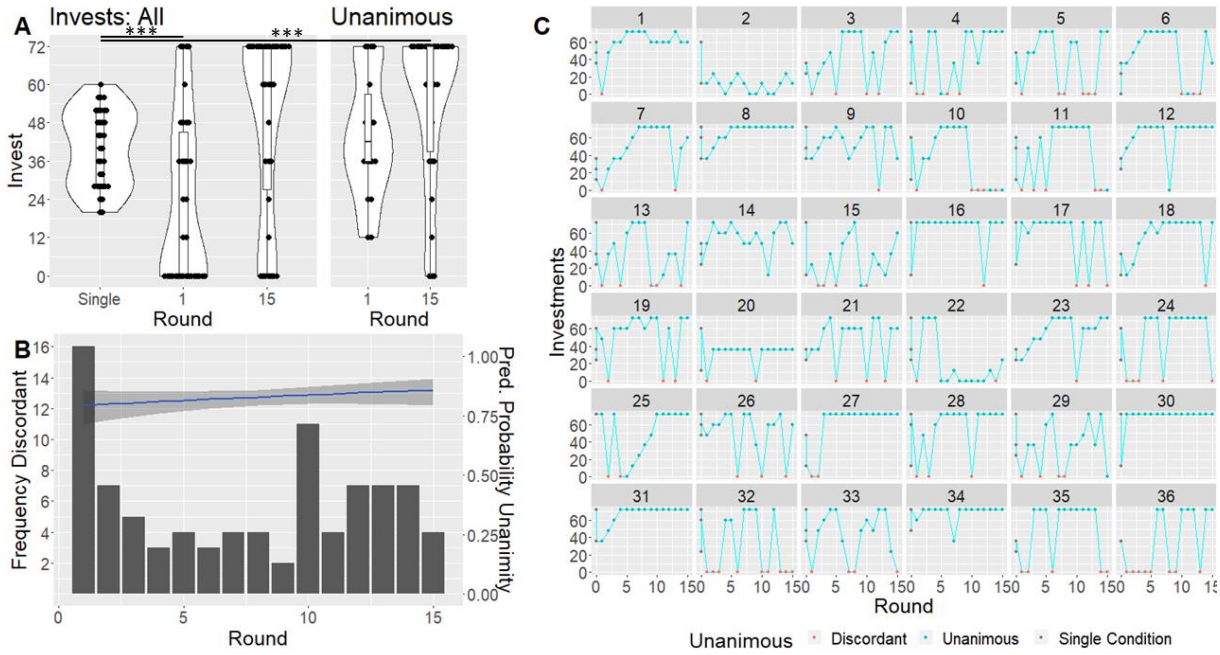
more in the single condition (*M* = 40 cent, *SD* = 11.92), compared to the first round of the group condition (*M* = 23.29 cent, *SD* = 26.41) with a positive and medium effect (difference = 18.18, *95% CI* [9.75, 26.62], *t*(32) = 4.39, *p* < .001; Cohen's *d* = 0.76, *95% CI* [0.38, 1.17]). There was no significant difference in investments between the single condition and the fifteenth round of the group condition (*M* = 48.35 cent, *SD* = 29.31); difference = -7.64, *95% CI* [-19.11, 3.83], *t*(32) = -1.36, *p* = 0.185; Cohen's *d* = -0.24, *95% CI* [-0.59, 0.11].

Figure 6

Investment data in Study 2



Note. **A** – Investments during the Single Condition (averaged within groups), Round 1, and Round 15. Violin plots represent density distributions, boxes represent interquartile ranges, dots represent raw data points. For Round 1 and 15 (group condition), separate data is shown for only unanimous investments. **B** – Bars represent the number of discordant decisions in each round. The blue line represents the predicted probability of reaching a unanimous decision. The shaded area around the line represents the 95% confidence interval for predictions. **C** – Investment decisions in each round for each group separately. Each panel represents one group, lines and dots represent investments.

*** p < .001

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There was a high number of zero investments during the first round due to discordant investment decisions. Therefore, we reanalyzed the data using only unanimous investments. The effects reversed in that unanimous decisions in the first round did not differ from the single condition (single condition – first round: difference = 1.41, *95% CI* [-5.82, 8.64], $t(16) = 0.41$, $p = 0.685$; Cohen's $d = 0.10$, *95% CI* [-0.39, 0.59]), while unanimous investments in the fifteenth round exceeded single investments (single condition – fifteenth round: difference = -20.00, *95% CI* [-30.18, -9.82], $t(15) = -4.19$, $p < .001$; Cohen's $d = -1.05$, *95% CI* [-1.71, -0.44]).

The second emergence hypothesis predicted that there would be less unanimous investments during the first, compared to the last round (EM 2.1; Figure 6B), and that the frequency of reaching a unanimous decision would increase in later rounds (EM 2.2). A Pearson's Chi-Square test indicated significant differences between round ($\chi^2(1) = 8.570$, $p = .003$) that were further analyzed with post-hoc comparisons (Bonferroni corrected): During the fifteenth round, only 4 of 34 investor groups were discordant in their decision, while 16 investor groups were discordant in the first round ($p = .044$). However, the number of unanimous decisions did not differ significantly (first round: 18, fifteenth round: 30, $p = .5$). Additionally, we fitted a logistic model (estimated using ML) to predict a unanimous decision depending on the round. However, the model's explanatory power is very weak (*Tjur's* $R^2 < .001$) and the effect of round is not significant ($\beta = 0.03$, *95% CI* [-0.02, 0.09], $p = 0.233$; std. $\beta = 0.14$, *95% CI* [-0.09, 0.37]).

Lastly, we investigated the third emergence hypothesis (EM3) stating that collective trust should change with later rounds. To this end, we fitted a linear mixed model (estimated using REML and Nelder-Mead optimizer) to predict investments depending on the round (formula: investment ~ round). The model included round and group as random effects

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(formula: ~round | group)[3]. The model's total explanatory power is substantial (*cond.* R^2 = 0.30) and the part related to the fixed effects alone (*marg.* R^2) is of 0.01. Within this model, the effect of round is statistically significant and positive ($\beta = 0.76$, *95% CI* [0.18, 1.35], $t(1721) = 2.55$, $p = 0.011$; std. $\beta = 0.12$, *95% CI* [0.03, 0.21]). This model outperformed less complex models including only the random intercept ($\chi^2(2) = 91.96$, $p < .001$) or only the random slope ($\chi^2(2) = 104.81$, $p < .001$). It should be noted that there was considerable variation between groups in the emergence of collective trust (Figure 6C). However, most groups were able to converge on a collective trust level as shown by their investments and henceforth varied around this level. While most discordant decisions were made during earlier rounds, it should be noted that in some groups discordant decisions were also present during later rounds.

Exploratory results

Reciprocity & forward signaling. In order to investigate whether investors and trustees behaved according to principles of reciprocity and forward-signaling, we conducted exploratory correlation analyses. First, a Kendall's rank correlation τ suggests that returns followed the principle of reciprocity with a significant and positive correlation between investments and returns; $\tau = 0.45$, $z = 12.22$, $p < .001$. However, this effect disappeared when zero investments and discordant decisions were excluded from the data; $\tau = 0.07$, $z = 1.66$, $p = 0.097$. To allow for differences in this association between groups, we calculated a repeated measures correlation (Bakdash & Marusich, 2017) that followed the same pattern: For all investments and returns, the correlation was significant, positive and large; $r = 0.58$, *95% CI*

[3] Note that a model including participants as random effects produced a singular fit, so that a less complex model was chosen for this analysis.

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[0.52, 0.64], $p < .001$. However, this effect changed direction and became very small after excluding zero and discordant investments: $r = -0.14$, *95% CI* [-0.24, -0.04], $p = .008$.

We also investigated forward-signaling. A Kendall's rank correlation showed a significant, positive, and large correlation between returns in round t and investments in round t+1; $\tau = 0.34$, $z = 8.83$, $p < .001$. This effect remained significant when only unanimous investments were included: $\tau = 0.34$, $z = 8.10$, $p < .001$. The repeated measures correlation for all investments (allowing for variation of association between groups) was calculated to be 0.22 (*95% CI* [0.14, 0.32], $p < .001$). For only unanimous investments, the repeated measures correlation was 0.31 (*95% CI* [0.21, 0.40], $p < .001$).

Embodiment. Overall, participants felt moderate to high embodiment ($M = 3.74$, $SD = 0.84$). Notably, we found a significant correlation between how embodied participants felt and how much they invested during the single round; $\rho = 0.22$, $p = 0.011$. However, there were no other significant associations with embodiment.

Discussion

First, the basic expectations of the OTG adaptation were met (OTGA 1 & 2): Investors during the single condition invested significantly more than zero, and trustee returns exceeded zero as well. We conclude that the adaptation was successful in this regard.

Second, we find some evidence that collective trust emerged in this study. Investments made during the group condition in the first round significantly differed from average investments in the single condition (EM 1), showing once more that averaging of individual trust is not an adequate way to measure group trust. However, there was no significant difference between collective trust in the fifteenth round and average individual trust. However, these results reversed when analyzing only unanimous investments, showing the large effect of discordant decisions in this study. We expected that more unanimous

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investments would be made during the later rounds of the game (EM 2.1), compared to the first, with the probability of unanimous investments steadily increasing over the rounds (EM 2.2). While the number of discordant decisions differed between the fifteenth and first round, the number of unanimous decisions did not differ significantly. We also failed to find the expected increase of probability with which a unanimous decision was reached. We could show that the collective trust level changed in later rounds (EM 3), corresponding to the expectation that a shared level of trust needs to be established through repeated interaction until convergence. However, there was considerable between-group variation in how collective trust emerged. While many groups seem to have reached a shared level of trust, some groups experienced discordant decisions in later rounds, contrary to expectations. In sum, we did not find clear evidence to support the emergence of collective trust in this study and argue that these findings could be the result of the minimal interaction that was possible in this study. As investors were only able to communicate their investment decisions through a proposal and decision phase, decision tendencies could not be expressed. Therefore, finding a consensus and reaching a unanimous decision was much harder in this study and might have impeded the emergence of collective trust. As collective trust is a construct that should emerge through interaction, it could be expected that minimal interaction will impair its emergence.

We explored whether trustees and investors might have relied on reciprocity or forward-signaling when determining their next return or investment. While we did not find convincing evidence of reciprocity, our data suggests that investors used returns of the previous round to determine their next investment. Even when excluding discordant investments, a high return in one round was often followed by a high investment in the following round, or vice versa. It could be that investors relied more heavily on this strategy

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as other communication and interaction was very limited. However, this should be explored further in future investigations.

We found that even though participants were not represented by avatars or could interact with them, they experienced moderate to high embodiment. As we found a significant association between embodiment and investments during the single condition, it could be speculated that participants who felt well represented in the experiment were more likely to exhibit trust in the first round, as they were expecting an actual person to reciprocate. However, the association was not present during the group condition. It could be that the association disappeared as group investments were made by multiple investors with varying levels of subjective embodiment. Yet, these results should be interpreted with caution and future research might address this question more closely.

In sum, this study suggests that collective trust might emerge even under conditions of minimal interaction and communication but might be hampered by limiting interaction. Due to the lack of information about other investors' tendencies and preferences, other sources of information, such as the trustee return in the previous round, might gain in importance. The emergence of collective trust might necessitate more social information about others in the investor group.

General Discussion

In this project, we aimed to build a working definition of collective trust and investigate its qualities with appropriate methodologies. To this end, we used the CTG (Ritter et al., 2022) to investigate the emergence of collective trust in Study 1. The CTG adapts the OTG (Berg et al., 1995) to the group level. Participants in the game can interact and communicate through movement and researchers can observe group processes in fine detail through analysis of recorded spatio-temporal data. In Study 2, we adapted the CTG to use a

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different response format, restricting possibilities of interaction and response further. In this study, participants could communicate solely through a proposal stage before submitting their final decision.

We found that the adaptation of the OTG was successful in both studies. Both investors and trustees exhibited trusting or trustworthy behavior as in many studies using the OTG (Berg et al., 1995; Johnson & Mislin, 2011). This shows that the adaptation to a different response format (Study 1: investment/return decisions through movement; Study 2: inclusion of proposal phase) is fit to investigate trust and in principle does not change the interpretation of the economic game.

When comparing the two studies in terms of the emergence of collective trust, we see some differences. In Study 1, the average of single investments differed significantly from unanimous investments in the first and fifteenth round of the group condition, supporting the argument that averaging of individual investments are poor predictors of group investments in the trust game. In Study 2, these findings could not be fully replicated. While the average investments in the single condition differed from those in the first round of the group condition, no difference could be found between the single condition and fifteenth round of the group condition. It should be noted that, in contrast to Study 1, investments in the first round of Study 2 were below the average of the single investments. In subsequent rounds, investments steadily rose and eventually reached the level of the single condition again in the fifteenth round, explaining the lack in difference between the single condition and the last round. Descriptively, single investments in Study 1 were lower than Study 2, while group investments in the last round were somewhat similar. These differences might have been due to the unusual response format. In Study 1, the response through movement that participants had to get used to in the single condition, might have inspired a more conservative investment. In Study 2, the change from a fairly classic response format (single choice with

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radio buttons) to the proposal format in the group condition might have taken adjustment on the participants' side, thereby causing the drop in investments from single to group condition.

