Social Gaze in Team Collaboration:
Multiparty Eye-Tracking and Gaze-Adaptive Video Meeting Systems

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List of Abbreviations

ADHD	Attention Deficit Hyperactivity Disorder
AOI	Area of Interest
ASD	Autism Spectrum Disorder
BFI-10	Big Five Inventory 10
CO	Instrument for the Assessment of Collective Orientation
CRQA	Cross-Recurrence Quantification Analysis
CSCL	Computer-Supported Collaborative Learning
CSCW	Computer-Supported Cooperative Work
FT	Face-to-Face Treatment
GCS	Group Cohesiveness Scale
GEQ	Group Environment Questionnaire
IOS	Inclusion of Other in the Self-Scale
KD2Lab	Karlsruhe Decision & Design Lab
KIT	Karlsruhe Institute of Technology
KUSIV3	Short Scale for Measuring Interpersonal Trust
MdRQA	Multidimensional Recurrence Quantification Analysis
NMQ	Networked Minds Questionnaire
OLS	Ordinary Least Squares
PVA	Proportionality Vector Analysis
VT	Video Meeting Treatment
WLG	Weakest Link Game
2SLS	Two-Stage Least Squares

CHAPTER 1

Introduction

1.1 Motivation

The adoption of remote work policies across various industries has fundamentally transformed the modern workplace, reshaping how individuals collaborate on a daily basis (Barrero et al., 2023; Mas & Pallais, 2017; Yang et al., 2021). Unlike conventional office-based arrangements, remote work enables employees to fulfill their responsibilities without being bound to a single fixed location. This flexibility not only has the potential to increase their productivity (Angelici et al., 2023; Choudhury et al., 2021) but also to benefit the organizations by reducing facility-related costs and providing access to a broader talent pool (Bloom et al., 2024; Chatterjee et al., 2022; Shen, 2023). Yet, alongside these opportunities, the rise of remote work has also introduced new challenges (see, e.g., Brucks & Levav, 2022; Carnevale & Hatak, 2020; Cohn et al., 2022; Emanuel & Harrington, 2024). To enable collaboration among geographically distributed employees, organizations have shifted team meetings to the virtual space. Instead of interacting face-to-face, virtual teams depend on digital collaboration tools—most prominently video meeting systems—to communicate (Standaert et al., 2021). While video meetings offer a fast and cost-effective way to collaborate, they lack the nonverbal richness inherent to face-to-face communication (Bicchieri & Lev-On, 2007; Bohannon et al., 2013; Kaiser et al., 2022).

This deficit can undermine successful collaboration because individuals rely on nonverbal signals to gauge team members' cooperativeness and adapt their behavior accordingly—a process known as type detection (Fischbacher et al., 2001; He et al., 2017). For instance, a team member who maintains open body language and closely attends to the speaker during a face-to-face meeting is likely perceived as cooperative, thereby encouraging others to reciprocate (Eckel & Petrie, 2011; Kurzban, 2001). In contrast, a team member displaying dismissive behaviors may be considered uncooperative, prompting others to reduce their efforts. Thus, collaboration is not only influenced by spoken words but also by the nonverbal signals exchanged between team members (see, e.g., Bicchieri & Lev-On, 2007; Brosig & Weimann, 2003; Ristic & Capozzi, 2022; Scharlemann et al., 2001).

Conventional video meeting systems transmit a broad range of these signals, including appearance, facial expressions, and gestures. However, these systems lack the capability to convey what others are visually attending to (Bohannon et al., 2013). Although team members can see each other's faces in video meetings, the absence of gaze information prevents them from perceiving social gaze dynamics, such as eye contact (Emery, 2000; Pfeiffer et al., 2022). Even an individual who frequently watches their team members' video feeds may be judged as unengaged or distracted because webcams are typically positioned above eye level, creating the illusion that gaze is constantly averted throughout the meeting (see, e.g., Basch et al., 2021; Kaiser et al., 2022). As a result, the absence of gaze information in video meetings might distort the accurate detection of each other's cooperativeness, posing a threat to successful team collaboration.

Given that video meetings have become a standard mode of communication in the modern workplace, understanding how the absence of gaze information influences team collaboration is pivotal to ensuring organizational success. Previous research has demonstrated that the absence of nonverbal signals impairs type detection and, in turn, affects economic behavior in teams (Bicchieri & Lev-On, 2007; Eckel & Petrie, 2011; He et al., 2017; Kurzban, 2001). However, experimental evidence on the isolated role of gaze in facilitating type detection remains highly limited (Fischbacher et al., 2022). By addressing this research gap, this dissertation aims to illuminate the role of gaze for successful collaboration and, in particular, to disentangle how differences in social gaze dynamics between face-to-face and video meeting settings affect cooperation and coordination in teams. In doing so, it offers both theoretical insights and practical implications, empowering organizations to make informed decisions regarding the optimal modes of team communication (Chatterjee et al., 2022). After all, the common saying goes, "the eyes are the windows to the soul" (see, e.g., Grossmann, 2017), raising concerns about what may be lost when our gaze remains unseen in the future of work.

1.2 Foundations

Previous research has laid the theoretical and methodological foundations for investigating the role of gaze in team collaboration. However, these remain fragmented across distinct disciplines. Social psychologists have previously examined how individuals use their gaze for perceptual and communicative purposes in social interactions, accelerating advancements in eye-tracking methodology (Emery, 2000; Gobel et al., 2015; Kleinke, 1986; Kuhn et al., 2016; Laidlaw et al., 2012; Pfeiffer et al., 2013; Valtakari et al., 2021). Concurrently, behavioral economists have provided crucial insights into the mechanisms that drive successful team collaboration (Balliet, 2010; Brandts & Cooper, 2006; Gächter et al., 2024; Riedl et al., 2016; Sally, 1995). Only by synthesizing empirical evidence and best practices from both disciplines, researchers can rigorously investigate the differences in gaze between face-to-face and video meeting settings and assess their impact on team collaboration. Accordingly, this section reviews foundational insights into the general purpose of gaze, beginning with its dual function in social interactions, followed by an overview of established eye-tracking methods and their application in behavioral economics.

The Dual Function of Gaze. During social interactions, gaze serves two primary functions (Gobel et al., 2015; Jarick & Kingstone, 2015). First, it fulfills a perceptual role by allowing individuals to scan their visual environment for relevant information. Second, given that others can observe the direction of gaze in face-to-face settings, it also acts as a communication signal by revealing an individual's focus of visual attention. For instance, Kuhn et al. (2016) found that individuals gaze at others less frequently in face-to-face than in video meeting settings. The authors concluded that participants were aware that their gaze revealed personal information, leading them to strategically adapt its direction in situations where others could observe it. Similarly, Laidlaw et al. (2012) showed that participants frequently looked toward other individuals when they were displayed via a live stream yet rarely directed their gaze at them when being physically present in the same room. These findings demonstrate that individuals adapt their gaze based on the presence of others, highlighting its role as a communication signal that reveals intentions and motives.

To examine the perceptual and communicative functions of gaze, researchers rely on a methodology capable of accurately capturing eye movements. While camera-based setups may suffice to count how often individuals turn their heads and gaze at others (see, e.g., Laidlaw et al., 2012), such approaches lack the temporal and spatial precision needed for more sophisticated analyses. Therefore, advanced eye-tracking technologies—offering precise and high-frequency measurements of eye movements—have been established to gain deeper insights into the nuanced dynamics of visual attention.

Eye-Tracking Methodology. Eye-tracking technologies are broadly classified into two types: desktop-mounted devices and head-mounted eye-tracking glasses, each suited for specific research settings (Valtakari et al., 2021). Desktop-mounted devices capture gaze relative to a corresponding digital screen, making them ideal for controlled experiments and tasks performed in virtual environments. In contrast, mobile eye-tracking glasses are designed to capture gaze within a broader visual scene, recording the environment from an individual's perspective to determine their focus of visual attention in dynamic, real-world settings.

Both eye-tracking technologies rely on similar principles to measure gaze (Holmqvist et al., 2011). Specifically, infrared light is projected onto the eyes, creating corneal reflections. Multiple cameras, either embedded in the frame of mobile eye-tracking glasses or integrated into desktop-mounted devices, capture these reflections. Advanced algorithms then analyze the reflections to determine the precise direction of gaze relative to the visual scene. Depending on the specific device, this process can generate up to 2000 data points per second, providing the foundation for precisely analyzing where, when, and how long individuals focus their gaze.

Beyond simply revealing the focus of visual attention, eye-tracking offers the means to uncover latent cognitive processes. A central principle underlying eye-tracking research is that the dwell time of gaze—defined as how long an individual looks at a particular aspect of the visual scene—correlates with the depth of cognitive processing (Duchowski, 2007; Holmqvist et al., 2011). Longer dwell times typically indicate deeper engagement, as individuals allocate more cognitive resources to interpret or evaluate the corresponding information. Since individuals can gaze at only one aspect within the visual scene at a time, they must also decide which information is the most relevant for further processing. Thus, by comparing the dwell times devoted to different aspects, researchers can infer the subjective value assigned to them (see, e.g., Fiedler et al., 2013; Wang et al., 2010). Overall, when effectively applied, eye-tracking not only reveals what individuals look at but also why they look at it and how deeply they engage with it.

Application in Behavioral Economics. In behavioral economics, eye-tracking has emerged as a powerful tool for investigating how individuals process and interpret information during decision-making, illuminating the relationship between gaze patterns and economic behavior (Lahey & Oxley, 2016). Research has shown that certain gaze patterns during decision-making predict cooperative behavior in various economic games—such as money allocation tasks, public goods dilemmas, and sender-receiver games (Fiedler et al., 2013; Wang et al., 2010).[1] Specifically, when individuals weighed choices tied to personal versus collective monetary gains, the choice they visually focused on more intensely—reflected in longer dwell times of gaze—tended to be the one they ultimately selected. Overall, these studies built upon the perceptual function of gaze to gain insights into underlying cognitive processes during decision-making. However, research on the communicative function of gaze remains highly limited (Fischbacher et al., 2022; Hausfeld et al., 2021). Thus, exploring how gaze, as a nonverbal signal during communication, affects economic behavior in teams presents valuable opportunities for future research.

1.3 Research Objective

Overall, this dissertation aims to advance the literature on the communicative function of gaze in team collaboration by introducing an interdisciplinary research framework that leverages theoretical insights into the dual function of gaze, state-of-the-art eye-tracking methodology, and behavioral economics. Through this approach, we sought to identify relevant social gaze dynamics (1), precisely measure how these dynamics emerge in face-to-face and video meeting settings (2), and evaluate how potential differences affect cooperation and coordination within teams (3).

In social interactions, gaze plays a critical role by enabling individuals to coordinate their attentional processes (Emery, 2000; Pfeiffer et al., 2013). As proposed by the Cooperative Eye Hypothesis (Tomasello et al., 2007), the unique morphology of human eyes—with the white sclera contrasting the dark pupil—evolved because it made it easier for observers to detect gaze and track its direction. In collaborative tasks, monitoring one another's gaze allows individuals to align their visual attention to relevant aspects within the visual scene. This mechanism, known as gaze-cueing (Frischen et al., 2007), facilitates the collaborative process by enabling team members to infer each other's anticipated actions (Grossmann, 2017; Hietanen, 2018). Consequently, exploring the extent to which individuals align their

[1] As the feeling of being observed can influence an individual's behavior, one might worry that the usage of eye-tracking alters economic behavior. However, Kee et al. (2021) found no considerable changes in eight standard economic games.

attentional processes during collaboration constitutes a promising avenue for understanding the impact of gaze on economic behavior in teams.

To quantify the coordination of visual attention during team collaboration, it is necessary to capture the gaze of each member synchronously. However, conventional eye-tracking research typically focuses on measuring the eye movements of one individual at a time, exploring how certain gaze patterns relate to specific dependent variables (see, e.g., Fiedler et al., 2013; Fischbacher et al., 2022; Hausfeld et al., 2021; Wang et al., 2010). While this approach has provided valuable insights, it is inherently limited in addressing the complexity of social gaze dynamics (Emery, 2000; Pfeiffer et al., 2013). In recent years, novel multiparty eye-tracking setups have emerged as a promising solution to this challenge (Valtakari et al., 2021). These setups enable researchers to capture and analyze social gaze dynamics within teams by measuring each member's eye movements during collaboration (see, e.g., Cherubini et al., 2010; Dale et al., 2011; Jermann et al., 2010; Jermann & Nüssli, 2012; Richardson & Dale, 2005). Despite this opportunity, a clear conceptualization of how to appropriately utilize multiparty eye-tracking as a diagnostic method in experiments and, in particular, how to process the collected data to operationalize and analyze social gaze dynamics within teams had yet to be established. Therefore, the first research question that guided this dissertation was:

> **RQ1.** *How can multiparty eye-tracking be harnessed as a diagnostic method to measure, operationalize, and analyze social gaze dynamics in team collaboration?*

A previous review by Valtakari et al. (2021) explored the possibilities and limitations of eye-tracking during social interactions, providing an overview of single and multiparty eye-tracking setups. While their review offered guidance on choosing between different frameworks, it remained unclear how multiparty eye-tracking has been implemented in experimental research to investigate the relationship between social gaze dynamics and collaborative outcomes. To address this gap and answer the first research question, we conducted a systematic literature review on diagnostic multiparty eye-tracking in synchronous computer-mediated collaboration. Specifically, we identified and analyzed 25 relevant studies, highlighting several opportunities for future research.

The majority of studies have focused on analyzing social gaze dynamics between two participants, with few exploring interactions within larger groups. Only two studies involved collaboration among three participants (Abdullah et al., 2021; Vrzakova et al., 2019), leaving a substantial gap in understanding the role of gaze within teams, in which interactions involve multiple individuals. Moreover, only three studies analyzed gaze in settings where participants could see each other during collaboration (Abdullah et al., 2021; Vrzakova et al., 2019; 2021). This design choice limited insights into attentional processes associated with task-related aspects, neglecting social gaze dynamics occurring directly between team members (e.g., eye contact; Pfeiffer et al., 2013). Among the studies reviewed, only one (Vrzakova et al., 2021) investigated the relationship between such social gaze dynamics and collaborative success. However, the authors restricted interactions to pairs, leaving a research gap regarding the role of social gaze dynamics in team collaboration involving multiple individuals, which motivated the second research question of this dissertation:

> **RQ2.** *How do social gaze dynamics affect team collaboration?*

A key factor to consider when addressing this research question is the setting in which collaboration takes place. The emergence of social gaze dynamics and their impact on team collaboration may vary significantly between face-to-face and video meeting settings (Bohannon et al., 2013). While both allow participants to see each other, they differ fundamentally in the availability of gaze information. Only in face-to-face meetings, individuals can accurately perceive whether or not they are being looked at (Kaiser et al., 2022). Thus, the absence of gaze information in video meetings may shape how social gaze dynamics emerge and impact team collaboration, which led to the third research question of this dissertation:

> **RQ3.** *How do the emergence and impact of social gaze dynamics in team collaboration differ between face-to-face and video meeting settings?*

To address the second and third research questions, we conducted a study comprising two laboratory experiments. The first experiment (n = 30) examined social gaze dynamics in face-to-face meetings. Our results revealed that cooperative behavior within teams increased with higher levels of eye contact and declined when team members frequently averted one another's direct gaze. The second experiment (n = 204) extended this investigation to compare the emergence and impact of these dynamics in face-to-face and video meeting settings, demonstrating that the degree to which team members reciprocated each other's direct gaze significantly enhanced cooperation. Importantly, this significant positive relationship was observed only when communication took place in face-to-face meetings, where gaze information was available. These findings highlight the communicative function of gaze as a nonverbal signal for prosocial motives within teams and underscore the potential consequences of shifting team meetings to the virtual space, where gaze information is absent.

However, one limitation of the second experiment was its reliance on comparing face-to-face and video meeting settings to manipulate the availability of gaze information. Despite controlling for various confounding factors, unaddressed differences between these treatments could have influenced the collaborative process. To address this limitation and, thus, draw causal conclusions about the impact of social gaze dynamics on team collaboration, it was necessary to hold the meeting setting constant while selectively manipulating the social gaze dynamic of interest.

A viable solution to achieving this is to restrict communication to video meetings and compare collaborative outcomes across two treatments: a conventional video meeting system, where gaze information is absent, and a gaze-adaptive video meeting system that processes eye movement data in real time to visualize gaze information (Reuscher et al., 2024). This approach allows researchers to systematically investigate how the option to perceive specific social gaze dynamics impacts team collaboration. In particular, it provides a framework to test whether the observed benefits of reciprocating direct gaze within teams—henceforth referred to as gaze contact—can be replicated in virtual environments. Accordingly, the fourth and final research question that guided this dissertation was:

> **RQ4.** *How does the option to perceive gaze contact during video meetings affect team collaboration?*

To answer this research question, we conducted a controlled laboratory experiment (n = 156). Specifically, we examined whether a gaze-adaptive video meeting system—designed to inform team members in real time when they look at each other's video feeds simultaneously—enhances cooperation and coordination in virtual teams compared to a conventional video meeting system without gaze-adaption. Notably, the option to perceive gaze contact during video meetings marginally significantly enhanced team cooperation, highlighting its potential to bridge the gap between face-to-face and computer-mediated communication.

1.4 Thesis Structure

The remainder of this dissertation is structured to systematically address the outlined research questions. **Chapter 2** presents the results of the systematic literature review conducted to address the first research question (RQ1), focusing on multiparty eye-tracking as a diagnostic method in computer-mediated collaboration. The review identified current methodological capabilities, highlighted gaps in the literature, and provided a foundation for the subsequent experimental investigations. **Chapter 3** addresses the second and third research questions (RQ2, RQ3) by presenting the results of two laboratory experiments on the role of social gaze in team collaboration. The first experiment examined the emergence and impact of social gaze dynamics in face-to-face team collaboration, while the second experiment extended this analysis to compare these dynamics across face-to-face and video meeting settings. **Chapter 4** focuses on the fourth research question (RQ4). Specifically, it presents the results of a controlled laboratory experiment designed to examine the effects of a gaze-adaptive video meeting system on cooperation and coordination in teams. **Chapter 5** synthesizes our findings, outlines their theoretical and practical implications, and suggests directions for future research. Finally, **Chapter 6** provides a conclusion, summarizing the key findings of the dissertation and reflecting on its overall contributions.

CHAPTER 2

Multiparty Eye-Tracking in Computer-Mediated Collaboration: A Systematic Literature Review

Abstract

In recent years, innovative multiparty eye-tracking setups have been introduced to synchronously capture the eye movements of multiple individuals engaged in computer-mediated collaboration. Despite its great potential for studying the role of interdependent attentional processes within groups, the method was primarily utilized as an interactive tool enabling shared gaze visualizations in remote settings. To address this gap, we conducted a systematic literature review on multiparty eye-tracking, providing a comprehensive overview of what to consider when using it as a diagnostic method in experiments and how to process the collected data to compute and analyze group-level gaze metrics. By synthesizing our findings within an integrative conceptual framework, we identified fundamental requirements for an appropriate implementation. In addition, we derived several avenues for future research, as multiparty eye-tracking was almost exclusively used to study the correlation between joint attention and task performance in dyadic interaction. Moreover, multidimensional recurrence quantification analysis, a novel method to quantify group-level dynamics in physiological data, emerged as a promising procedure for addressing the highlighted research gaps. By scaling up to multiple data streams, the computation method enables scholars to investigate more complex cognitive processes within larger groups.