Regarding unanimity of decisions, we find clear differences between studies. While Study 1 saw the probability for unanimous decisions rise steadily, this could not be shown in Study 2. We argue that the proposal format restricted interaction too much so that collective trust could not emerge as easily. While in Study 1, a group process could develop through interaction and participants were able to signal their investment tendencies via movement, Study 2 only allowed one round of proposals. It could be that proposal formats require multiple rounds of proposals until a unanimous decision is reached (Kocher & Sutter, 2007). This was not implemented in Study 2 as the goal was to keep the procedure as close to Study 1 as possible, meaning that unanimous investments might also be discordant and cause a penalty.

In both studies, we found that the level of collective trust changed over time. It should be noted, however, that there was considerable variation between groups in the process over rounds. Most groups changed their investments substantially during earlier rounds and, once a shared level was reached, only varied slightly around this level. However, some groups were more dynamic, possibly reacting more strongly towards trustee responses, and few groups experienced discordances also later in the game. Yet, this process heterogeneity does not contradict predictions of the collective trust decision. On the contrary, collective trust is a concept allowing for heterogeneity between groups as it acknowledges that each group consists of individuals and their interaction so that it is only consequential that distinct groups will experience distinct emergence processes. As an emergent process, collective trust allows for this dynamic approach, as long as the general process (i.e., developing a shared mental model of trust through repeated interactions) is met.

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Besides the emergence of collective trust, this project also explored whether concepts such as reciprocity and forward-signaling are associated with collective trust. Interestingly, there are distinct differences between the studies. While results of Study 1 did not convincingly support either reciprocity or forward-signaling, results of Study 2 suggest that investors and trustees might have relied on forward-signaling to determine their behavior. We argue that the difference between studies might be due to the differing response formats: In Study 1, trustees could observe how investors arrived at their decision (e.g., Were they quick or slow to trust? Was unanimity reached quickly or not?) and investors could in turn observe the trustee's return behavior (e.g., Was the trustee quick (willing) or slow (reluctant) to return high amounts?). Moreover, the investment decisions in Study 1 might have been influenced by the interaction between investors much more, since they also relied on the information-rich environment of the CTG. In contrast, Study 2 limited interaction between investors to the proposal stage, and interaction between trustees to the display of investment or return amounts. As this paradigm provided so little information, these few pieces of information might have gained more weight in the investment decision, as there was simply little else to base it on. It could be that reciprocity and forward-signaling are concepts employed by investors and trustees only when little other information is available. This is in line with idiosyncrasy-credit theory of leadership (Hollander, 1958), postulating that repeated interaction can lead to building up relationship credit between leaders and followers. If a certain amount of credits (or trust) exists after many interactions, basic principles of reciprocity or forward-signaling might not have as much weight anymore. However, this remains speculative and should be thoroughly tested in future studies.

Lastly, we used the movement data in Study 1 to explore the emergence process of collective trust. We find that many of the movement indicators change over time and indicate that the group investment decision process became faster and, possibly, less complex over

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time. This is in line with expectations of the emergence of collective trust. Within the first round, investors do not yet have a shared level of trust or an entrained process by which the investment decision is determined. This puts investors under high amounts of social and process uncertainty (Calcutt et al., 2019; Charness & Sutter, 2012; Hönl et al., 2017). Within the first round, investor groups then interact through movement and signal their investment tendencies to each other (e.g., by remaining on their preferred investment field longer or quickly moving towards their preferred field). Possibly, group processes such as leadership and followership emerge during those rounds to reduce uncertainty. For example, one investor could signal leadership to other investors by moving first (first mover principle: Boos et al., 2014). However, this process would have to emerge during the first round, making early rounds more demanding and increasing decision latencies. Additionally, over the rounds a shared level of collective trust should emerge so that even without a clear group decision process, the investors can rely on their knowledge about this shared level to determine their investment decision (e.g., “This is what my group usually invests.”). However, the determination of leader-/followership and detailed decision processes goes beyond the scope of this paper and should be explored in future studies. For the aim of this project, we argue that the explored patterns in movement parameters support claims that collective trust is an emergent process.

Limitations

We want to draw attention to limitations that might affect the interpretability of the presented results. First, it is important to note that this paper should serve as a starting point for future studies using behavioral measurements of collective trust. The current findings should be interpreted in light of the fact that no counter-balancing of the presentation order of conditions was possible. While participants were informed that they would not play again

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with the same trustee, it is possible that the results of this paper were influenced by some anchor and carry-over effects from the single to the collective condition. While our main objective was to investigate the emergence of collective trust, future studies specifically interested in the differences between individual and collective trust might endeavor to conduct either a between-subjects design or a carefully balanced within-subject experiment in which the factors round repetition and simulation of trustee are held constant across conditions.

Second, we note that the replication of the trustee returns in the OTG (OTGA 2) was only tested within the group condition as the trustee in the single condition was computer programmed. This choice was made in order to control for the influence of trustee returns in the single condition. As trustees in the group condition were playing as individuals, we argue that trustee data in the group condition is still a valid reference point to determine the success of the OTG adaptation. However, future research might also investigate trustee behavior in the single condition.

Third, it has been argued that the measurement of trust in trust games could be confounded with risk propensity (Chetty et al., 2021; Sitkin & Pablo, 1992). While other research has argued that this trait risk propensity is a poor predictor of behavior in the trust game (Houser et al., 2010), future research might endeavor to disentangle trust and risk-taking behavior in the CTG further.

Fourth, it might be argued that ecological validity of the CTG is low. However, research has indicated that movement paradigms usually correspond closely to realistic human behavior (Thrash et al., 2015). Future research might address the aspect of ecological validity by implementing more realistic avatars (Fysh et al., 2022).

Lastly, the CTG restricts investments to discrete steps (as represented by the fields on the playing field) and does not allow investment on a continuous scale. Further, the principle

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of the CTG is based on responding through movement. It is possible that the direction in which one needs to move in order to invest is a confounding factor (e.g., participants are drawn to the middle and invest higher amounts). This was tested for in a pilot study (Ritter et al., 2022) and its effect was judged to be small but cannot be ruled out completely.

Implications for research and practice

In this study, we used the CTG paradigm to investigate the emergence of collective trust. We argue that the CTG has proven a suitable tool to investigate research questions related to trust in groups. The adaptation of the OTG seemed to be successful, so investment and return data collected with the CTG should be comparable to other applications of the OTG while providing unique insights into the decision process through movement data. The unique movement paradigm allowed investors and trustees to interact and communicate, while also remaining completely anonymous to each other. To the knowledge of the authors, the CTG is the only paradigm that allows this level of interactivity while excluding as many confounding factors, such as environment or personal characteristics of other participants. While other studies were able to investigate these processes through the resource-intensive process of recording and analyzing group discussions (Kolbe & Boos, 2019). The CTG provides an inexpensive and time-saving alternative as a large amount of process data can be quantified and analyzed easily.

Future studies might choose to adapt the CTG in specific ways. For example, the penalty after discordant decisions could be replaced by a rule that allows investors to move until a unanimous decision is reached. This would more closely resemble other studies in which a repeated proposal system or unrestricted group discussions were employed (e.g., Kocher & Sutter, 2007). Further, future applications of the CTG could make use of the

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possibility to include pre-programmed agents to investigate concepts such as trust repair (Tomlinson & Mryer, 2009).

Conclusion

Crucially, this project suggests that collective trust should be defined and, importantly, measured as an emergent construct and allow for interaction between individuals in a group. The averaging of individual trust in both research and practice is, therefore, not an adequate way of determining the level of trust a group extends towards another individual, group, or organization. Instead, researchers and practitioners alike should draw on innovative tools, such as the CTG, to measure trust on a group level. We agree with Kolbe and Boos (2019) that while these measurements might be more laborious, their more elaborate results are worth the effort.

doi: 10.53846/goediss-9589

Open Practices

Data collected and analyzed for Study 1 and Study 2 can be found under the following links with accompanying analysis scripts: https://s.gwdg.de/3lMe9s (anonymous peer-review link). Open materials of Study 1 were published by Ritter and colleagues (2022) under the link: https://s.gwdg.de/qIunjE (anonymous peer-review link).

Acknowledgements

We want to thank (redacted for peer review) for support during data collection, (redacted for peer review) for his helpful comments on our manuscript.

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Chapter 5: Analysis and visualization of emergent group processes

In this chapter, I propose a combination of the HoneyComb paradigm (Boos et al., 2019), network analysis, and visual analytic approaches to tackle the challenges of measuring group processes. These techniques were developed to analyze and visualize spatio-temporal data and can be used to identify emergent group processes within the HoneyComb paradigm. It is the aim of this chapter to outline a methodological approach that can make use of the advantages of process or interaction analysis (e.g., Lehmann-Willenbrock & Allen, 2018), while being able to gather and analyze complex movement data reliably and with ease. In this way, group processes can be captured in their dynamic, fluid, and emergent qualities (Kozlowski et al., 2016).

This chapter advances the study of emergent processes in group decision making by contributing new methodological strategies. Methodological developments are an integral part of theory development (Gigerenzer, 1991). Only by analyzing and visualizing emergent processes during group decision making will we be able to understand how groups can use them to reduce uncertainty. To illustrate the presented methods, I will draw on data from the empirical studies presented in Chapter 3 and extend the presented method descriptions of these chapters.

Within this chapter, I provide a broad methodological introduction to the HoneyComb paradigm (Boos et al., 2014, 2019) as means of measuring emergent group processes (e.g., leadership, exploration/exploitation patterns). Additionally, I present some exemplary analyses that were conducted as part of this dissertation and that can be classified into three analysis levels (game, round, move). While many of the strategies and approaches presented in this chapter have been applied in previous research (e.g., Fu et al., 2017b; Lehmann-Willenbrock & Allen, 2018; Nagy et al., 2010), the current chapter builds on this literature and applies it to the study of basic processes in moving human groups. I argue that the formalization of three different analysis levels and the combination of both network and visual analytic techniques with spatio-temporal data can contribute a fresh look to the investigation of emergent group processes.

Measuring emergent processes in groups

The Input-Process-Output (IPO) heuristic (McGrath, 1964) is a well-known conceptualization of how groups transform input into output variables and how this transformation is mediated by the group process. While the input (e.g., information distribution; Stasser & Titus, 2003) and output (e.g., groupthink; Janis, 1972) are researched fairly well, the “P” of the IPO heuristic is often treated as a black box (Kolbe & Boos, 2019).

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Processes in groups are dynamic, emergent over time, and changing their pattern (Kolbe & Boos, 2019; Kozlowski, 2015). Yet, research has often focused on higher level constructs or "what is" (group states) in a group instead of looking into emergent processes or "what happens" (group dynamics; Kolbe & Boos, 2019; Kozlowski, 2015; Roe, 2008). Many have suggested that the classic approach to group processes impedes our understanding of their nature (Kozlowski & Klein, 2000). Instead, group process research should focus on getting a richer picture on evolving patterns, breakpoints, and emergence of group phenomena (Roe, 2008), such as coordination, learning, and leadership. In the last years, many have called on the field to acknowledge these issues (Keyton, 2016; Kozlowski, 2015; Kozlowski & Chao, 2012; Lehmann-Willenbrock & Allen, 2018). An increasing amount of research has followed that call, addressing the dynamic, emergent, and fluid nature of group processes (Grand et al., 2016; e.g., Kolbe et al., 2009; Kozlowski et al., 2016; Kozlowski & Chao, 2012; Lehmann-Willenbrock & Allen, 2018; Riethmüller et al., 2012).

Already, a number of methods exists that are able to deal with this challenge. In their methodological paper, Lehmann-Willenbrock and Allen (2018) outline a number of analytical approaches (e.g., pattern analysis, lag sequential analysis) that can be used to investigate temporal dynamics in groups and teams. While these methods have been used for some time and promise interesting findings, they have some drawbacks. First, they often require coding of verbal or nonverbal interactions. This is both laborious and time-intensive (Kolbe & Boos, 2019) and when applied, the data tends to be complex and difficult to analyze (Rack et al., 2019). Second, in many cases they require researchers to develop a theoretically guided coding scheme (e.g., pattern analysis; Lehmann-Willenbrock & Allen, 2018) that can be applied to the data. In this way, data-driven and hypothesis-generating analyses of group interactions will become more difficult to achieve. Third, some of them rely on commercial software that can be costly (e.g., INTERACT; Lehmann-Willenbrock & Allen, 2018). One aspect of future group science must be to further develop suitable methodologies to address these issues (Keyton, 2016), providing a fit between theoretical concepts and methodology (Edmondson & McManus, 2007). As Kozlowski (2015) notes: "[W]e cannot make progress until we develop innovative methods to capture team process dynamics directly" (p. 272).