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2.1 Introduction

In synchronous collaboration, defined as working together in real time to achieve a common goal (Borghoff & Schlichter, 2000), gaze plays an important role by signaling engagement, facilitating rapport building, and regulating conversational flow (Frischen et al., 2007; Grossmann, 2017; Hessels, 2020; Hietanen, 2018). During the last decade, dual eye-tracking methods have been introduced to capture and analyze interdependent gaze patterns between individuals by implementing two eye-tracking devices synchronously (see, e.g., Richardson & Dale, 2005). These patterns—known as social gaze dynamics—include joint attention (i.e., at least two individuals look at the same object), mutual gaze (i.e., two individuals look at each other), and gaze aversion (i.e., one individual looks at another who looks away; Emery, 2000; Pfeiffer et al., 2013). Previous research on social gaze has revealed its fundamental role in face-to-face settings (Hessels, 2020). However, in the context of computer-mediated collaboration, researchers have mainly used dual eye-tracking as an interactive tool to design and evaluate shared gaze visualizations (D'Angelo & Schneider, 2021), neglecting its potential as a diagnostic method.

Given that digital collaboration tools have been established as an efficient alternative to face-to-face meetings, understanding the factors that affect computer-mediated collaboration is more important than ever (Bloom et al., 2024; Chatterjee et al., 2022; Shen, 2023). Dual eye-tracking is a promising methodology for investigating interdependent attentional processes between individuals in remote settings. For instance, Jermann et al. (2010) observed that individuals adapt their gaze depending on the expertise of their partner during computer-mediated collaboration. Further studies focused on quantifying joint attention and testing its correlation with various collaborative processes (Cherubini et al., 2010; Dale et al., 2011; Jermann & Nüssli, 2012). As collaboration often involves more than two individuals, scholars extended the basic dual eye-tracking setup by including additional eye-tracking devices to study larger group sizes (Vrzakova et al., 2019). Accordingly, in this study, we refer to the method of synchronously tracking the eye movements of at least two individuals as multiparty eye-tracking.

Despite the great potential of multiparty eye-tracking as a diagnostic method, guidelines on how to utilize it have yet to be established. To bridge this gap, we sought to provide a comprehensive overview of experimental findings, methodological challenges, and novel opportunities associated with multiparty eye-tracking. Specifically, we developed an integrative conceptual framework, synthesizing what needs to be considered when synchronously capturing the eye movements of multiple individuals (1) and how to process the collected data to analyze the role of social gaze dynamics in computer-mediated collaboration (2).

2.2 Methods

To address the identified research gap, we conducted a systematic literature review following the guidelines of Kitchenham and Charters (2007). The review process comprised three stages: planning, conducting, and reporting. During the planning phase, we formulated an effective search strategy by developing a search string and defining criteria for selecting relevant literature. In the conducting phase, we implemented the search strategy across appropriate research databases. The extracted data was then used to develop a conceptual framework for state-of-the-art diagnostic multiparty eye-tracking in computer-mediated collaboration. This framework served as the basis for detailed reporting of findings.

2.2.1 Search Strategy

The development of the search strategy began with an initial exploration on Google Scholar using the following terms and operators: "eye tracking" AND "collaboration." Next, we iteratively refined the search string based on a review of relevant studies and keywords. The final version, comprising three distinct parts, is detailed in Table 2.1.

The first part targeted commonly used terms for eye-tracking experiments, while the second part included keywords specific to multiparty eye-tracking setups. The third part focused on the context of collaboration. Our initial exploration revealed that collaboration was often referred to as joint problem-solving, prompting us to include this term. We chose not to add a separate component to limit our search strategy to studies explicitly referencing computer-mediated communication. Instead, remote interaction was defined as an inclusion criterion.

(1)	(“eye tracking” OR “eye movements” OR gaze)
(2)	AND (dual OR dyad* OR triad* OR multiparty)
(3)	AND (collaborat* OR “problem solving”)

Table 2.1: First, second, and third part of the final search string.

To ensure comprehensive coverage of relevant literature, we compared various electronic databases by verifying their capability to retrieve a pre-identified sample of highly relevant studies. Ultimately, we selected Scopus, Web of Science, ACM Digital Library, and EBSCOhost as the most suitable databases. This selection reflected the interdisciplinary nature of the topic and ensured coverage across diverse research domains.

2.2.2 Selection Criteria

In a further step, we defined the inclusion and exclusion criteria to guide the review and selection of relevant literature for data extraction (see Table 2.2).

In line with the scope of this study, only eye-tracking studies were selected. Due to the focus on collaboration, the first criterion was further specified to the synchronous eye-tracking of at least two participants. Additionally, the experimental task had to involve a shared objective and collaborative activity with a measurable outcome variable, such as team performance. To address the context of computer-mediated collaboration, only studies featuring remote interaction with individual and visually separated systems were selected. Finally, studies primarily concerned with the evaluation of shared gaze visualizations based on multiparty eye-tracking approaches were excluded since related findings are already covered by D’Angelo and Schneider (2021) and do not contribute to the specific objective of this review.

2.2.3 Data Extraction

During the conducting phase, we applied the final search string to the selected databases. Initially, titles and abstracts of the identified studies were screened based on the defined selection criteria. This process was then repeated for full texts. To ensure comprehensive

Inclusion	Synchronous Eye-Tracking
	Experimental Collaboration Task
	Remote Interaction
Exclusion	Evaluation of Shared Gaze Visualization

Table 2.2: Four criteria for selecting appropriate studies.

coverage, we conducted a forward and backward search on Google Scholar, examining the references of the remaining studies and reviewing all articles that cited them. Through iterative analysis of the final sample of studies, key aspects relevant to the research question were identified. The extracted data was organized into a structured table (see Appendix A: Table A.1). Finally, these findings were synthesized into a conceptual framework to answer our research question.

2.3 Results

2.3.1 Review Process

The search strategy yielded 1665 initial results (ACM Digital Library: 1354; Scopus: 189; Web of Science: 84; EBSCOhost: 38). After screening titles and abstracts, 1529 irrelevant studies were excluded. A further 114 studies were excluded following full-text reviews. A forward and backward search of the remaining 22 studies identified three additional relevant studies. Consequently, the final sample comprised 25 relevant studies (see Figure 2.1).

2.3.2 Conceptual Framework

The integrative conceptual framework was developed through a bottom-up analysis of the extracted data, categorizing the identified aspects (see Figure 2.2). The framework outlines five key dimensions relevant to multiparty eye-tracking. The first three dimensions address relevant aspects to consider when synchronously capturing the eye movements of multiple individuals. Specifically, the first dimension—**Task & Context**—provides detailed information on the experimental tasks and collaborative activities performed by participants.

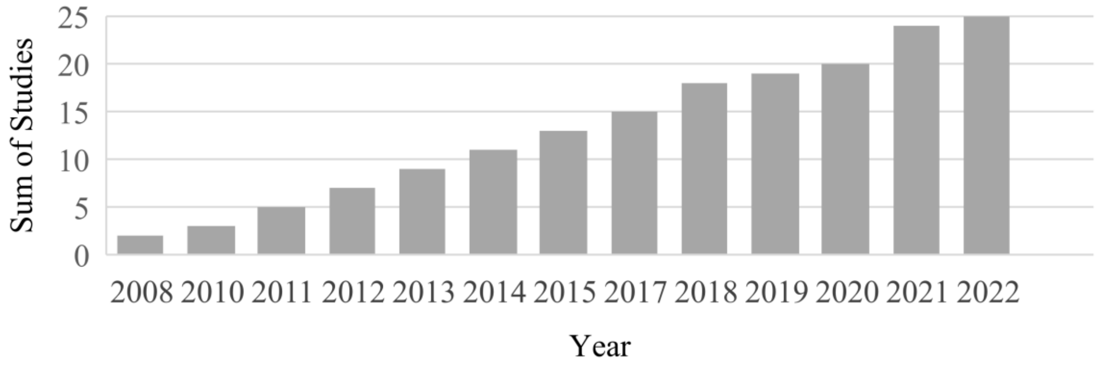

Figure 2.1: Cumulated number of studies by year of publication.

The second dimension—**Remote Interaction**—highlights key characteristics of the interaction context in which these tasks were conducted. The third dimension—**Data Collection**—summarizes the eye-tracking devices used in the studies and the modalities of any additional communication signals collected. The remaining two dimensions focus on how the synchronized eye movement data was processed to derive group-level insights. In particular, the fourth dimension—**Data Processing**—covers the procedures employed to analyze the data, while the fifth dimension—**Group-Level Metrics**—synthesizes the operationalized eye-based constructs and the dependent variables investigated in the studies.

Dimension 1: Task & Context. Based on the activities performed by collaborators, most tasks could be assigned to either a computer-supported cooperative work (CSCW; 52%) or computer-supported collaborative learning-related context (CSCL; 36%). The remaining tasks were labeled as artificial (12%). CSCW-related tasks included software design activities referred to as collaborative programming (28%) and cooperative decision-making tasks (24%). For instance, in a programming task, errors in a given software code had to be identified and marked (Villamor & Rodrigo, 2018). One of the decision-making tasks required two participants to discuss and agree on eight key attributes of a car deal to maximize their collective payoff (Vrzakova et al., 2021). Experimental tasks associated with CSCL included the collaborative solving of mathematical problems using educational collaboration tools (24%) and the joint creation of concept maps derived from previously processed learning materials (12%). The three tasks described as artificial included a psychological change blindness task (4%; Tchanou et al., 2020) and two puzzle games (8%; Dale et al., 2011; Kuriyama et al., 2011).

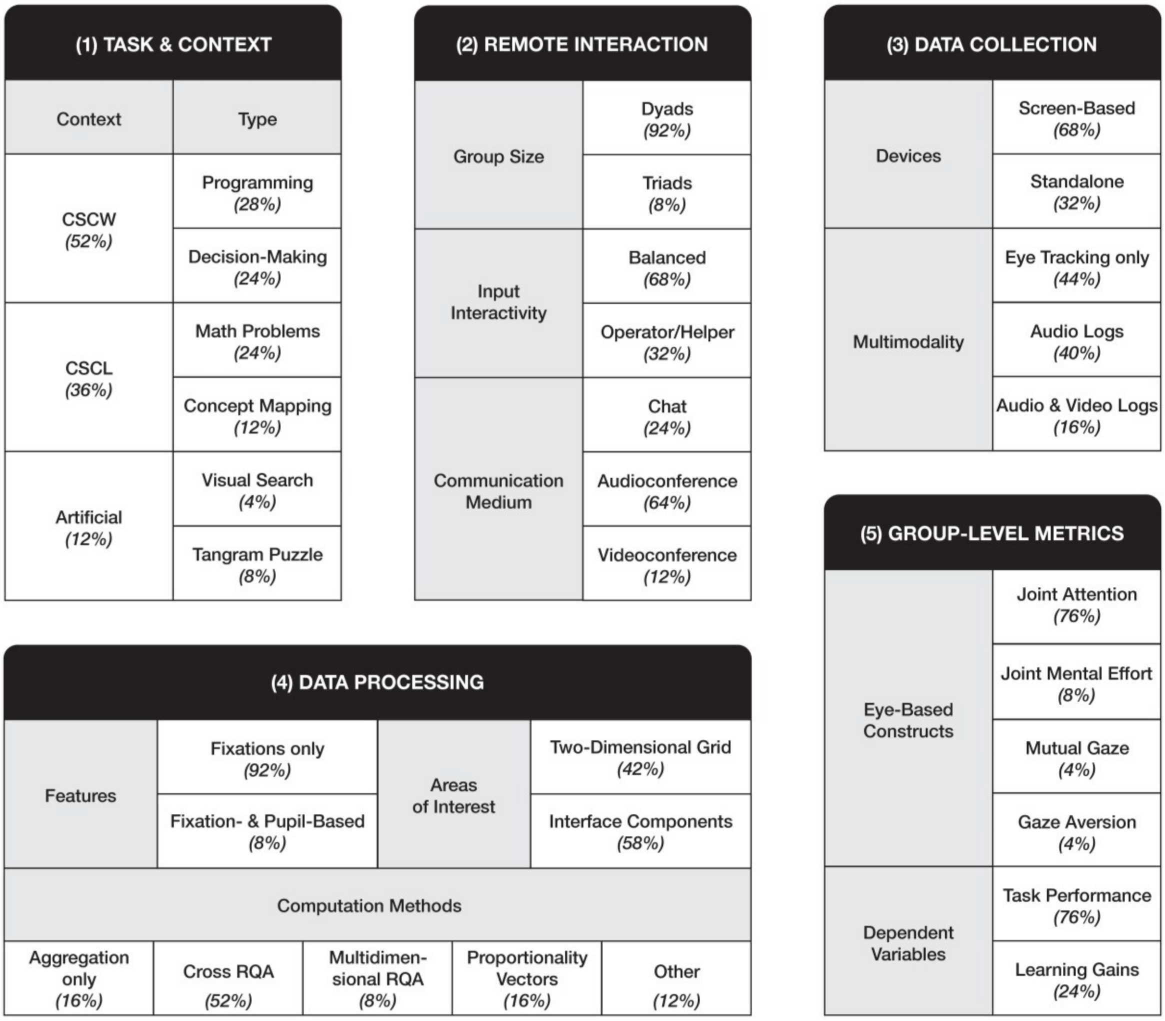

Figure 2.2: Integrative conceptual framework.

Dimension 2: Remote Interaction. Most studies investigated behavior in dyadic interaction (92%). Only two studies synchronously tracked the eye movements of three participants (8%). Furthermore, the ability to interact with the interface differed among the eye-tracked participants in eight studies, as they were assigned either an operator or helper role (32%). In the remaining studies, all participants could interact with the interface equally using manual input devices (68%). Furthermore, the richness of communication was determined by the provided collaboration tool, ranging from simple chats (24%) to audio (64%) and mixed-media video meetings (12%).

Dimension 3: Data Collection. In line with the focus on computer-mediated collaboration, only desktop-mounted eye-tracking devices were used in the studies. These were either screen-based devices integrated into monitors (68%) or standalone devices set up next to the screen (32%). Moreover, most studies captured not only the participants' eye movements (44%) but also other communication modalities, such as speech and body language by recording audio (40%) and video logs (16%).

Dimension 4: Data Processing. The computation methods used in the examined studies were based on either the position or duration of gaze points (92%). Two studies additionally performed calculations with pupil size data (8%; Sharma et al., 2021b; Tchanou et al., 2020). In general, data processing followed a similar procedure to compute group-level metrics based on the synchronized eye movement data of individual participants. First, the interface was divided into smaller segments by applying two-dimensional grids (42%) or defining specific components of the user interface (58%) as areas of interest (AOIs). Next, individual gaze metrics, such as the duration of fixations to the AOIs (see, e.g., Jermann & Nüssli, 2012), were calculated. In a subsequent step, the participants' individual metrics were used to perform the following group-level calculations: Cross-recurrence quantification analysis (CRQA; 52%), multidimensional recurrence quantification analysis (MdRQA; 8%), proportionality vector analysis (PVA; 16%) and other alternative approaches (12%), such as fixation clustering (Cherubini et al., 2008). In the remaining studies, computations were limited to simple aggregations, such as the participants' proportional distribution of gaze to distinct AOIs (16%; Abdullah et al., 2021; Bednarik & Kauppinen, 2013; Molinari et al., 2008; 2017).

Dimension 5: Group-Level Metrics. Most studies performed group-level computation methods to quantify joint attention (76%). One study extended the analysis of social gaze dynamics to mutual gaze (4%) and gaze aversion (4%; Vrzakova et al., 2021). In addition, two studies operationalized the extent of joint mental effort (8%) by calculating cognitive load at the group level based on synchronized pupil size data (Sharma et al., 2021b; Tchanou et al., 2020). Overall, researchers investigated correlations between these group-level metrics and either learning gains (24%) or task-specific performance variables (76%).

2.4 Discussion

By conducting the systematic literature review, we identified key aspects to consider when synchronously capturing and analyzing the eye movements of multiple participants during computer-mediated collaboration. This section critically examines methodological differences in the diagnostic use of multiparty eye-tracking and discusses implications for future research within the context of the proposed conceptual framework.

Despite adhering to the guidelines established by Kitchenham and Charters (2007), the review process was subject to some limitations. First, the iterative development of the search string, which involved progressively adding relevant keywords, may have inadvertently excluded some relevant studies. Second, the explicit choice of selection criteria and the reliance on specific databases for executing the search might have limited the comprehensiveness of the review, potentially overlooking relevant studies from less commonly used sources or interdisciplinary fields. Lastly, the relevance of the extracted data was assessed subjectively, which might have influenced the conceptualization of the conceptual framework.

2.4.1 Synchronized Collaboration

To investigate the eye movements and gaze patterns of collaborating participants within a shared visual space, user interfaces were either shared in real time, included synchronized areas, or were duplicated within dyads (see, e.g., Molinari, 2017; Sharma et al., 2013; Vrzakova et al., 2021). Depending on these configurations, the degree of synchrony varied across tasks. Real-time interface updates, such as those in the programming task used by Vrzakova et al. (2019), enabled participants to jointly attend to on-screen changes. In contrast, unsynchronized content served more as an aid for verbal coordination on multiple aspects (Abdullah et al., 2021; Cherubini et al., 2008). While verbal coordination might be essential for effective collaboration, unsynchronized tasks do not allow individuals to anticipate visually recognizable actions by others (e.g., editing code in a programming task). Consequently, simple coordination tasks with static interfaces fail to capture the nuanced aspects of interactive gaze dynamics during computer-mediated collaboration.

Moreover, the ecological validity of the activities performed varied between tasks. For instance, gaze patterns observed in a synchronized visual search task, such as the change blindness task presented by Tchanou et al. (2020), may not be comparable to those identified in more naturalistic activities. This is because eye movements are closely tied to the attentional demands of a specific task (Duchowski, 2007; Holmqvist et al., 2011). While artificial tasks can provide foundational insights into the functions of gaze in computer-mediated collaboration, studies involving more naturalistic tasks are better suited to informing the design of CSCW and CSCL-related applications.

2.4.2 Remote Interaction

When investigating gaze behavior in virtual environments, certain properties of the interaction context must be considered. First, the number of participants influences the complexity of the interaction. For example, the conceptualization of joint attention is deterministic in dyadic interactions (AB) but can occur in four distinct combinations in triadic interactions (AB, AC, BC, ABC; Pfeiffer et al., 2013). Thus, group size systematically influences the complexity of visual patterns in computer-mediated collaboration. Although many CSCW and CSCL-related activities involve more than two collaborators, only two studies have examined eye movements in triadic interactions, highlighting a significant research gap (Abdullah et al., 2021; Vrzakova et al., 2019).

Additionally, nine studies assigned participants to operator or helper roles, creating imbalances in collaboration since only one participant could actively interact with the interface. This disparity complicates the validity of comparisons within dyads, as attentional processes and associated eye movements likely differed between roles. For instance, Belenky et al. (2014) introduced a mathematical task where one participant entered answers while the other provided verbal support. However, most reviewed studies provided participants with manual input devices, allowing more balanced contributions to task completion.

Furthermore, the richness of the computer-mediated communication differed between studies as the degree of synchronization between participants and the presence of verbal and nonverbal signals was determined by the collaboration tool featured (Baltes et al., 2002). For example, chats restricted communication to text-based messaging, whereas mixed-media video meetings enabled speech as well as the transmission of facial expressions, gestures, and body language in real time. In addition, dynamic interface components, such as chat boxes or videos, might have naturally drawn visual attention, leading to systematic differences in gaze patterns compared to audio-based meetings without interactive elements. Consequently, findings on gaze behavior cannot be compared across studies without accounting for the specific layout and features of the digital collaboration tool.

2.4.3 Multiparty Eye-Tracking Setup

To capture the interdependent dynamics of gaze, the participants' eye movements must be tracked synchronously. While this requirement was addressed by the inclusion criteria of this review, we observed substantial differences between multiparty eye-tracking setups. Recent studies have adopted standalone desktop-mounted eye-tracking devices instead of screen-based systems, expanding their applicability and enabling integration into more naturalistic settings. Additionally, some studies employed chin rests to prevent head movements and confine participants' field of view to the screen (Jermann & Nüssli, 2012; Sharma et al., 2012). While such approaches enhance data quality, they reduce the generalizability of results by restricting natural behavior during computer-mediated collaboration. To improve ecological validity, researchers should consider using unconstrained, state-of-the-art desktop-mounted eye-tracking devices (see, e.g., Villamor & Rodrigo, 2018).