One way to measure emergent processes is to observe moving groups of humans (or animals; Moussaïd, Garnier, et al., 2009). Movement or spatio-temporal data can provide insights into group processes above and beyond verbal communication. They can be used to investigate both applied (e.g., crowd or pedestrian behavior; Dyer et al., 2008; Helbing et al., 2005; Hoogendoorn & Daamen, 2005; Jelić et al., 2012) and basic research questions about fundamental principles of group coordination or leader-/followership (e.g., Moussaïd, Helbing, et al., 2009). Furthermore,

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advancements in virtual assessment of group movement behavior (Moussaïd et al., 2018) have made it possible to record spatio-temporal data in multi-user environments (Bode et al., 2014; Narang et al., 2017) to test actual group behavior with comparable ease.

The HoneyComb paradigm (Boos et al., 2014, 2019) continues this line of work by applying the measurement of spatio-temporal group data to the study of basic group processes, such as group coordination and leader-/followership. Doing so, this paradigm addresses the pressing issue recently raised by Banks and colleagues (2021) to include actual behavior in the study of leader-/followership and account for the emergence, dynamics, and fluidity of these processes. In summary, we aim to provide a methodological approach that can make use of the advantages of process or interaction analysis, while being able to gather and analyze complex data reliably and with ease.

The HoneyComb paradigm

The HoneyComb paradigm (Boos et al., 2019) as a game-based assessment can provide many of the required qualities: It is a multi-player assessment tool recording spatio-temporal data, allowing researchers to observe the interactions of real groups in real time which is fundamental to the study of group decision making (Stasser & Abele, 2020). The HoneyComb paradigm allows the implementation of repeated interactions to investigate group processes that emerge over multiple interactions (e.g., collective induction; Chapter 3). It provides a controlled experimental environment and the possibility to restrict the communication channels that groups can use to interact. This has the advantage that researchers can create studies with high internal validity and exclude many confounding variables that might otherwise impact group interaction (e.g., physical appearance or communication styles; Wilson & Eckel, 2006). Lastly, the HoneyComb paradigm allows for many customization options and can include monetary incentives (Chapter 3) or economic games (Chapter 4) in order to frame group decision tasks.

The HoneyComb paradigm (Boos et al., 2019) was originally developed by Boos, Pritz, and Belz (2014) and is programmed and maintained by Johannes Pritz. In the HoneyComb paradigm, multiple participants concurrently partake in an experiment and, therefore, can interact with each other in real time. The general aim is to observe a group of real participants interacting with each other on the virtual playing field, while following game instructions or solving a task. The participants' behavior is logged by gathering spatio-temporal data on each individual for each step in the process. This provides the opportunity to research individual and group movement jointly, thereby detecting emergent phenomena. Moreover, the continuous logging of movement data makes it possible to observe the dynamics, and the implementation of repeated game rounds allows to follow group processes over time to investigate their fluidity.

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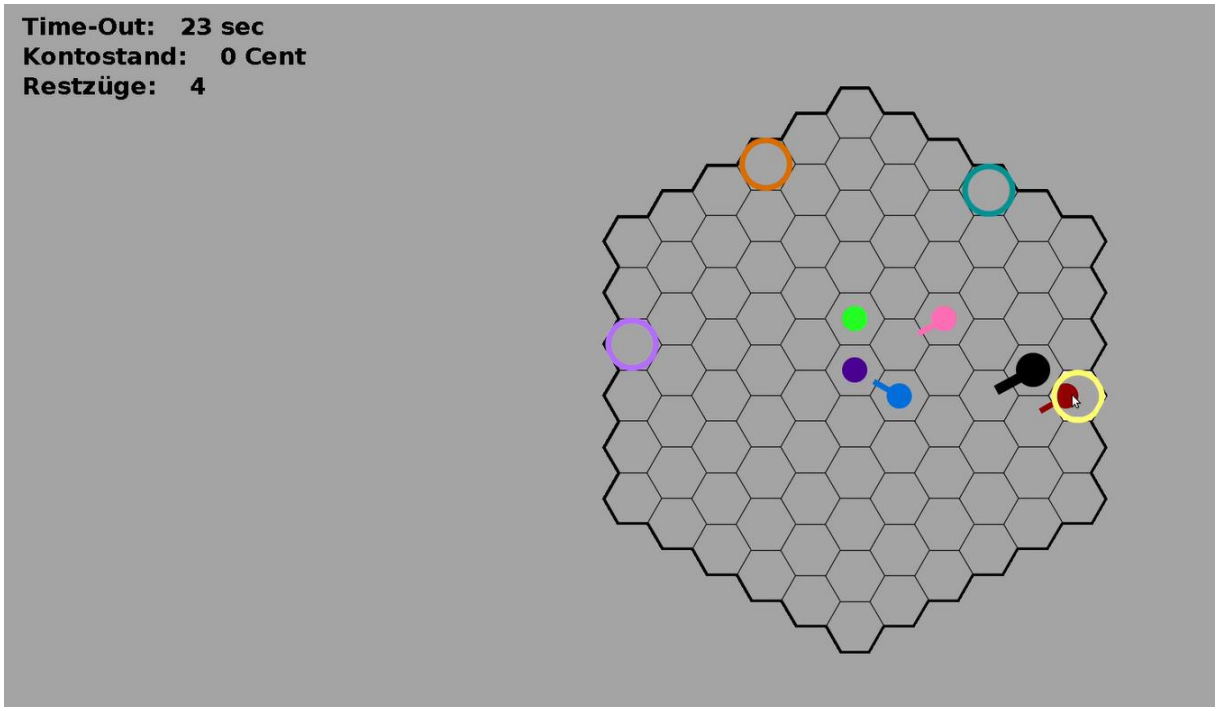
This means that by offering this wide range of possibilities and by being a dynamic setup itself, the HoneyComb paradigm seems to be a methodological fit to the research topic of emergent group processes (Edmondson & McManus, 2007). In the following, the general principle and functionality of the HoneyComb paradigm will be described shortly (also see Boos et al., 2019, for a video illustrating experimental set-up).

To collect data with the HoneyComb paradigm, all participants need individual computer workstations on which the virtual playing field is displayed. Both in-person (see Chapter 3.1 and Boos et al., 2019) and online data-collection are possible (Chapters 3.2 and 4). The playing field, as seen in Figure 1, consists of hexagonal fields in the shape of a honeycomb. Its size can be varied in order to fit experimenters' needs but has been successfully tested with a radius of five and seven fields from the center, resulting in a total of 97 or 169 fields, respectively.

Figure 1. The HoneyComb virtual playing field.



Note. The HoneyComb virtual playing field from the perspective of a player (Screenshot from Chapter 3.2). The player's own avatar is represented by the large black dot (right side of the playing field). Many of the other players have already moved; some are still displaying a "tail" indicating the direction from which they came. Upper left: Information on remaining time ("Time-Out"), current account balance ("Kontostand"), and available moves remaining to the player in this round ("Restzüge").

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Participants, who will further be referred to as players, are represented on the field as avatars. Depending on the game condition, players can see other players' avatars represented as black (e.g., Belz et al., 2013; Boos et al., 2014) or colored dots (Chapters 3 and 4) with their own dot being twice the size (see Figure 1). Players can move around on the playing field by using their mouse to click on one of the six fields adjacent to the one they are standing on at the moment; fields cannot be skipped. In the original paradigm, players can move around freely with a mandatory rest period in between moves of 1500ms. This was implemented to minimize the influence of computer literacy (Boos et al., 2019). Additionally, for 4000ms after an avatar has made a move, a small tail is shown to indicate the direction from which the avatar came, as also shown in Figure 1. The program can be designed using only black and gray hues or using customizable colors, for example, to identify each player individually with a colored avatar (Figure 1). These and many other parameters (e.g., shape of the avatars) can all be customized according to the researchers' needs.

Depending on the experiment, the number of moves or the available play time can be restricted. The remaining moves or seconds can be displayed in one (or all) corners of the screen next to the playing field (Figure 1). Depending on the purpose of the experiment, players are given specific instructions. As can be seen in Figure 1, reward fields can be implemented that players need to reach in order to earn money in the experiment. These can be hidden and scattered across the playing field (Chapter 3.1; Boos et al., 2015) or visible to all players and on the edge (see Figure 1 or Boos et al., 2014). Another possibility of varying the paradigm is to restrict the viewing radius: In the global view (see Figure 1, Chapter 3.2; Belz et al., 2013), players are able to see all other players regardless of their position on the playing field. In the local view, players can only see the avatars of those players who are standing on a field within the visual radius (e.g., two fields) of them (e.g., Chapter 3.1; Boos et al., 2014).

The HoneyComb paradigm is highly customizable to researchers' needs. Previous studies have used the paradigm to investigate the fundamental principle of flocking in human groups (Belz et al., 2013), emergence of leadership in groups (Boos et al., 2014), competition for resources within groups (Boos et al., 2015), and human group decision making and followership (Chapter 3). It should be noted that HoneyComb is programmed in a highly-reductionist environment and can restrict communication to movement on the playing field. While this might decrease external validity for applied research questions, internal validity is increased to the benefit of investigating basic principles of human interaction and exclusion of confounding factors, such as communication style. For example, Boos and colleagues (2014) have shown that leadership behavior in the HoneyComb game does not correlate with personality traits (Big-Five and agency/communion), which was substantiated in Chapter 3.2. Recent findings (Mitchell et al.,

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2022) corroborate the disentangling of personality traits, such as extraversion and communication skill, and their effect on emergence of leadership, showing the advantages of a reductionist environment such as the HoneyComb paradigm.

Set-up and Experimental Procedure

When collecting data with the HoneyComb paradigm, participants are usually recruited in groups of six to twelve. Each participant is seated in front of an individual workstation (e.g., a notebook) and a mouse. If data is to be collected online, a Remote Desktop Machine needs to be set up to run the HoneyComb program. During in-person data collection, the workstations need to be separated by partition walls and participants are given single-use earplugs to wear during the entire experiment in order to prevent all forms of verbal and nonverbal communication. In this way, the movement behavior exhibited by the players is the only possible information source left. Often, participants can familiarize themselves with the game in practice rounds before playing the experimental rounds (e.g., Chapter 3.2). If needed, the game can be set up to have multiple rounds either in order to get multiple measurements of each participant's movement behavior or, if the avatars are identifiable, in order to follow emergent processes in the group over time, such as leadership (Chapter 3). After the last game round, participants can be asked to answer a set of questionnaires on the screen. This can include experiment-specific measures, control variables (e.g., computer literacy, embodiment of avatars), or general demographic data.

A more detailed description of the paradigm as well as a video demonstrating set-up and procedure of this method can be viewed in the *Journal of Visualized Experiments* under the link https://www.jove.com/video/58719/ (Boos et al., 2019).

Data Structure

The data collected with the HoneyComb paradigm is stored in two files: a log of all movements (*.csv-file) and a file with start and end positions and information on payouts and questionnaire answers (.*txt-file). To log the movement of all players continuously, each move is recorded as the time-stamped, new position of a player with an accuracy of 50ms (Boos et al., 2019). This means that every time a player makes a move, their new hexagonal coordinates are recorded with an associated time-stamp in a table. For each row, the playing group (i.e., group ID), the player ID, coordinates, and time stamps are recorded. Additionally, specific events can be logged, for example, when a player has reached a reward field and was paid a certain amount of money. When players do not move for a longer period of time, the server periodically logs their position with the addition of a "not moved" variable. The separate text file logs the answers to the questionnaire and specifics of the group session (e.g., condition, game setup, etc.).

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Saving the data in this format has several advantages: First, it is very detailed. By saving each move, researchers can follow the whole group process from beginning to end; no "snapshots" are selected but a "movie" is created (Kozlowski, 2015; Leenders et al., 2016). Second, the format allows researchers to run classical analyses, such as hierarchical/mixed modeling, with only a small amount of data restructuring (Boos et al., 2019; also see Chapter 3). Third, this method of data logging sets virtually no limits to the type of analysis researchers want to run. The movement logs are raw scores which can be transformed into different formats and aggregated in different ways if need be. This is especially important as classical frequentist analyses are not necessarily suited to make the most of data on emergent processes (Kozlowski, 2015; Kozlowski et al., 2016; Lehmann-Willenbrock & Allen, 2018).