Furthermore, many studies collected audio and video logs to explore the relationship between gaze and other communication signals. In particular, the connection between eye movements and speech has been extensively analyzed, as referring expressions can precede joint attention (Dale et al., 2011; Kuriyama et al., 2011; Olsen et al., 2018; Sharma et al., 2013). Given the natural interplay between eye movements and other communication signals (Hessels, 2020), future research on computer-mediated collaboration should adopt multimodal data collection approaches.

2.4.4 Computation Methods

Cross-Recurrence Quantification Analysis (CRQA). Most studies employed CRQA to measure the degree of convergence between two participants' gaze locations over time (Coco & Dale, 2014; Wallot et al., 2018). This method identifies recurrent states between two temporal streams of eye movement data by first segmenting each participant's time series into equal intervals (e.g., one-second slices). Each interval is then assigned to the AOI that contains the majority of gaze points during the specified duration. Finally, the recurrence rate is quantified by calculating the proportion of converging AOIs between the two participants along the segmented time series (see Figure 2.3).

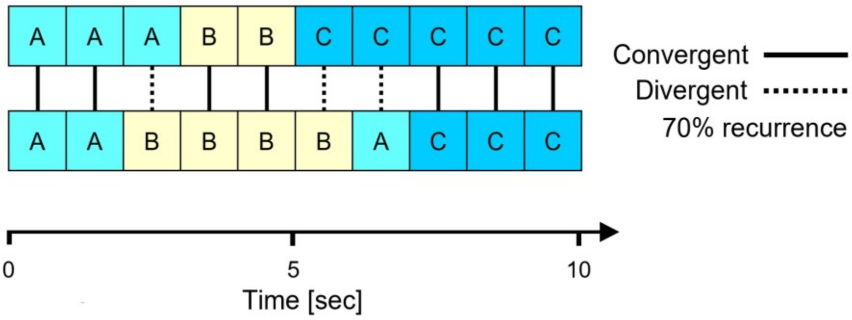

Figure 2.3: Cross-recurrence quantification analysis with exemplary times series of two participants with assigned areas of interest (A, B, or C) per one-second intervals.

This process can be extended to account for any time lag between data streams by shifting one participant's segmented series relative to the other. This is crucial because gaze is typically not visually transmitted in computer-mediated communication. Thus, the focus of visual attention may not converge in real time but rather after a short delay (Dale et al., 2011). For instance, Richardson and Dale (2005), the first to apply CRQA to eye movement data, investigated the temporal coupling of visual attention between speakers and listeners. They found the highest recurrence rate at a lag of approximately two seconds (see Figure 2.4). While CRQA can be applied to any dynamic data stream with temporal order, such as changes in pupil size over time (Sharma et al., 2021b), the examined studies almost exclusively applied it to gaze coordinates to infer spatial convergence.

Multidimensional Recurrence Quantification Analysis (MdRQA). Recently, Vrzakova et al. (2019) used MdRQA, a novel extension of CRQA, to quantify dynamic states of visual attention among multiple participants. Unlike CRQA, which measures the degree of convergence between two time series, MdRQA captures the extent of recurring state compositions across multiple time series (Wallot et al., 2016). For example, Figure 2.5 illustrates a set of time series with episodes in which three participants looked at the same AOI (composition 1), only two participants focused on the same AOI (composition 2), and three participants distributed their gaze across different AOIs (composition 3).

MdRQA enables the analysis of more complex interactions by operationalizing constructs of interest based on specific AOI compositions (Vrzakova et al., 2021). For instance, episodes of gaze aversion are not characterized by convergence but by systematic divergence in gaze positions between participants—a pattern that CRQA could not measure.

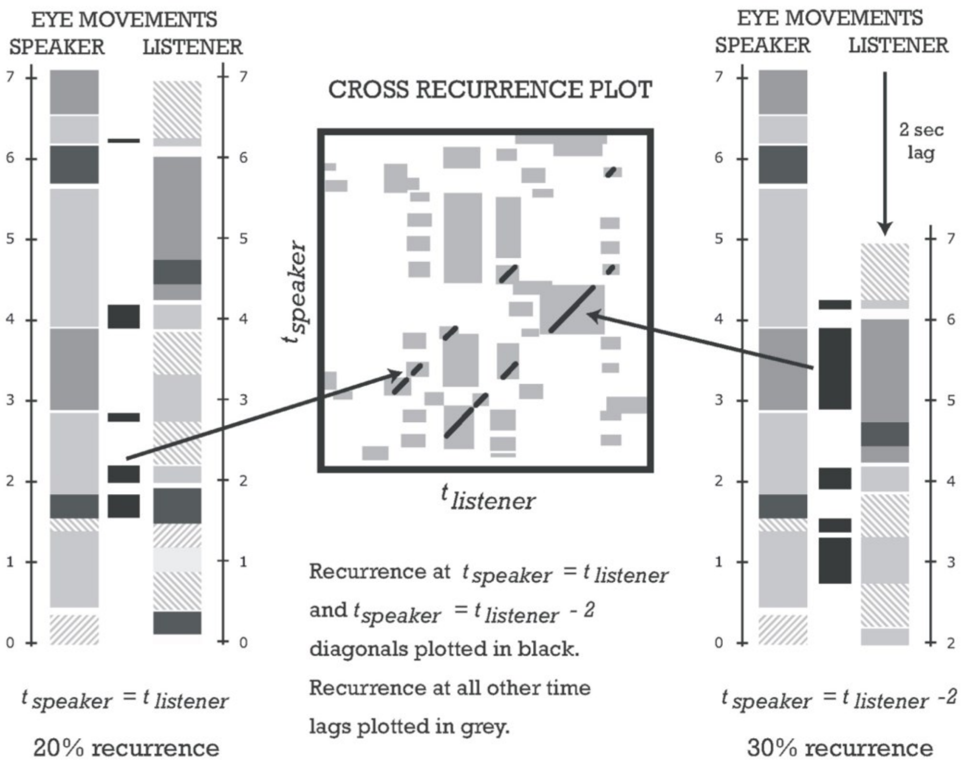

Figure 2.4: Time series of two participants (speaker, listener) at temporal synchrony (left) and a lag of two seconds (right). Illustration from Richardson & Dale (2005).

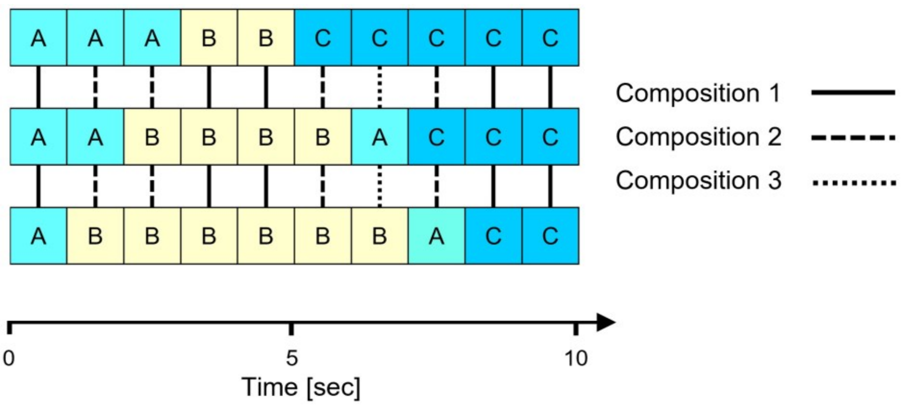

Figure 2.5: Multidimensional recurrence quantification analysis with exemplary time series of three participants with assigned areas of interest (A, B, or C) per one-second intervals.

Despite their usefulness for analyzing temporal dynamics between multiple data streams, both recurrence analysis methods have been found to be subject to confounding effects, limiting the validity of group comparisons. For a detailed discussion of these challenges and potential solutions, see Coco and Dale (2014) for CRQA and Wallot et al. (2016) for MdRQA.

Proportionality Vector Analysis (PVA). Sharma et al. (2013) introduced PVA as an alternative method to measure gaze similarity between two participants. This approach analyzes two-dimensional vectors representing the proportion of time each participant spent looking at specific AOIs within a defined period of time (e.g., AOI_A: 20%; AOI_B: 40%; AOI_C: 40%). Unlike methods that assess the rate of gaze convergence at specific time lags, PVA quantifies the extent to which participants exhibited a similar distribution of gaze across AOIs.

PVA involves two main steps (Sharma et al., 2021a). First, the entropy of each participant's vector series is calculated to determine whether their gaze was focused on specific AOIs or was distributed across many within a given timeframe (see Figure 2.6). Next, the similarity between gaze patterns is computed by either calculating the scalar product or using the reverse function of each proportionality vector's correlation matrix (Olsen et al., 2018; Sharma et al., 2015). Consequently, a similarity value of one indicates a consistent distribution of gaze within dyads, while lower values reflect less similar patterns (see Figure 2.7).

Compared to recurrence quantification analyses, PVA is computationally simpler, requiring fewer procedural steps. However, the conceptual differences between gaze convergence and gaze similarity must be carefully considered when analyzing gaze patterns in remote interactions. Unlike CRQA, PVA does not account for the exact sequence of gaze to defined AOIs (Villamor & Rodrigo, 2017; 2018).

Alternative Approaches. Sharma et al. (2012) introduced a segmentation method to distinguish between convergent and divergent gaze patterns during dyadic interactions. This method starts by dividing each participant's time series into equal slices. Consecutive slices with the same number of fixated AOIs are then grouped and segmented into extended sequences of stable patterns. Subsequently, the segmented series from both participants are

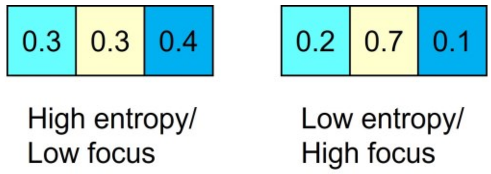

Figure 2.6: Individual focus size based on high (left) and low entropy (right) of gaze across three areas of interest. Adapted from Sharma et al. (2021a).

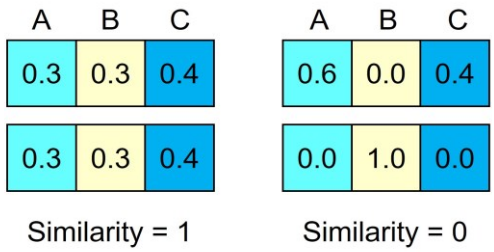

Figure 2.7: Similarity of gaze distribution between three areas of interest for perfectly matching (left) and completely different entropy values (right). Adapted from Sharma et al. (2021a).

temporally aligned to identify and merge intersections into a new time series of convergent episodes (see Figure 2.8).

This segmentation method is particularly useful for comparing gaze dynamics characterized by varying degrees of visual coupling between participants. However, its operationalization of convergence—based on the range of fixated AOIs—may be misleading, as it does not account for the spatial alignment of gaze between participants (Sharma et al., 2021a). The concept is closely related to gaze dispersion, a construct later introduced by the authors in the context of PVA (Sharma et al., 2013).

Furthermore, Cherubini et al. (2008) developed a clustering method to identify spatial zones of interest within an interface based on the position of single fixations. This approach divides the interface into a two-dimensional grid to compute a gaze density matrix, with fixations assigned to each cell. A Gaussian filter is then applied to smooth the data, and gaze density peaks are identified using a contour function. Finally, the mean distance between participants' gaze density peaks is calculated to quantify the degree of visual coupling.

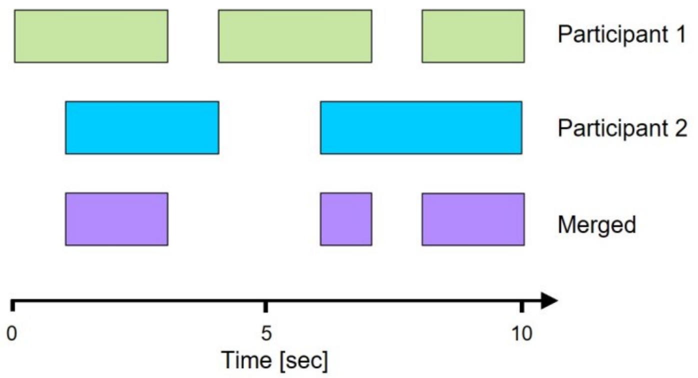

Figure 2.8: Exemplary time series depicting two participants' prolonged sequences of stable gaze patterns (green, blue) and their convergent episodes (purple). Adapted from Sharma et al. (2012).

2.4.5 Eye-Based Constructs

Four distinct eye-based multiparty constructs were operationalized: joint attention, mutual gaze, gaze aversion, and joint mental effort. The first three constructs—collectively known as the core dynamics of social gaze (see Figure 2.9; Emery, 2000; Pfeiffer et al., 2013)—were calculated from spatial gaze data, representing interdependent processes of visual attention among collaborators. In contrast, joint mental effort was derived from pupil-based data, leveraging the positive correlation between pupil size and cognitive load (Tchanou et al., 2020; Sharma et al., 2021b).

Social Gaze Dynamics. The majority of studies examined the role of joint attention, defined as either gaze convergence, gaze similarity, or gaze overlap (Çakır & Uzunosmanoğlu, 2014; Sharma et al., 2021a). Generally, joint attention was positively correlated with learning gains and task performance (Jermann & Nüssli, 2012; Sharma et al., 2015, Tchanou et al., 2020). For instance, Belenky et al. (2014) demonstrated that student pairs achieved greater learning gains when they maintained high levels of joint attention while interacting with an intelligent tutoring system. Similarly, Villamor and Rodrigo (2018) found that dyads achieved significantly better performance when their gaze aligned frequently. Furthermore, their findings indicated that higher-performing participants often took the lead during the collaborative process, as their gaze preceded that of their peers.

However, findings are not entirely consistent across studies. For example, Cherubini et al. (2008) did not observe a link between joint attention and task performance using an

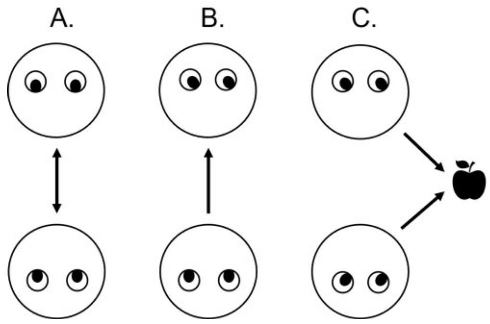

Figure 2.9: Mutual gaze (A), gaze aversion (B), and joint attention (C). Adapted from Pfeiffer et al. (2013).

alternative fixation clustering method. Notably, a re-analysis of the same dataset using CRQA revealed a significant positive relationship between joint attention and team performance (Cherubini et al., 2010). These discrepancies highlight the importance of appropriate methodological approaches in studying joint attention and its impact on collaborative outcomes.

Mutual gaze and gaze aversion were explored in just one of the reviewed studies (Vrzakova et al., 2021). In particular, the authors found a negative correlation between gaze aversion and team performance, suggesting that higher levels of gaze aversion may hinder collaboration. In contrast, mutual gaze showed no significant impact on team performance.

Joint Mental Effort. Sharma et al. (2021b) performed CRQA to assess the convergence of pupil size between participants, thereby calculating the eye-based multiparty construct of joint mental effort. Specifically, a high recurrence rate indicated that participants worked closely together as their cognitive load converged over time. The study revealed that joint mental effort was significantly higher in high-performing dyads. Furthermore, the authors found a positive correlation between joint attention and joint mental effort.

2.5 Conclusion

By conducting the systematic literature review, we identified several aspects that need to be considered when applying multiparty eye-tracking in experiments. First, we identified fundamental requirements related to data acquisition. To make valid comparisons between individual participants, any confounding factors in the experimental task that might elicit systematic differences in gaze patterns need to be ruled out a priori. This includes, for example, the precise synchronization of the visual environment between collaborating participants and the assignment of equal operating roles. To achieve these objectives and enhance the overall generalizability of findings, future studies should consider using controlled, artificial tasks rather than highly specific activities such as pair programming. Moreover, we recommend audio and video meeting systems to facilitate computer-mediated collaboration in experiments, as writing and reading chat messages attract visual attention and, thus, systematically influence gaze dynamics. Finally, a replication of findings on the role of social gaze in computer-mediated collaboration with at least three participants is necessary, as research has been highly limited to dyadic interactions. MdRQA is a promising computation method that can address some of the identified research gaps. Since it scales up to more than two synchronized data streams, it enables researchers to examine attentional processes in larger groups. In addition, more complex multiparty eye-based constructs, such as mutual gaze and gaze aversion, can be studied because the method does not measure basic alignment but the extent to which systematic state compositions recur over time.

CHAPTER 3

Social Gaze, Cooperation, and Team Cohesion: A Multiparty Eye-Tracking Study

Abstract

Understanding the factors that promote cooperative behavior in teams is essential for organizational success. While the role of verbal communication in fostering cooperation and team cohesion is well established, the impact of nonverbal signals—particularly eye contact and related patterns, known as social gaze dynamics—has been neglected. In this study, we conducted two multiparty eye-tracking experiments, enabling us to explore the relationship between social gaze, cooperation, and team cohesion. In both experiments, teams of three participants engaged in a two-stage task: a structured pre-play communication stage (1) and a social dilemma game (2). During pre-play communication, eye-tracked participants performed a real-effort task mirroring the ensuing social dilemma. This allowed us to capture social gaze dynamics and assess their relation to subsequent cooperation and team cohesion. Experiment 1 focused on the role of social gaze during face-to-face meetings, revealing that cooperative behavior increases with the level of eye contact and decreases when team members frequently avert each other's direct gaze. Experiment 2 compared the emergence and impact of these dynamics between face-to-face and video meeting settings and provided initial evidence that the extent to which direct gaze is reciprocated within teams influences subsequent cooperative behavior. Overall, our findings highlight potential downsides of increasingly shifting team meetings to the virtual space, where the absence of gaze information affects the emergence and impact of social gaze dynamics.

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3.1 Introduction

In the modern workplace, organizational success often depends on the ability of teams to work together efficiently and effectively. However, the conflict between prioritizing individual gains and maximizing collective benefits can significantly challenge the productivity and success of a team (Balliet & Van Lange, 2013; Delfgaauw et al., 2022; Fischbacher & Gächter, 2010; Van Lange et al., 2013). To mitigate this issue, it is crucial to understand the factors that drive cooperative behavior. Previous research has largely focused on verbal aspects of team communication, such as commitments and agreements, while neglecting the potential power of nonverbal signals (for reviews, see Balliet, 2010; Sally, 1995). In this study, we aimed to address this research gap by conducting two experiments specifically examining the role of interdependent attentional processes within teams, known as social gaze dynamics (Emery, 2000; Pfeiffer et al., 2013).

Recent studies have shown that individuals can intuitively assess others' choices and prosocial motives by observing their gaze (Fischbacher et al., 2022; Hausfeld et al., 2021). However, these studies involved experimental setups that tracked the gaze of only one individual during decision-making, visualizing it on the counterpart's computer screen. This approach aimed to understand the role of gaze as a strategic signal by displaying the direction of visual attention in standard economic games. Although such designs allow for the study of gaze in highly controlled environments, they present gaze information in an artificial form (e.g., dynamic gaze focus mapped onto a payoff matrix; Fischbacher et al., 2022), substantially restricting the generalizability of findings. To overcome this limitation, we introduced a multiparty eye-tracking setup, enabling the synchronous measurement of eye movements across multiple participants in naturalistic team settings.