Data analyses: Levels and approaches

When dealing with group processes, the empirical data basis is both complex and information-rich (Rack et al., 2019): One can analyze the data on the group or individual level, focus on micro or macro processes. Different perspectives on the process, such as hierarchical or sequential viewpoints, can be interesting for different research questions. Considering all this, it is a daunting task to analyze group processes, such as coordination, as a whole. Yet, group research will need to do just that (Keyton, 2016; Kozlowski, 2015; Kozlowski et al., 2016). Gathering spatio-temporal data, for example, by employing the HoneyComb paradigm, is a step in this direction (Goldman et al., 2014) but the sheer volume of the data can be difficult to handle (Rack et al., 2019). Often researchers can be tempted to use summary measures on the continuous data that is gathered (Kolbe & Boos, 2019; Kozlowski, 2015) which might suffice for some research objectives. However, when analyzing large amounts of data, typical analysis strategies can fall short because they either have difficulties incorporating the complexity of the data or because results can be confusing and hard to interpret (e.g., Rack et al., 2019). Nonetheless, the goal must be to make more of the data as only that can show the process in all its detail, even if it requires substantial (manual) labor (Kolbe & Boos, 2019; Lehmann-Willenbrock et al., 2017; Rack et al., 2019).

A fitting analysis technique (Edmondson & McManus, 2007) should be able to incorporate the temporal sequencing of the behavior of both the individual players and the group and it should account for multiple predictors and context factors all at once (Lehmann-Willenbrock et al., 2017). Thus, a suitable analysis technique should be able to display a lot of detailed information all at once while still being understandable and interpretable. This chapter presents two general methods that have proven useful in dealing with spatio-temporal data: visual analytics and network analysis. Additionally, I describe three different analysis levels with which spatio-

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temporal data in the HoneyComb paradigm can be addressed: the game, round, and move level. Lastly, I describe four approaches to analyzing this data and give some examples of these analyses based on data from Chapter 3. The two general methods (visual and network analytics) constitute general ways of approaching and handling spatio-temporal data and can be applied on all three analysis levels and within all four analytic approaches. The three levels of analysis refer to analytical "lenses" that researchers use to either focus on the process as a whole or "zoom in" to identify basic building blocks of a group process. On each of these levels, all four analytic approaches can be applied. The analytic approaches constitute general categories with which researchers can study a process: in a hypothesis-testing (confirmatory) or hypothesis-generating (exploratory) way and focusing on static characteristics of a process or dynamic developments within it.

Three different analysis levels of group decision processes

As described by Kozlowski and colleagues (2016) the investigation of emergent group processes requires multi-level approaches. Within the HoneyComb paradigm, three different levels can be identified: the game level, the round level, and the move level. The *game level* refers to the outcome of the group process as a whole. This means that analyses on the game level will be mostly concerned with the question of overall performance of a group (e.g., choice score in Chapter 3) and less with the specific group process that has brought about the analyzed result. As such, the game level in the HoneyComb paradigm is analogous to many outcome variables (the "O" in the IPO heuristic, McGrath, 1964). For example, Chapter 3.1 provides an example of a game-level analysis when looking at how often each of the leaders was followed by participants throughout the whole game.

The *round level* focuses on the development of group processes over time or over multiple iterations of the process. This means that the outcome or specific characteristics of each group process iteration (e.g., leadership patterns) are analyzed. In this way, analyses on the round level can provide insight into how group processes change over time and how specific group-level constructs such as leadership emerge over repeated interactions of the group. For example, Chapter 3.2 reports an analysis of cumulative leadership scores over all 30 rounds. By displaying how leadership scores accumulated over rounds, it could be shown that leadership is not simply instated at the first interaction but is emergent and solidifies over numerous group interactions.

The *move level* focuses on one specific group process, so exactly one iteration of the task or one game round of the HoneyComb paradigm. Analyses on the move level can reveal information on the basic building blocks of group processes, such as specific behavioral patterns or signaling that group members use in order to facilitate group decision making. For example, Boos and

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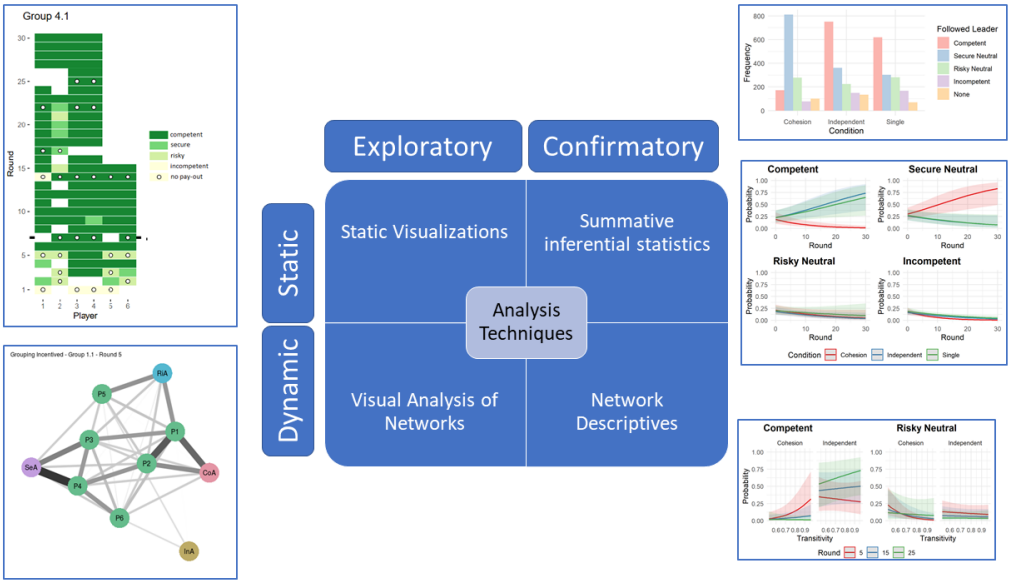
colleagues (2014) show the first-mover principle (i.e., the emergence of leaders who move first), a behavioral pattern rooted in single moves within one group iteration.

These three analysis levels provide different lenses to researchers investigating emergent group processes. Depending on the research question, analyses on different analysis levels might be chosen or combined to gain insight into the inner workings of groups. The three levels are mainly frameworks that can be filled with different analytical approaches to spatio-temporal data. Researchers will have to state clearly which analysis level and strategy they chose and to what end.

Figure 2. Overview of analysis techniques for spatio-temporal HoneyComb data.



Note. The overview shows different types of analysis strategies that can be used to analyze spatio-temporal data of the HoneyComb paradigm. Example graphs clockwise from top-right: Game-level analysis of leader choices, round-level analysis of probability to follow specific leaders, round-level analysis of effects of clustering on leader choices (all from Chapter 3.1), round-level network analysis, follow-plot (based on data from Chapter 3.1, shown in this chapter).

Four different analytical approaches for investigating emergent processes

As can be seen in Figure 2, we propose four different approaches to analyzing spatio-temporal data collected using the HoneyComb paradigm. Classic analytic strategies (e.g., regressions, group comparisons) are grouped under *summative inferential statistics* as a confirmatory and static analysis strategy. This approach can be necessary to conduct summative hypothesis tests or to investigate process results and many examples on both the game and round level can be found in Chapter 3. However, for future applications of the HoneyComb paradigm, the exploration of additional analytical strategies should be considered. The three other analytical

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approaches proposed here are network descriptives (confirmatory & dynamic), visual analytics of networks (exploratory & dynamic), and static visualizations (exploratory & static). All these three rely on the application of network analysis (e.g., Butts, 2008; Wasserman & Faust, 1994), visual analytics (e.g., Rack et al., 2019), or both. Therefore, these concepts shall be explained in short. Afterwards, one example of combining analytic approaches is presented.

Network analysis of spatio-temporal data

Networks play a central role in our daily experiences and societies, influencing our professional, social, and leisure lives (Fu et al., 2017a). Social networks are complex systems in that the whole that they represent is more than the sum of its individual parts. Transcending the focused view on the individual can be beneficial, especially when the structure of a network influences crucial parts of a process (e.g., the rate of information dissemination in a group; Carlson et al., 2014). Additionally, networks are highly dynamic entities (Fu et al., 2017b). Connections between network members are forged and broken which in turn influences the forging and breaking of other connections (Brandes et al., 2009). Especially now that new technologies have made it possible to collect longitudinal network data relatively easily, it is increasingly common to incorporate temporal dynamics into the consideration of social networks (e.g., by representing time-stamped interactions among members of a group; Leenders et al., 2016). This can provide insights into underlying mechanisms of otherwise static topological structures and help in uncovering underlying processes that transform one initial network into a seemingly completely different one at the end of the process (Fu et al., 2017b). In order analyze and visualize emergent processes, as was the aim of this dissertation (third research question), the use of dynamic networks seems indispensable. In the following, some examples shall illustrate how data can be transformed into dynamic networks and how this approach has been used in past research.

The first example study by Brandes and colleagues (2006) uses dynamic network analysis to investigate bilateral political conflict situations and the interactions between the involved (global) players. This study extracts time-stamped dyadic interaction data, such as newspaper reports about urges, warnings, or even armed interactions, between conflict parties and attaches weight to each of the interactions. For example, an armed conflict between two partners would be a highly negative interaction while a declaration of alliance would be highly positive. This data is used to investigate social networks to visually summarize the bilateral conflict structures. The resulting smooth animations of the changing networks powerfully visualize the dynamics of a conflict and can reveal new and interesting patterns even to experts on the specific conflict (Brandes et al., 2006; Brandes & Lerner, 2008).

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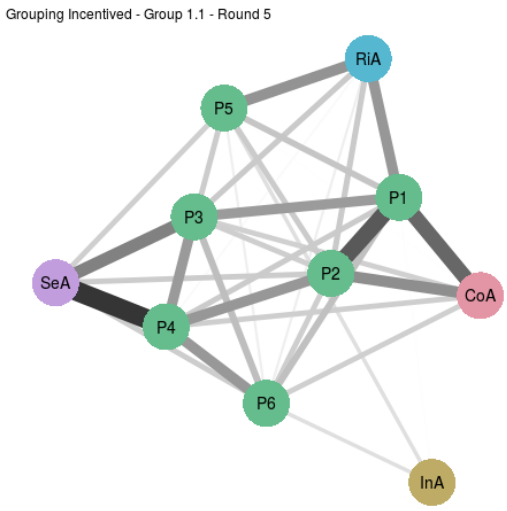
The second example stems from studies of animal movement. In fact, networks are a widely applied method in studying animal groups, especially in terms of hierarchy (Zafeiris & Vicsek, 2018), and have been used to study a variety of species, such as dogs (Ákos et al., 2014), primates (e.g., Wittig et al., 2008), fish (Rosenthal et al., 2015), or pigeons (Nagy et al., 2010). Hierarchical networks are a specific type of network that can illustrate leader/follower behavior of individuals in groups, dominance relations, or decision strategies. Nagy and colleagues (2010) observed small groups of pigeons during flights. They showed that when pigeons had a navigation task, they adjusted their flight direction according to the individual with the highest expertise in navigation and not according to the pecking order that guided free flights (no navigation task) and feeding. Hierarchical and non-hierarchical social networks have also been used to study human behavior (e.g., Boos et al., 2017; Contractor et al., 2006; Tóth et al., 2018; Wisdom et al., 2013).

Figure 3. Example network (round level).



Note. Example network from Group 1.1 (cohesion condition) in round 5 (data from Chapter 3.1). The network is drawn on the round level of analysis. Green nodes represent players 1 through 6. Red agent (CoA) represents the competent leader; purple (SeA) - secure leader; blue (RiA) - risky leader; and yellow (InA) - incompetent leader. Edges represent how close the avatars were to each other. Thick edges represent less distance between avatars, thin edges represent more distance between avatars.

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Dynamic networks like the ones described here provide a "powerful family of tools for the representation and analysis of relational data" (Butts, 2008, p. 37). In the following, I want to give a short overview over the most important terms in network or graph analysis (more comprehensive introductions can be found here: Butts, 2008; Snijders, 2005; Wasserman & Faust, 1994), followed by the description of how dynamic network analysis can be applied to spatio-temporal data in the HoneyComb paradigm.

Social networks are composed of individual nodes, sometimes also called vertices, and ties, also called relationships, edges, or links. The nodes can represent different entities, for example, persons, teams, organizations, or even cognitive constructs or documents, files, et cetera. In our case and as seen in Figure 3, the nodes represent players and pre-programmed agents in the HoneyComb paradigm (data from Chapter 3.1). It is assumed that the nodes of a network represent a finite number of entities that can be uniquely identified and that are distinct from each other (Butts, 2008). The nodes are connected by the edges to form a graph-based structure that is often complex (Fu et al., 2017b).