In particular, we aimed to investigate the impact of social gaze dynamics on cooperation and team cohesion across two commonplace modes of team communication: face-to-face meetings and video meetings. Therefore, we conducted two controlled laboratory experiments. In both experiments, teams of three participants engaged in a two-stage team task: a structured pre-play communication stage followed by a social dilemma game (Nalbantian & Schotter, 1997). During the pre-play communication stage, eye-tracked participants worked on a (payoff-irrelevant) real-effort task designed to mirror the key elements of the ensuing (payoff-relevant) social dilemma game. Crucially, we employed a multiparty eye-tracking setup to measure each team member's eye movements synchronously, allowing us to capture social gaze dynamics within a naturalistic team setting (1) and relate them to cooperation levels in the ensuing dilemma (2). The main difference between the two experiments was the mode of team communication and whether the availability of gaze information was experimentally manipulated to draw causal inferences.

In the **first experiment**, teams performed the pre-play communication stage in a face-to-face meeting, enabling us to test the relationship between social gaze and subsequent cooperation as well as team cohesion. The **second experiment** encompassed two treatments. In the first treatment, teams performed the pre-play communication in a face-to-face meeting. In the second treatment, they communicated in a video meeting. While face-to-face meetings encompass the whole spectrum of nonverbal signals (e.g., gaze, body language, and gestures), conventional video meeting systems are not capable of conveying what others are visually attending to. By comparing these two treatments, which primarily differ in the availability of gaze information, we were able to study differences in the emergence of social gaze dynamics between face-to-face and video meeting settings and their impact on subsequent cooperation and team cohesion.

Our results provided valuable insights into the role of social gaze and the potential consequences of missing gaze information in video meetings. In the **first experiment**, we found that cooperative behavior increased as team members spent more time making eye contact during team meetings. Consistent with this finding, the **second experiment** demonstrated that the extent to which team members reciprocated each other's direct gaze in face-to-face meetings significantly enhanced overall cooperation. However, in video meetings, the absence of gaze information eliminated this positive effect, raising concerns about increasingly shifting team communication to the virtual space.

This study contributes to the broader literature studying the link between communication and cooperation as well as to the small but growing economic research on nonverbal signals. Accordingly, in Section 3.2, we first provide an overview of the related literature and our contribution to it. Section 3.3 presents the general study design and methods common to both experiments before detailing the specific procedures and results of the **first experiment** in Section 3.4 and the **second experiment** in Section 3.5. Finally, Section 3.6

concludes with a general discussion, synthesizing our findings, contributions, and limitations that need to be addressed in further studies.

3.2 Related Literature

3.2.1 Cooperation and Team Cohesion

Performance in teams strongly depends on the willingness of its individual members to cooperate. However, cooperation often comes with certain costs, such as the effort or time required. While the output is typically shared equally within a team, individuals must bear the costs to achieve it on their own (Nalbantian & Schotter, 1997; Thielmann et al., 2020). Since each team member decides individually how much to contribute, teams often fail to achieve the socially optimal level of cooperation due to conflicting personal and collective interests (see, e.g., Kollock, 1998; Van Lange et al., 2013).

Numerous studies have revealed that communication helps to overcome this typical social dilemma in team cooperation (for reviews, see Balliet, 2010; Sally, 1995). Specifically, the opportunity to communicate before or during a social dilemma game has been shown to increase cooperation rates by up to 40% (He et al., 2017). In addition, this effect increases with group size and is particularly pronounced when communication takes place in face-to-face meetings (Balliet, 2010). Bicchieri and Lev-On (2007) further investigated whether the mode of communication affects cooperative behavior. They found that the communication effect persists in remote settings but depends on the degree to which a given digital collaboration tool resembles the nonverbal richness of face-to-face communication. In particular, communication via video meetings has been shown to produce significantly higher and more stable cooperation rates than chats and audio-based channels (see, e.g., Brosig & Weimann, 2003). Similarly, recent studies have revealed that the specific mode of communication affects a variety of team dynamics, such as trust, promise-keeping, and truth-telling (Babutsidze et al., 2021; Cohn et al., 2022; Conrads & Reggiani, 2017).

Overall, these findings suggest that cooperative behavior depends on the richness of nonverbal signals, determining the amount of information exchanged among team members (Kahai & Cooper, 2003). In an attempt to reveal the key mechanisms of the communication effect, He et al. (2017) identified two crucial factors: verbalized commitments (e.g., agreements) and type detection—the ability to infer others' cooperativeness by interpreting more subtle verbal and nonverbal signals. While verbalized commitments promoted cooperation by highlighting social norms, type detection allowed individuals to discern cooperative from less cooperative team members and adapt their behavior accordingly. The authors showed that the largest fraction of the communication effect could be attributed to type detection (73.3%), indicating that face-to-face communication increases cooperation by providing additional information that allows team members to recognize each other's cooperativeness.

In addition to the profound effect of communication on cooperative behavior, a large body of literature revealed a close link between team cohesion and cooperative behavior (see, e.g., Delfgaauw et al., 2022; Gächter et al., 2024). Team cohesion is a multifaceted construct that has consistently been shown to have a large and robust positive effect on team performance (Balliet et al., 2014; Casey-Campbell & Martens, 2009; Chiocchio & Essiembre, 2009). According to Salas et al. (2015), team cohesion includes several subdimensions of which the most pertinent are belongingness (i.e., the degree to which team members are attracted to each other), social cohesion (i.e., the closeness of social relationships), and task cohesion (i.e., the bonding between team members based on shared objectives). Despite its multifaceted nature, prior research has predominantly focused on isolated dimensions of team cohesion. For example, Delfgaauw et al. (2022) investigated the dimension of social cohesion. In contrast, Gächter et al. (2024) suggested capturing team cohesion according to the belongingness dimension. Their findings align with previous research, showing that high-cohesion teams are significantly better at coordinating on superior equilibria in strategic situations. In addition, the authors found that team cohesion increases cooperation primarily by shaping beliefs about the willingness of other team members to cooperate.

Taken together, these findings suggest that successful cooperation is significantly influenced by the level of team cohesion as well as the mode of communication, which determines how much information can be exchanged within teams. Our study extends these strands of literature by examining whether social gaze, as one specific aspect of nonverbal communication, affects cooperation and team cohesion.

3.2.2 Gaze Patterns and Economic Behavior

The study of gaze has gained popularity in behavioral economics because it provides insights into underlying cognitive processes (Lahey & Oxley, 2016). In particular, eye-tracking has been used to understand how visual attention relates to economic behavior. For instance, previous research has shown that cooperative behavior in several economic games—such as money allocation tasks, public goods dilemmas, and sender-receiver games—can be explained through a post-hoc analysis of individuals' gaze during information acquisition (see, e.g., Fiedler et al., 2013; Wang et al., 2010). These studies demonstrate that observing a counterpart's gaze could allow individuals to derive beneficial insights, potentially enhancing their strategic decisions.

Extending this line of research, recent studies have used eye-tracking as an interactive tool, allowing participants to observe their counterpart's gaze during decision-making in real time. For instance, Hausfeld et al. (2021) revealed that the option to observe gaze enabled participants to infer their counterpart's hidden choices in a series of simultaneous 2x2 box choice coordination games. Moreover, when the eye-tracked participants knew that their gaze was transmitted, they strategically adapted it during decision-making to facilitate coordination. A related study examined whether (visualized) gaze information could help participants identify their counterpart's prosocial motives in a money allocation task (Fischbacher et al., 2022). The authors found that participants who observed the allocators' gaze were able to judge their prosocial motives. However, when allocators were incentivized to appear more prosocial, they strategically adapted their gaze, making it more difficult for observers to accurately predict their hidden choices. Taken together, these studies show that gaze functions as a strategic signal, enabling individuals to infer others' choices and prosocial motives.

Building upon these findings, we sought to investigate the strategic role of gaze in more naturalistic team settings. Specifically, instead of visualizing one participant's gaze during decision-making, we measured a whole team's social gaze dynamics during free-form communication and tested their impact on subsequent cooperative behavior. To outline the underlying assumptions that informed our approach and hypotheses, the next section reviews the relevant literature on social gaze dynamics.

3.2.3 Social Gaze Dynamics

Previous research has shown that human faces, especially the eyes, automatically attract visual attention (Laidlaw et al., 2012; Langton et al., 2000). However, since others can observe one's gaze in face-to-face settings, attentional shifts to these stimuli are not only attributable to their inherent salience but also involve strategic considerations following a cognitive top-down mechanism (see, e.g., Kuhn et al., 2016). Accordingly, eye movements serve both a perceptual and a communicative purpose—a concept known as the dual function of gaze (Gobel et al., 2015). In social interactions, gaze patterns that involve multiple individuals are conceptualized as social gaze (Emery, 2000). Its three core dynamics are mutual gaze (i.e., individuals are directly looking at each other), gaze aversion (i.e., an individual gazes at another who is looking somewhere else), and joint attention (i.e., individuals are looking at the same object or aspect within the visual scene; Pfeiffer et al., 2013).

Hessels (2020) provided a comprehensive literature review on the role of social gaze in face-to-face settings. Primarily, social gaze dynamics have been identified as key factors for effective communication (Ho et al., 2015; Kleinke, 1986). Specifically, prolonged episodes of mutual gaze have been shown to be positively correlated with desirable factors, such as trust, rapport building, and establishing common ground between individuals (see, e.g., Broz et al., 2012; Foddy, 1978). In contrast, gaze aversion has been linked to adverse outcomes. For example, Vrzakova et al. (2021) observed a negative correlation between gaze aversion and the quality of agreements in dyadic negotiations. The authors concluded that individuals interpret their counterpart's averted gaze as a signal of socio-emotional discomfort, thereby incorporating it into their decisions. Consequently, social gaze plays an important regulatory role in face-to-face communication and may shape economic behavior when working together in teams.