Edges are defined by the two nodes they connect and it is assumed that there is a qualitative distinction between an existing edge (relationship present) and a nonexistent edge (relationship is not present) (Butts, 2008). In our case, edges represent the distance of avatars on the playing field to each other. This will be further explained below. The analysis of network structures can be qualitative-visual (see Figure 2: dynamic & exploratory) or quantitative; it can focus on either the network as a whole (i.e., the overall structure and specific relationships between nodes) or on a specific perspective, called an ego-network (Fu et al., 2017b). Networks and their analysis are based on mathematical graph theory and networks or graphs can be represented by formal mathematical notations (see Wasserman & Faust, 1994). However, a mathematical explanation of graph theory will be beyond the scope of this chapter, or even this dissertation. By using this approach on the HoneyComb data, we aim to reveal characteristics and patterns in the movement of groups (Boos et al., 2017), such as the spreading of social information or the emergence of subgroups or clusters. This can happen on both the move and round level. Exemplary ways to transform spatio-temporal data of a group into networks and their visualizations are described that might be used to describe the patterns of group processes we observe in empirical experiments (e.g., in Chapter 3).

There are different possibilities of representing a network numerically. The most common form is an adjacency matrix (Butts, 2008): Each node is represented in a row and in a column. If there is an edge from node i to node j then the ijth cell is set to 1, otherwise it is set to 0. In the network seen in Figure 3, a connection from i to j always implies a connection from j to i so the adjacency

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matrix will always be symmetric. This is called an *undirected network*. As the networks need to represent differing degrees of association between all nodes, the adjacency matrix is not restricted to include only zeros and ones. In contrast, weights are assigned to each edge; this is called a *weighted network*. In sum, from symmetric and weighted adjacency matrices we create undirected and weighted networks. Movement data or spatio-temporal data can be transformed into a network in a relatively easy way as long as the objective of the analysis is clear. There seem to be at least three central decisions that have to made in this transformation: What time is used? How is space encoded? Is the data aggregated and, if so, how?

The first decision needs to be about time: At which time-points is the relational data extracted from spatio-temporal data and with what frequency? For example, the HoneyComb paradigm provides the coordinates of all players after each step that was made. One possibility would be, therefore, to calculate a new adjacency matrix after every step any avatar took. This was done to create the move level networks that can be seen in Supplementary Animation 1 (https://s.gwdg.de/OgPvxi). For Figure 3, the decision was made to represent the end point of one round of the HoneyComb game within one network.

The second decision needs to be about space. For the HoneyComb data, associations between players are measured as the distance between players to get a measurement of "nearness"[1]. This poses somewhat of a methodological pickle if ties are supposed to indicate distance between nodes: According to the definition of edges (Butts, 2008), ties between the nodes in a network need to represent an entity that is clearly present or absent. However, a distance can be either large or small, but never absent. In order to transform distance into a measure that can be used for network analysis, researchers need to choose some form of cut-off or dichotomization and transform distance into a variable that is sensible for the specific research questions. For example, researchers might determine a radius around an individual (based on theory or prior data) that is relevant for behavior. This is in line with research that shows social influence in collective behavior is often restricted to local zones around individuals (Lukeman et al., 2010). If a local visual radius is implemented in the HoneyComb paradigm (Chapter 3.1), edges might be drawn between individuals who are in each other's visual radius at a given point of time.

The third decision needs to be about aggregation. As described under "Data structure" spatio-temporal data can record group movement in very fine detail. This is important in order to provide insights into the basic processes (i.e., on the move level). However, depending on the research question, this amount of detail can be overwhelming or counterproductive (e.g.,

[1] Note that the term "closeness" is not used in order to avoid confusion with the centrality parameter *closeness* in network analysis.

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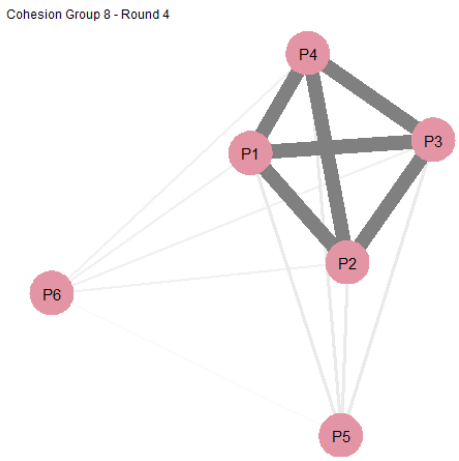
Kozlowski, 2015) so that appropriate aggregations (e.g., the round level) might be necessary. How and the degree to which data is aggregated needs to be left to the discretion of the researcher and should be chosen according to the research question at hand (also see Rack et al., 2019). I provide examples of minimal and medium aggregation: For Figure 4 and Supplementary Animations 2 and 3 (https://s.gwdg.de/OgPvxi), no aggregation was applied. The adjacency matrices underlying these networks were calculated on the move level and their purpose was to provide insight into the actual movement behavior on the playing field. Therefore, representing the situation on the playing field after each move as new adjacency matrix provided the best way to capture this particular group process. An example of medium aggregation levels can be seen in the static network in Figure 3 or the dynamic networks in Supplementary Animation 1. For the purpose of visualizing the relationship between players and agents on the round level, a single adjacency matrix at one time (i.e., the end of each round) would not be very informative about the association between players and pre-programmed leaders. As the follower behavior in Chapter 3 relied heavily on players learning from past encounters with other players and leaders, it was decided to reflect this influence in the following way: Instead of using adjacency matrices from a single time (i.e., the end of one round), the matrices were aggregated over the last five interactions (rounds) as a moving average.

Figure 4. Example network (move level)



Note. Example network from Group 8 (cohesion condition) in round 4, after the 8th move (data from Chapter 3.2). The network is drawn on the move level of analysis. Pink nodes represent players 1 through 6. Thick edges represent less distance between avatars, thin edges represent more distance between avatars.

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Once the spatio-temporal data is set up in a series of adjacency matrices, it can be used to draw networks. This means that one adjacency matrix is needed for each specific time point of a group process that should be represented. For example, the adjacency matrix underlying Figure 4 represents the distance relationships between players exactly after the 8th move. The next adjacency matrix would represent distance relationships between players after the 9th move, and so forth. From each of these adjacency matrices, one static network (Figure 3 and 4) is drawn. A very simple form to do that would be to arrange all nodes in a circle and draw the edges between them. However, this can be confusing, especially when many ties between nodes exist, so often it is advisable to use some form of layout algorithm (Butts, 2008). These algorithms are based on force-directed placement schemes: By a hypothetical physical process, nodes repulse each other generally, while this is balanced with attraction between those nodes that are connected by a tie. An often used algorithm is the Fruchterman-Reingold algorithm (e.g., one of the default layouts of the *qgraph* package; Epskamp et al., 2012) that places nodes close to nodes with which they have ties, but prevents them from occupying the same location. Additionally, the number of edge crossings is minimized while maintaining a somewhat stable edge length.

In order to create dynamic network animations (Supplementary Animation 1, 2 and 3), the set of ordered adjacency matrices is used. Each adjacency matrix represents one time point within the process, according to the decisions made during data transformation. In this way, it is possible to visualize not only one static network from each matrix but to produce an animation (e.g., a movie or GIF) from the whole process. This means that the original information stored in spatio-temporal data has now been extracted according to researchers' needs and can be summarized in a stream of networks, thereby retaining the qualities of the process under scrutiny. The network is now dynamic, can reveal emergent qualities, and show how the process is fluid over time.

Once the networks are drawn and put together in an animation, the researcher is faced with the task of interpretation that is, at least in a first step, qualitative. The researcher can observe the processes by which associations between nodes wax and wane by seeing the nodes move closer together or moving apart. Simply by observing the network dynamics, researchers can identify whether a process in a certain group moves steadily towards one pattern or whether there are breakpoints. This would be an example of the *dynamic & exploratory* analytic approach (see Figure 2). Possibly the dynamic networks reveal that there is, in fact, no clear pattern to the process but that the process changes from time-point to time-point, seemingly at random. Therefore, first conclusions can be drawn from these observations although the drawn dynamic networks can also simply serve as a basis for exploring specific aspects of the process. Follow-up analyses could involve focusing on a specific node (e.g., centrality analyses: King & Sueur, 2011;

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Lusseau & Conradt, 2009), focusing on specific groups that exhibit a typical (or atypical) pattern in the dynamic network, or to use network descriptives to quantify the observed patterns. This would constitute the *dynamic & confirmatory* analysis approach and was applied in Chapter 3.1 when the influence of clustering on follower choices was explored.

In sum, the analysis of spatio-temporal data from the HoneyComb paradigm can illuminate dynamic and emergent group processes. To use this analysis approach, researchers need to carefully choose steps of data transformation (i.e., time, space, and aggregation) in order to leverage the advantages of these analysis and visualization techniques. Whenever researchers decide to represent spatio-temporal data as (dynamic) networks, the crucial questions researchers need to answer is what relationships they want to investigate so that the data can be treated accordingly. The same is true for decisions about visual analytics as presented below.

Visual analytics

Visual analytics (VA) techniques are a way of visual behavioral data analysis (Lehmann-Willenbrock et al., 2017) and can "better cope with complex data and maybe even detect new patterns that would become obvious *due* to the new methods" (Rack et al., 2019, pp. 54, original emphasis). VA can augment the researcher's expertise in data interpretation and analysis through specifically designed representations. Algorithms and other analytic processes can precede VA in order to further improve the analytical displays (Kerren & Schreiber, 2012). In early stages of the research process, VA techniques can aide hypothesis generation by highlighting connections and interrelations in the data that might not have been expected (Rack et al., 2019). In later stages, researchers can select specific VA techniques, building on established qualitative and quantitative methods, in order to test their predictions. VA can be combined with deep learning (e.g., for video analysis; Rack et al., 2019) but it is also possible to analyze manually coded data with this approach (Lehmann-Willenbrock & Allen, 2018). In summary, VA can pose a highly useful analysis technique for group research. It can be used to comprehensively investigate and interpret large amounts of complex data and concurrently integrate different levels of the research subject (Rack et al., 2019).

In Chapter 3.2, VA was used when visualizing cumulative leadership over rounds. Another example is presented here (based on data from Chapter 3.1). The following behavior of participants was visualized in Figure 5 to gain insight into exploration/exploitation patterns. This plot, as an example of the *static & exploratory* analytic approach (see Figure 2), showcases the advantages of using VA to present high density data to visualize patterns. In Figure 5, the combination of the variables round (rows), participants (columns), choice (color), and payout (dot) allows us to see emerging patterns "at a glance". The transition from exploration to

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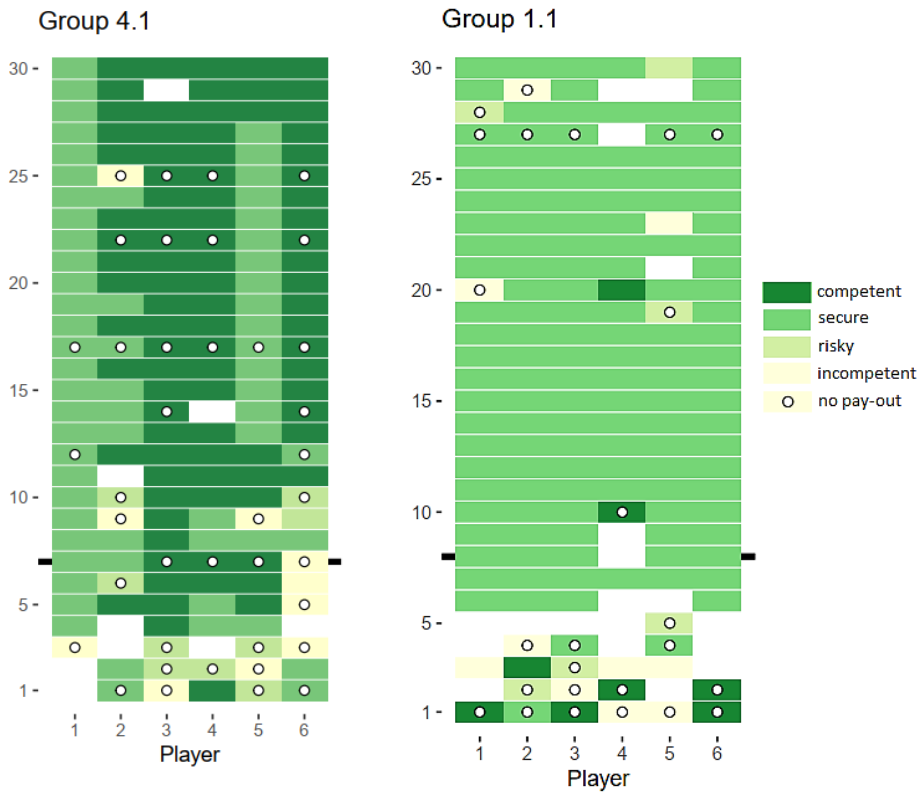
exploitation around round 5 seems to be a clear break-point of the group process in the cohesion condition (right panel), but less in the independence condition (left panel). Note that the quantitative measure of exploration (mean half-change round of the group, see Chapter 3) as represented by the black line indicates the same exploration length for both groups but cannot capture the qualitative differences between them.

Figure 5. Follow-plots.



Note. Follow plot of two example groups from Chapter 3.1. Group 1.1 was in the cohesion condition; Group 4.1 was in the independence condition. Each row represents one game run (i.e., one trial starting with everyone in the center and ending when all reached a reward field or exhausted their allowed moves). Each column represents one player. Each cell is colored according to which pre-programmed agent the player followed: dark green - competent leader; medium green - secure leader; lime - risky leader; beige - incompetent leader; uncolored - no leader. If in a given round, a leader did not pay out (determined by chance) then the cell is marked with a white dot. The black line is drawn at half-change round (see Chapter 3).

Combining analytical approaches: An example

In the following, I want to present an example of how these different analytical approaches can be combined in order to gain a deeper insight into the group process. For this example, I have drawn on move-level data from the empirical study presented in Chapter 3.2. This example

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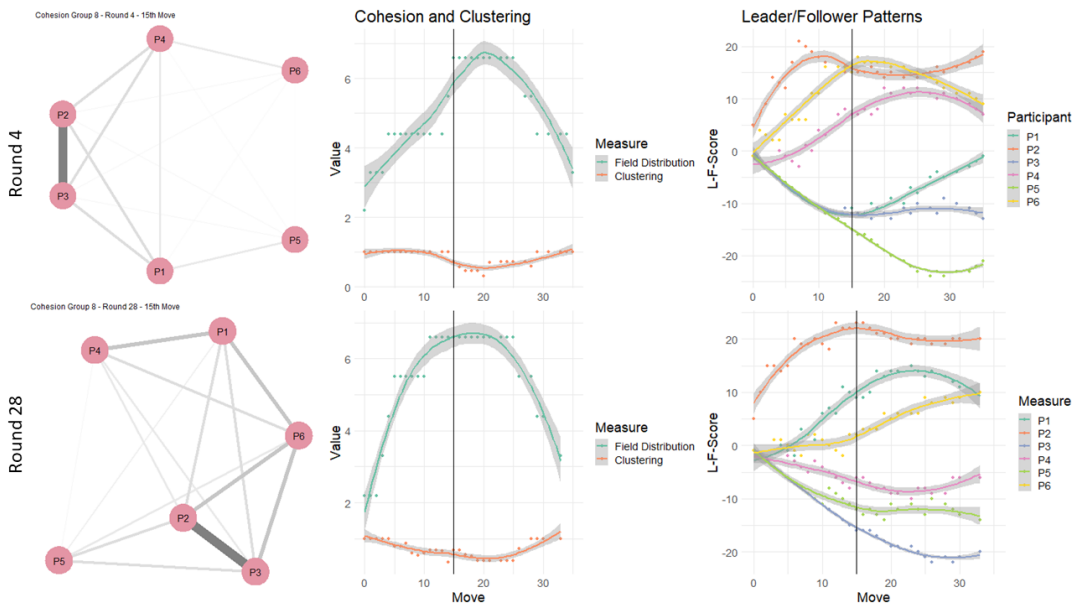
focuses on one group from the cohesion condition but could in the future be applied to between-group comparisons. Graphs can be seen in Figure 6 and Supplementary Animations 2 and 3.

I combine two analytical approaches in this example: The static & exploratory visual analytic approach and the dynamic & exploratory approach of dynamic network analysis. To illustrate how these techniques can be combined, I use data of one group (group 8, cohesion condition, Chapter 3.2) in two rounds: an early round (round 4) and a later round (round 28). These two rounds were chosen to show how these analysis and visualization techniques might highlight within-group developments or changes in group processes from earlier to later stages. All of these visualizations rely on the same data (spatio-temporal movement logs).

Figure 6. Combination of network and visual analytic approaches (move level).



Note. Based on data from Chapter 3.2, move level analysis are performed on group 8 (cohesion condition). The upper row of graphs is drawn from move level data in round 4, the lower row of graphs is drawn from move level data in round 28. Networks are calculated according to the descriptions in this chapter after the 15th move within each group. Black lines in the graphs indicate the moment at which graphs were calculated. Nodes represent players, edges represent the "nearness" between them. The middle graphs show two measures of spatial clustering: field distribution (i.e., the percentage of fields currently occupied by players) and transitivity (i.e., spatial clustering of players as the global clustering parameter of the distance network between players). Note that clustering (transitivity) ranges between 0 and 1. The right graphs show the cumulative L-F-scores (i.e., points gained from increasing the distance to others and lost for approaching others, see Chapter 3.2 for detailed definition and explanation) on the move level with different colors representing different players.

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The variety of illustrations that can be seen in Figure 5 shows how much information spatio-temporal data can provide beyond the form of just movement. Visualizations are possible of emergent (spatial) clustering within the group (Supplementary Animations 2 and 3; Figure 6, left and middle), overall (spatial) cohesion of the group (field distribution; Figure 6, middle), and patterns of leader-/followership (Figure 6; right).

Comparing the dynamic animations of round 4 (Supplementary Animation 2) and round 28 (Supplementary Animation 3), what immediately strikes the eye is that the group seems to have clustered less in the earlier round. We can see that the participants move away from each other after the start of the round and do not have strong ties again until the very end of the round. In comparison, the ties between the participants remain rather strong in the later round so that we can assume that the group might have shown high clustering throughout the whole process of the later round. This is further supported when looking at the static networks in Figure 6 (left). Both networks are "snapshots" of the process at about the same time, right in the middle of the process (after the 15th move). We can see that the upper network seems to be only loosely connected (or sparser) while more ties can be seen in the lower network. Another clear difference is that in round 4, the group split into two clusters while they stayed together in the later round. If we look at the quantitative measures of spatial distribution (Figure 6; middle) this cannot easily be seen. This shows the advantage of a combination of quantitative measures with dynamic network analysis.

In Figure 6 (right), we can see the progression of behavioral leader-/followership patterns on the move level. In Chapter 3.2, we showed a bifurcation of leader-/followership patterns on the round level. This showed the emergence of leadership roles over repeated interactions. The same bifurcation of leadership patterns can be seen on the round level (Chapter 3.2). Some participants seem to inhabit a more following role (e.g., participants 3 and 5) and others seem more inclined to take the lead (e.g., participant 2). In the comparison of leadership patterns, we see that some participants seem to occupy intermediate roles (e.g., participant 6) that might be subject to change over rounds. Additionally, inspection of the progression of leader-/followership patterns (Figure 6; right) suggests that these patterns are more stable in later rounds (Figure 6; bottom-right) as evidenced by less changes in slope of L-F-score progressions or order of participants, compared to earlier round (Figure 6; top-right).

When combining the dynamic network with the visualization of leadership patterns, we can reconstruct the group process in much detail, as shall be illustrated for the earlier round: In the fourth round, participants 2 (P2) and 6 (P6) seem to have taken the lead. However, as we see in the dynamic network animation, the cluster of P1, P3, and P4 seem to have followed P2, while

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P6 was temporarily more separated from the cluster. P5 seems to have hung back as he/she took a clear follower role and was separated from the group (also see Figure 6; upper left). Later on, P6 seems to have rejoined the group, possibly even overtaking P2 temporarily. While P3 and P4 stay together and follow P2 and P3, P1 seems to separate from the cluster and look for a different reward field. P5, having hung back, decides to follow P1 which explains the late rise in P1's L-F-score (Figure 6; upper right). The group ends the round separated into two clusters: P1 with P5, and P2, P3, P4, with P6. This reconstruction of the group process is what was called a "movie" of the group process (Kozlowski, 2015; Leenders et al., 2016), explaining not "what is" but "what happens" in a group (Roe, 2008).

Limitations & Outlook

The presented HoneyComb paradigm and analysis techniques allow researchers to gain deep insights into the workings of the groups they study. However, some limitations should be considered. One of the biggest strengths of the HoneyComb paradigm is the exclusion of other communication channels, except for movement on the playing field, and the reductionist environment. While this provides a strong basis for experimental research interested in basic properties of emergent processes, the question of external validity arises. While it has been shown that behavior in virtual environments is often predictive of behavior in more naturalistic settings (Moussaïd et al., 2016, 2018), the reductionist environment of the HoneyComb paradigm might be less suited to investigate more applied research questions. However, as the paradigm is highly customizable, the inclusion of more communication channels (e.g., via a chat) is theoretically possible and could be explored in the future.

It should be noted that the sole analysis of movement data of a group can only allow conclusions about behavioral aspects of group processes. This has two consequences. First, behavioral patterns, such as leader-/follower behavior or spatial clustering, might not necessarily correspond to affective or cognitive aspects of these group processes. While Chapter 3.2 could show that behavioral patterns for leadership and clustering correspond to self-reports of participants, future research should investigate whether findings on the behavioral patterns apply to affective and cognitive processes. Second, the observation of behaviors makes it difficult to distinguish between different processes. While the research presented in this dissertation (Chapter 3 and 4) could identify a number of different emergent processes, it remains unclear to which extent and in which relation these processes might contribute to group processes, such as group decision making. The disentanglement of the distinct contributions of these processes needs to be continued in future research.

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Finally, the analysis strategies presented here are examples of the vast possibilities that come with the application of network and visual analytics to spatio-temporal group data. The next steps should be to use the identified strategies systematically on empirical data. Additionally, more aspects of network analysis could be used that were beyond the scope of this chapter. For example, the inclusion of network parameters (e.g., e.g., node centrality; King & Sueur, 2011; Lusseau & Conradt, 2009) into the presented example could provide an additional layer of information on the group process.

Conclusions

The aim of this chapter was to illustrate how the HoneyComb paradigm (Boos et al., 2019) in combination with network and visual analytics can be used to investigate emergent group processes. The HoneyComb paradigm can address many drawbacks of classic methodologies, as argued in this chapter. First, it can be used to collect rich spatio-temporal data and record emergent group processes "on the fly", allowing deep insights into concepts that are typically hard to assess. Second, it provides insights into actual behavior of real groups, thereby addressing recent concerns about the state-of-the-art in organizational behavior research (Banks et al., 2021). Third, its reductionist environment allows researchers to disentangle basic group processes, such as leadership, from confounding factors like communication skills (Mitchell et al., 2022) or physical appearance (Stefanidis et al., 2022). The three presented analysis levels (game, round, and move level) as well as the four analytic strategies that were presented can complement the HoneyComb paradigm and provide many advantages. First, different analytic approaches will highlight different aspects of the group process. Second, group processes can be compared both within groups (e.g., early vs. late interactions) to illuminate how processes change over time and between groups. This can provide insights into intergroup differences or the effects of manipulations. Third, some qualities of the group process might become apparent using one approach but not the other. Therefore, the combination of different network and visual analytic strategies can provide a fuller understanding of emergent processes.

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 doi: 10.53846/goediss-9589

Chapter 6: General Discussion

In the introduction to this dissertation, we met Christie, Jeff, Henry, and Laura. Having just met each other in a new city, their task of deciding on a restaurant seemed daunting. There are simply too many unknowns. Which restaurants are good? What do the others like? And how will the group go about deciding? Psychologically speaking, these four people were dealing with both informational and personal uncertainty and had not yet developed a process that could cope with it. What could they do?

It was the goal of this dissertation to illuminate the emergent processes that might reduce uncertainty during group decision making. Specifically, the research presented within this dissertation aimed to answer the following three research questions: Can groups reduce uncertainty through emergent processes? Which processes can be identified? How can we analyze and visualize these emergent processes?

To answer these questions, a theoretical framework was developed in Chapter 2, drawing on theory and empirical evidence from biology, machine-learning, organizational behavior, and psychology, into which four empirical projects were embedded: two on informational uncertainty (Chapter 3) and two on personal uncertainty (Chapter 4). Lastly, analysis methods and visualizations of emergent processes, such as leadership, were explored in Chapter 5. As discussed in Chapter 2, this dissertation follows the interdisciplinary approach of Boos, Kolbe, Kappeler, and Ellwart (2011) by applying findings and methodology from group decision making in animal groups to further the study of human group decision making under uncertainty.

In Chapter 3, two empirical papers were presented in which groups were faced with informational uncertainty. In both papers, groups had to infer the best out of four options by repeatedly choosing from the options (exploration) until they had gathered sufficient information to settle on the one they thought best (exploitation). Groups in these studies have to reduce uncertainty by inferring the best option through collective cognition (Couzin, 2009) or, specifically, a process called collective induction (Laughlin, 1999; Laughlin & Shippy, 1983). In short, results of Chapter 3 demonstrated that the quality of information available to the groups will have a large impact on the group decision process. When information about the quality of options is corrupted, groups will make sub-optimal decisions (e.g., settling on the second-best leader; Chapter 3.1). This finding was replicated in a simulation study (Chapter 3.2, Study 1) using the ε-greedy paradigm (Sutton & Barto, 2018). The simulation study predicted that the amount of time spent on exploration will affect the decision quality of groups. However, this

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could not be replicated in the empirical studies. One reason for the lack of effect in Chapter 3.2 (Study 2 and 3) could be that the experimental paradigm suffered from a ceiling effect. Specifically, it was suspected that the task was too easy (i.e., held too little uncertainty). However, Chapter 3.2 was able to identify emergent processes that might have guided groups during the decision making process. Specifically, leader-/followership emerged spontaneously within most groups in the third study, as measured by a behavioral marker (L-F-scores). Importantly, it could be found that behavioral leadership was associated with self-reports of leader-/followership, but not typical personality trait correlates (self-confidence, achievement maximization, decisiveness, and risk propensity). Additionally, it could be shown that behavioral markers of group cohesion within the HoneyComb paradigm (Boos et al., 2019) were associated with self-reports of group entitativity and interactivity. In sum, the data presented in Chapter 3 suggests that groups can effectively reduce uncertainty although it remains unclear how the identified processes differentially contribute to the uncertainty reduction. However, with the identification of emergent leader-/followership and group entitativity, two candidate processes are identified that should be explored in the future. Chapter 3 was able to identify leadership, group cohesion, and collective cognition as possible mechanisms to reduce uncertainty in group decision making.

In Chapter 4, empirical findings are presented on the reduction of personal uncertainty through the emergence of collective trust. In a newly formed group, individuals are unable to predict how other group members think or behave, resulting in personal uncertainty. In these situations, making a joint (or consensus) decision will be especially hard. Chapter 4 focuses on group investment decisions in the Collective Trust Game (Chapter 4.1) and the role that the emergence of collective trust might play in these decisions. We understand collective trust as a collective cognitive construct that emerges through repeated interactions of a group and reflects the shared level of trust a group holds for another individual, group, or organization (Chapter 4). Chapter 4.1 describes the Collective Trust Game (CTG) that was developed as part of this dissertation. The CTG is based on the Trust Game (Berg et al., 1995), an economic game that is widely used to assess the behavioral component of interpersonal trust: Three participants play the role of investors and one participant plays the role of the trustee. In the beginning of the game, both investors and trustees are endowed with an amount of money. In the first phase, the three investors need to decide how much, if any, of their endowment they would like to send to the trustee (i.e., invest). They indicate their investment by moving on the playing field. Investors are required to reach a unanimous decision (i.e., need to stand on the same field). The invested amount is tripled by the experimenter and sent to the trustee who then needs to decide how much, if any, of that money they want to return to investors by moving on the playing field as

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well. The game is repeated for multiple rounds to allow for the emergence of group processes and constructs and, specifically, collective trust. The CTG was used in Chapter 4.2 to investigate how collective trust, as a shared cognitive construct, emerges. Participants in the CTG face personal uncertainty as they cannot predict the investment preferences or investment behavior of other participants in the beginning of the game. By interacting repeatedly, participants learn about each other's preferences and reduce initial personal uncertainty. It could be found that collective trust seems to emerge over repeated interactions as indicated by the rise in unanimous investment decisions as well as the reduction of decision latencies of the investors. This indicates that repeated interactions within a group are able to reduce personal uncertainty. Information about the preferences of other group members is collected and integrated into a higher-level cognitive construct that is shared among group members: collective trust.

The interactivity within the CTG (and HoneyComb, in general) seems to be important for group processes to emerge. This was shown by the results of the comparison study in Chapter 4.2 in which the emergence of collective trust was hampered when only minimal interaction was possible between participants. Lastly, some findings indicate that the emergence of collective trust might have gone hand-in-hand with the emergence of a structured group decision process of the investor group. This was indicated by the decreasing within-group variance of movement parameters. This indication should be investigated in more detail in future research. In sum, Chapter 4 seems to suggest that the emergence of a shared cognitive construct, such as collective trust, can reduce personal uncertainty within groups.

In Chapter 5, the HoneyComb paradigm (Boos et al., 2019) is presented with a methodological focus as a tool to investigate emergent group processes. Additionally, empirical data from the two papers presented in Chapter 3 is used to illustrate ways in which group processes can be analyzed and visualized. Advantages of recording spatio-temporal data are discussed as well as three possible levels of analysis: the game level (overall process), round level (output of one process iteration), and move level (one process iteration in detail). Furthermore, four analytical approaches are proposed that can be used to analyze spatio-temporal data and visualize emergent group processes. Specifically, network and visual analytical strategies are explained and an example highlights how different analytical approaches might complement each other. Depending on the specific research question, different analysis levels and analytic approaches might be combined to provide deep insights into the unfolding of group processes, such as leadership, group cohesion, or process break-points. In sum, Chapter 5 focused on the methodological contributions that this dissertation has made to the study of emergent group processes.

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In the following, I will apply the findings of each of those chapters, to the three research questions that were laid out in the beginning of this dissertation. Table 1 shows a summary of the findings of Chapters 3 through 5. Furthermore, limitations of the presented findings and future directions for research on group decision making under uncertainty will be discussed.

Table 1. Summary of results.

	Chapter 3	**Chapter 4**	**Chapter 5**
Uncertainty type	Informational	Personal	
Types of task	Intellective inference task	Judgmental task	
Consensus decisions	Not required Often observed	Required Success to reach unanimity increases with repeated interactions	
Uncertainty reduction	Group converges on one option Group exhibits exploration/exploitation shift Self-reported explicit identification of the best option with high certainty (Ch 3.2)	Group increasingly converges on unanimous decision (Ch 4.2) Decrease of decision latencies (Ch 4.2)	
Collective cognition	Limiting of social information (interaction/communication through movement) detrimental for decision performance (Ch 3.2)	Limiting of social information (interaction/communication through movement) is detrimental for decision performance (Ch 4.2)	
Exploration / Exploitation	Exploration/exploitation is not random (Exploration is more frequent in earlier interaction)		Exploration/exploitation shifts are sudden (break-points)
Leader-/Followership	Leader and follower roles manifest over rounds (Ch 3.2) Emergence of leadership might impact decision performance (Ch 3.2)		Leader and follower roles emerge on the move basis
Group cohesion / Entitativity	Self-reported entitativity & interactivity Observed spatial clustering: dispersion measures & network clustering (Ch 3.2)		Clustering of groups emerges both on movement level and round level

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Can groups reduce uncertainty through emergent processes?

The data presented in this dissertation suggests that groups can use emergent processes to reduce uncertainty in group decision making. We find this uncertainty reduction in the following way: Instead of choosing randomly from differing options, groups will engage in a shorter exploration phase until they converge on one option that is then exploited by the group (Chapters 3 and 5). This is in-line with a large body of literature demonstrating that groups are able to deal with informational uncertainty through exploration (Franks et al., 2003; Mehlhorn et al., 2015; Seeley & Buhrman, 1999; Stahl et al., 2001; van der Post & Semmann, 2011; Yahosseini et al., 2018) and pooling of private information (Belz et al., 2013; Conradt, 2012; Conradt & Roper, 2005; Couzin et al., 2002; Couzin & Krause, 2003; Laughlin, 1999; Moussaïd et al., 2009, 2017; Pyritz et al., 2011; Wang et al., 2021). Chapter 3.2 also provides self-report data on uncertainty reduction: After having engaged in the group process, participants were able to identify the best out of four options with high self-reported certainty. Additionally, we see that groups are able to establish a shared cognitive construct (collective trust) which seems to reduce personal uncertainty (Chapter 4). Data presented in this dissertation showed that groups were able to reach more unanimous decisions in shorter times after repeated interactions. This corroborates previous findings about the reduction of personal uncertainty through repeated social interactions (e.g., Kramer et al., 2001; Weary & Edwards, 1994), although most works focus on dyadic interactions, in contrast to the group processes investigated in this dissertation.

Taken together, these findings indicate that repeated interactions within a group can provide both social information about the environment (What do the others know?; e.g., Faria et al., 2010; Grand et al., 2016; Hoare & Krause, 2003; Yahosseini et al., 2018) and individual preferences (What do the others like?; e.g., Armbruster & Delage, 2015; Conradt, 2012; Cox, 2002; Kramer, 2010). This information can be pooled on the collective level (Moussaïd et al., 2009): Individual information about the environment becomes collective cognition (Couzin, 2009), for example, in an intellective collective induction task (Laughlin, 1999). Individual preferences or judgments can be accumulated to a collective preference or judgment (collective trust) in a judgmental task (Laughlin, 1999). Therefore, this dissertation suggests that the pooling of private information (i.e., information that other group members hold) through collective cognition can reduce both informational and personal uncertainty, depending on the nature of the information that is pooled. While this finding might seem trivial at first, it should be noted that we could observe uncertainty reduction in groups in a reductionist movement paradigm that did not allow for any communication, except the movement on the virtual playing field. This shows that the reduction of both informational and personal uncertainty can rely on very basic principles that do not necessarily require verbal communication.

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Which processes can be identified?

The data presented in this dissertation can identify three emergent processes that might contribute to uncertainty reduction: collective cognition, group cohesion, and leader-/followership.

Collective cognition

In line with a multitude of previous work (e.g., Couzin, 2009; Couzin et al., 2002; King, Narraway, et al., 2011; King, Sueur, et al., 2011; King & Sueur, 2011; Lukeman et al., 2010), we found that groups were able to use collective cognition to gather information about their environment (Chapter 3) and themselves (Chapter 4). In Chapter 3, groups had to combine private information held by individuals to use collective induction on a problem-solving group task. While we did not require that groups reach a consensus, we often observed that members of the groups chose the same reward fields, effectively displaying a consensus decision. The decisions that groups made were not always advantageous (Chapter 3.1) which shows that the forming of consensus decisions did not solely rely on the use of environmental information. Notably, collective cognition emerged using only a local sharing of information between participants in Chapter 3.1. This is in line with previous research highlighting the importance of information exchange between neighbors in a group (i.e., locally), rather than between an individual and the whole group (i.e., gloabally; Couzin, 2009; Couzin et al., 2002; Couzin & Krause, 2003; King, Sueur, et al., 2011; Lukeman et al., 2010; Moussaïd et al., 2009). In Chapter 4, a group was required to reach a consensus before making an investment decision in the CTG. We see that groups are less likely to reach a consensus during their first interactions but will become more likely to do so later on. I argue that this indicates that groups experience personal uncertainty in the beginning of an interaction which will be reduced due to the building of a collective cognitive construct: collective trust. Once collective trust is established, individual group members can adjust their decisions accordingly and, therefore, reach a consensus easier. This reduction of uncertainty through interaction is in line with research on group discussions that have been shown to serve as forms of information retrieval, sharing, summarizing, and generation (Bonito, 2007; Ervin et al., 2017; Propp, 1997).

In Chapter 3, we see the emergence of exploration/exploitation patterns. Instead of randomly choosing options or sampling information, groups seem to engage in an exploration phase first before transitioning to the exploitation of one option. This is in line with findings on individual (e.g., Bechara et al., 1994; Cohen et al., 2007; Mehlhorn et al., 2015) as well as group decision making (Yahosseini et al., 2018). It is argued that the emergence of a collective exploration/exploitation pattern (as also visualized in Chapter 5) supports the idea of collective

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cognition. When a group uses collective cognition processes, uncertainty can be reduced faster through collective pooling of information. It could be that groups use a criterion of certainty to decide when to transition from exploration to exploitation (i.e., a shift to exploitation happens, once one option is identified to be best with sufficient certainty; e.g., Bechara et al., 1994; Tickle et al., 2021). If that is true, the use of collective cognition could determine when this criterion is reached. Once sufficient information has been gathered and pooled, the group can collectively transition to exploitation. This is not to say that this collective transition needs to be intentional, although it can be (Koçak et al., 2022). Groups might employ mutual reinforcement of behaviors or choices (e.g., Giraldeau et al., 2002; Kao & Couzin, 2014; Salganik & Watts, 2008) or quorum responses (e.g., Ward et al., 2008). Another process has been demonstrated for goose flocks (Stahl et al., 2001): Leaders might transition to exploitation of feeding spots after profitable spots had been explored by lower-ranking individuals. Sridhar and colleagues (2021) have also identified critical transitions in group decision making. The application of their methodology to the behavior observed within the presented studies could shed light on possible break-points within human group decision making processes. Within this dissertation, the mechanism that drove collective exploration/exploitation shifts in the presented data has not been identified but will be an interesting objective for future research. The emergence of exploration/exploitation patterns was independent of experimental manipulations of group cohesion. This was surprising as previous research has predicted that more cohesive groups would be less successful in the pooling of information due to shortened exploration phases (Yahosseini et al., 2018). This relationship should be investigated in future research as it could further illuminate the mechanisms by which groups use collective cognition to aggregate private information (Moussaïd et al., 2009).

Chapter 4.2 presented data on decision latencies: With repeated interactions, investor groups became faster in making an investment decision. Decision speed has been associated with certainty about choices (Kiani et al., 2014) and I argue that this is another indication for the reduction of personal uncertainty through the emergence of collective trust (i.e., a collective cognitive construct). Future research might extend these findings to investigate the formation process of collective trust in more detail. For example, the inclusion of self-reports (as in Chapter 3.2) of collective trust could complement the behavioral measure of collective trust with an affective or cognitive component.

Lastly, Chapter 3 and 4 indicated that groups that have access to richer social information outperform groups that can use only limited (or corrupted; see Chapter 3.1) social information. While more research and further experimental testing need to substantiate this finding, Chapter 3.2 and 4.2 presented data that saw groups performing better in the HoneyComb paradigm,

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compared to less interactive response formats. This difference was especially pronounced for the reduction of personal uncertainty (Chapter 4.2). While it might be trivial that the amount of information available affects how quickly uncertainty is reduced (Chapter 3.2), this dissertation shows that it is not only the environmental information that will make an impact. The possibility to interact beyond the simple exchange of outcome information (i.e., individual choices, Chapter 3.2, Study 2; individual preferences, Chapter 4.2, Study 2) will give groups an edge in reducing informational but, especially, personal uncertainty. Indeed, interaction seems to be fundamental to group decision making (Ervin & Keyton, 2019; Stasser & Abele, 2020). This, of course, has an implication for group research methodology: To investigate emergent processes, we must allow processes to emerge within interaction. This dissertation adds to the many calls that the study of (organizational) behavior needs to include actual behavioral studies (Banks et al., 2021; Kozlowski, 2015; Lehmann-Willenbrock et al., 2017).

Group cohesion

The studies presented in Chapter 3 specifically focused on the effect of group cohesion on group decision making. However, no conclusive evidence could be found that group cohesion has either detrimental effect (as predicted by Gavrilets & Richerson, 2017; March, 1991; van Ginkel & van Knippenberg, 2012), or a positive effect (as predicted by Derex & Boyd, 2015; Mason & Watts, 2012; Simons, 2004). This could be due to some methodological limitations that were identified in the experimental set-up and a follow-up study should test for this effect. Data of Chapter 3.2 did show, however, that a feeling of "group-ness" (i.e., entitativity; Blanchard et al., 2020) emerged. In Chapter 4, we required that investor groups make a consensus decision so that the effect of behavioral group cohesion (i.e., spatial clustering) cannot be assessed. However, it would be interesting to investigate whether the emergence of a collective cognitive construct (e.g., collective trust) could go hand-in-hand with the emergence of affective or cognitive group cohesion as found in Chapter 3.2.

Leadership

This dissertation provides data that positions leadership as a promising candidate process for uncertainty reduction in group decision making. In line with previous works (among many: Boos et al., 2014; Conradt, 2012; Couzin et al., 2005; Sridhar et al., 2021), Chapter 3.2 and 5 show that leader-/followership patterns emerge spontaneously within the observed moving groups and that these roles seem to manifest over time (Chapter 3.2). Additionally, it could be shown that the observed behavioral leader/follower patterns were associated with self-reported leadership, but not typical personality trait correlates (e.g., self-confidence, achievement motivation). This is in line with previous findings of leadership in human moving groups (Boos et al., 2014, who investigated the Big-5 and agency/communion), but contradicts results of studies assessing

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leadership in other contexts in humans (e.g., Bergner, 2020; Johnstone & Manica, 2011; Judge et al., 2002) or animals (e.g., Coleman & Wilson, 1998; Kareklas et al., 2018; Kurvers et al., 2009; Ward et al., 2008). According to Landis and colleagues (2022), I argue that personality can affect leadership in human groups but that this affect is highly contextualized. Other inter-individual difference factors, such as cognitive ability, social feedback, or motivation to lead (Bergner, 2020; Bergner et al., 2019; Gillet et al., 2011; Nakayama et al., 2012), might contribute significantly to leadership emergence and mediate the effect of personality on leadership. I argue that the findings presented in this presentation fall in line with explanations of basic leadership processes (e.g., Van Vugt, 2006; Van Vugt et al., 2008; van Vugt & Ronay, 2013) which might be less influenced by communication style or physical appearance (e.g., Mitchell et al., 2022; Stefanidis et al., 2022). To disentangle effects and further the understanding of leadership emergence, future studies should assess additional inter-individual differences (e.g., cognitive ability; Bergner, 2020) to assess their effect on leadership in human moving groups.

This dissertation was able to identify the emergence of leadership in groups that decide under uncertainty. Chapter 2 discussed a possible distinction between a direct effect of leadership on uncertainty reduction (i.e., via emergence of knowledgeable or skilled leaders) and an indirect effect (i.e., via mediating effects of collective cognition or group cohesion). Data presented in Chapter 3.2 does not support a direct effect as leadership was not associated with individual performance or exploration of options. First exploratory results (Chapter 3.2) indicate that groups in which leaders emerge outperform leaderless groups in line with previous research (Koçak et al., 2022), suggesting that leadership might play a mediating role (indirect effect). This is in line with findings that leadership might emerge to direct the combination of individual preferences of group members (e.g., Conradt, 2012; Conradt et al., 2009) and the balancing of goal- and group-oriented behavior (Sridhar et al., 2021). However, this should only be a starting point for future investigations. In Chapter 3.1, leadership was not investigated directly. Instead the study focused on followership and, more specifically, on how followers can identify the most advantageous leader. According to follower-centric approaches to leadership (e.g., Bligh & Kohles, 2012; Carsten et al., 2010; Oc & Bashshur, 2013), it will be interesting in the future to investigate whether first-follower effects can be detected within this data. Leader-/followership patterns were not investigated within the reduction of personal uncertainty (Chapter 4) in this dissertation but will be an interesting avenue for future research.

How can we analyze and visualize emergent processes?

This research question was addressed mostly within Chapter 5. Additionally, some ways in which emergent processes can be made visible were employed in Chapters 3 and 4. In all these chapters,

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I argue that the collection of high frequency data on group processes is an important step in investigating them. I agree with Kozlowski (2015, p. 272): "One can target and aggregate high frequency data [...], but one cannot get any resolution on the phenomenon if the data does not exist". Once the data is collected, the application of suitable analysis techniques will decide whether the advantages of the collected data can be leveraged. While some research questions might require analysis on the outcomes of the group process alone (i.e., the game level), process analysis will need to look beyond that. Analyses of the changes in processes (round level) as well as the detailed progress of one iteration of a process (move level) are promising ways of uncovering candidate emergent processes for group decision making under uncertainty. Using network and visual analytic approaches, we can identify and visualize patterns of exploration/exploitation (e.g., Chapter 5 – Figure 5), leader-/followership patterns (e.g., Chapter 3.2 – Figure 7; Chapter 5 – Figure 6), and group clustering (e.g., Chapter 5 – Figures 3, 4, and 6). Additionally, latencies of decisions can be tracked using spatio-temporal data (e.g., Chapter 4.2 – Figure 5) and their constant decrease over repeated interactions can indicate the reduction of subjective uncertainty within a given decision task (Kiani et al., 2014).

Limitations

While specific limitations have been discussed in each of the previous chapters (Chapters 3 through 5), general limitations of this dissertation shall be summarized here.

First, all empirical data were collected using very reductionist behavioral paradigms (HoneyComb paradigm, Boos et al., 2019; Collective Trust Game, Chapter 4, or less interactive comparison studies). As discussed in Chapter 5, this provides the advantages of high internal validity: All information that participants might use to make their decisions is available to researchers as well and can be analyzed. Without the confounding of environmental information, the used paradigms are able to identify the basic group processes that might guide group decision making. Additionally, the reductionist paradigms can provide higher replicability compared to ecological tests (Bonavita et al., 2022). However, the strength of the reductionist paradigm might also be a limitation: In more naturalistic settings, group members might rely on exactly those information sources that were excluded in the presented studies.

Second, the focus on the emergence of behavioral patterns poses a difficulty: Behavioral leadership as investigated in the presented studies might be hardly distinguishable from patterns of spatial cohesion. While the investigations of self-reports within the paradigm (Chapter 3.2) can aid to disentangle these processes, this limitation should be kept in mind while interpreting the results presented in this dissertation. Therefore, future applications of the HoneyComb paradigm might continue the quest to disentangle these processes, for example, by collecting

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more and more detailed reports on cognitive and affective determinants of the observed behavior.

Third, this dissertation conceptualized behavioral leadership in terms of initiation (as defined in Pyritz et al., 2011). While initiation sometimes coincides with leadership in terms of direction, it has been found that this is not always the case (e.g., Pyritz et al., 2010). Future research might investigate whether a similar differentiation between initiation and direction can be found in the HoneyComb data.

Fourth, this dissertation does not claim to have identified or even discussed all processes that might be relevant in uncertainty reduction during group decision making. For example, Ervin and Keyton (2019) discuss a qualitative difference between informational social influence (i.e., group members accepting others' knowledge as evidence about reality) and normative social influence (i.e., offerings of social rewards or threats to induce cognitive or behavioral change). These processes were not distinguished but might hold interesting information about the emergence of collective cognition. Additionally, recent work has challenged the view that humans use probabilistic inferences to make decisions (Szollosi et al., 2022) which was a fundamental assumption of Chapter 3 in this dissertation. Mehlhorn and colleagues (2015) suggest that exploration/exploitation patterns rely on more complex transition processes that have not been considered in this work. Lastly, this dissertation conceptualizes certainty broadly as the certainty about a correct option or prediction of others' behaviors. However, another form of certainty, the certainty about having made an error, might influence decision making as well (Margarido Moreira, 2016). Future research might use these limitations as starting points to guide the conceptualization of new research programs and the design of empirical studies.

Future Directions

Throughout this dissertation, starting points and directions for future investigations have been discussed. The most central ones shall be summarized here:

First, I suggest that future studies should place the amount of social information participants can use center-stage. Specifically, this means that future experiments might compare group decision making to individual decision making (see Chapter 3.1) and compare the influence of local and global information pooling (via the visual radius, Chapter 3).

Second, the studies presented in Chapter 3.2 might be followed up with an empirical study that increases the difficulty (and, therefore, uncertainty) to investigate whether the identified processes (e.g., leadership) will still emerge and whether new ones might be detected.

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Third, the inclusion and extension of methodological approaches as presented in Chapter 5 will provide more and deeper insights into the mechanisms that have been investigated within this dissertation. The use of network centrality parameters (e.g., King & Sueur, 2011) might complement current measures of behavioral leadership.

Fourth, the predecessors of consensus decisions might be investigated using methodological approaches from Chapter 5 or other analysis strategies, such as lag sequential analysis (Lehmann-Willenbrock et al., 2017).

Fifth, as discussed in Chapter 3.2, the use of simulation studies is promising to enrich the field of group decision making under uncertainty. As it has been shown that behavioral mechanisms within the HoneyComb paradigm can be explained by basic optimization processes (epsilon greedy: Chapter 3.2; future state optimization: Hornischer et al., 2022), other optimization methods might hold interesting insights as well (e.g., structural transitions; Hornischer et al., 2019). Next to applying differing variants of reinforcement learning algorithms (Cohen et al., 2007; Hązła et al., 2021; Tickle et al., 2021), approaches of agent-based modeling might create the opportunity to test boundary conditions and influence parameters to inform the designs of empirical studies (Archibold et al., 2019).

Sixth, it should be investigated whether the mechanisms discussed in this dissertation will apply to more naturalistic settings. Future research might use the analysis techniques presented in this work and apply them to group movement in the real-world (e.g., pedestrian behavior; Helbing et al., 2005; Jelić et al., 2012; Lombardi et al., 2020; Moussaïd et al., 2012) or to group discussions. Possibly the application to group discussion could allow the triangulation of these processes with both the analysis strategies presented in this dissertation and other process analysis approaches (see Lehmann-Willenbrock & Allen, 2018) to identify convergent or divergent relationships.

Conclusion

This dissertation aimed to combine theory and evidence from biology, machine-learning, organizational behavior, and psychology to shed light on emergent processes in human group decision making under uncertainty. This pooling of information from individual fields towards an interdisciplinary understanding of group decision making has proven fruitful once again (as in Boos et al., 2011), much like the pooling of information from individuals within group decision making.

When faced with the task of making decisions under uncertainty, groups can draw on a number of emergent processes. The works presented within this dissertation were able to show that

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groups engaging in repeated interactions can reduce both informational and personal uncertainty. In order to reduce uncertainty, groups might integrate privately held information on the collective level (collective cognition) and rely on leader-/followership processes. Additionally, the reduction of uncertainty seems to rely on a group's ability to interact in order to exchange social information. While no final conclusions can be drawn on the distinct contributions of each of those processes to group decision making yet, innovative combinations of network and visual analytic strategies presented in this dissertation might illuminate basic group decision making processes in the future.

Thinking back to Christie, Jeff, Henry, and Laura: Having identified some of the most central processes intuitively, I trust they have found a nice place to eat. Bon appétit!

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