With this in mind, the absence of gaze information in computer-mediated communication has several consequences for virtual teams. On the one hand, virtual team members cannot recognize whether they are being looked at or not. Thus, they cannot strategically evaluate whether others are attempting to engage in mutual gaze or are deliberately avoiding it. On the other hand, they cannot use their own gaze as a strategic signal by actively directing it toward other individuals. As a result, the emergence and impact of social gaze dynamics are likely to differ between face-to-face and video meeting settings.

3.3 General Study Design and Methods

In order to examine the relationship between social gaze dynamics and cooperation as well as team cohesion, we conducted two experiments at the Karlsruhe Decision & Design Lab (KD2Lab).[2] In the following, we outline the general study design and methods common to both experiments before detailing the differences between the first experiment (Section 3.4) and the second experiment (Section 3.5).

3.3.1 Team Task

To investigate the relationship between social gaze dynamics and cooperative behavior, we designed a team task involving three participants per session. The team task comprised two stages: a structured pre-play communication stage and a social dilemma game. Specifically, the pre-play communication stage was structured around a payoff-irrelevant real-effort task that mirrored the key elements of the ensuing social dilemma game (see Figure 3.1). During this initial stage, we employed a multiparty eye-tracking setup to synchronously measure each team member's eye movements.

This approach was essential as it allowed us to capture social gaze dynamics within a natural team setting, which related to the level of cooperation in the subsequent stage. Additionally, we chose to collect eye movements during free-form communication because "gaze should not be treated as an isolated phenomenon, but as one aspect of the interaction, which is multimodal by nature" (Hessels, 2020). In the following, we provide a detailed description of both stages.

Stage 1: Pre-Play Communication with Real-Effort Task. To encourage vivid communication between team members, we used a real-effort task with a creative element. The

[2] The KD2Lab was funded by the Deutsche Forschungsgemeinschaft and the Karlsruhe Institute of Technology (INST-12138411-1FUGG).

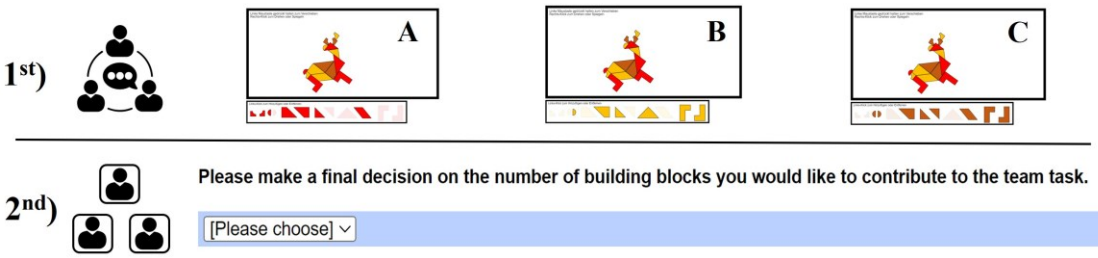

Figure 3.1: Pre-play communication stage in teams (top) and the second stage in private (bottom).

task was to create a tangram—a puzzle composed of geometric pieces that can be arranged to create various shapes reminiscent of animals or objects. Tangrams are frequently employed in eye-tracking studies as collaborative problem-solving tasks because they require close cooperation and visual coordination among participants (see, e.g., Carletta et al., 2010; Dale et al., 2011).

In our setup, each team member had twelve pieces they could contribute to build a unique shape. Thus, teams needed to pool their resources and coordinate their contributions. Importantly, although this stage was not payoff-relevant, participants were aware that it mirrored the subsequent social dilemma, in which their payoff depended on the total amount of contributions and the individual costs for contributing each piece. Therefore, the pre-play communication stage provided an opportunity to make mutual agreements on how many tangram pieces to contribute to the team task.

Stage 2: Payoff-Relevant Decision in Private. After completing the pre-play communication stage, participants proceeded to the second stage, where they made their payoff-relevant contribution to the team task in private.

In the following, we outline the simple group incentive model by Nalbantian and Schotter (1997), which helped us to design a payoff structure that induces the social dilemma between maximizing personal gains and contributing to the team's overall utility. Each participant, $i = 1, 2, 3$, had a budget of twelve tangram pieces. Suppose a participant decided to contribute a certain number of pieces to the tangram in the second stage, denoted by $x_i \in \{0, \ldots, 12\}$, this created costs given by a quadratic cost function, $c_i = c(x_i) = \frac{1}{2}x_i^2$. The team's output was then given by $\mathrm{X} = \sum_{i=1}^{3} x_i$. In order to capture the leveraging effects in team cooperation, the team's revenue R was determined by multiplying the team's output with the factor 12, $R = 12X$. Finally, the revenue was split equally between the team members.

Assuming risk-neutral and money-maximizing participants[3], each team member solved the following maximization problem:

$$\max_{x_i \in \{0,\ldots,12\}} \pi_i = \frac{1}{3}R - c_i = 4\sum_{i=1}^{3} x_i - \frac{1}{2}x_i^2$$

$$x_i^* = 4$$

Note that teams needed to solve the following maximization problem to find the highest surplus TS:

$$\max_{x_i \in \{0,\ldots,12\} \forall i \in \{1,2,3\}} TS = R - \sum_{i=1}^{3} c_i = 12\sum_{i=1}^{3} x_i - \frac{1}{2}\sum_{i=1}^{3} x_i^2$$

$$x_i^{TS} = 12$$

Accordingly, we expected a selfish money-maximizing participant to contribute four pieces, whereas the team surplus would have been maximized if all participants contributed twelve pieces. These output levels served as our benchmark values to measure the degree of cooperation. If team members contributed more than four pieces in the second stage of the team task, this signaled cooperation. The higher the deviation from the individually optimal contribution, the higher the cooperation.

Since most participants opted for the highest possible contribution of twelve tangram pieces in the first experiment, we slightly adjusted the payoff structure in the second experiment. Specifically, we raised incremental costs for additional contributions to increase incentives toward selfish money-maximizing decisions, $c_i = c(x_i) = x_i^2$. In addition, the team's revenue R was determined by multiplying the team's output with a higher factor, $R = 18X$. Thus, in the second experiment, we expected selfish money-maximizing participants to

[3] Note that we did not assume all participants to be risk-neutral or solely interested in their own monetary payoff. However, this simple model served as a guideline to illustrate the underlying social dilemma and helped us to benchmark our findings.

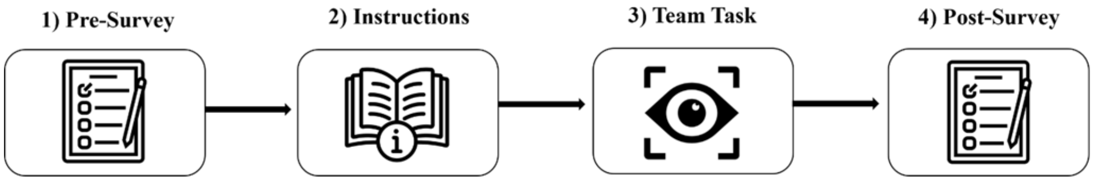

Figure 3.2: General procedure common to the first and second experiments.

contribute three pieces, whereas the team surplus would have been maximized if all participants contributed nine pieces.

3.3.2 Procedure and Measures

In both experiments, participants went through four distinct phases with a total duration of 40 minutes (see Figure 3.2).[4] Each experimental session consisted of three participants of the same gender forming a team. We decided to maintain gender homogeneity to minimize confounding effects on team communication that could arise in heterogeneous teams (see, e.g., Hardt et al., 2024). At the beginning of each session, participants completed a brief survey capturing demographic information, dispositional collective orientation (Hagemann, 2017; 2020), interpersonal trust (Beierlein et al., 2014), and personality traits (Rammstedt et al., 2014). In the second phase, participants were provided with full instructions regarding the team task, payoff structure, and session outline (for detailed instructions of the first and second experiment, see Appendix B.1 and Appendix B.2).[5] Next, they entered the pre-play communication stage of the team task. Therefore, we equipped the participants with eye-tracking glasses and led them from their individual cubicles to a separate room. After the pre-play communication stage, we guided them back to their individual cubicles, where they made their payoff-relevant decision in private. They knew that they would not meet the other participants again. After making their decision, they filled out a short survey eliciting self-reported team cohesion (Aron et al., 1992; Carless & De Paola,

[4] Participation required German language skills at native-speaker level and unrestricted or appropriately corrected vision and hearing. Furthermore, wearing glasses was defined as an exclusion criterion because head-mounted eye-tracking glasses had to be worn during the experiments. In addition, participants who had already been included in the first experiment were excluded from participating in the second experiment.

[5] Scales and instructions were implemented using SoSci-Survey (v3.4.0; Leiner, 2022).

Figure 3.3: Pupil Invisible eye-tracking glasses connected to the Pupil Labs Companion Device (left) and a participant wearing both devices during the first stage (right).

2000; Wongpakaran et al., 2013), social presence (Biocca et al., 2003), and familiarity between team members.

Eye-Tracking Equipment. Eye movements were recorded during the team task's pre-play communication stage using three Pupil Invisible eye-tracking glasses (Pupil Labs, 2023). The head-mounted devices featured an unobtrusive, lightweight design and thus did not restrict the participants' freedom of movement (see Figure 3.3). While recording, the eye-tracking glasses were connected to mobile phones (Pupil Labs Companion Device; OnePlus 8) via a single USB-C cord to calculate gaze data in real time at a sampling rate of 200 Hz (Pupil Labs Companion App, v1.4.23).

Pre-Survey. The Instrument for the Assessment of Collective Orientation (CO) measured an individual's tendency to cooperate in a goal-oriented manner, to seek input from others, and to contribute to achieving a team's objective (Hagemann, 2017). The scale comprised two dimensions, which were assessed by 16 items and rated on a five-point Likert scale ("strongly disagree" to "strongly agree"). Ten of these items load on the factor of belongingness (e.g., "For most tasks, I would rather work alone than as part of a team") and six items on dominance (e.g., "When I'm convinced of something, I stick to my opinion, whatever other team members say"). The CO showed good reliability (Cronbach's α = .84; McDonald's ω = .85) and evidence of convergent, discriminant, and predictive validity (Hagemann, 2020). We controlled for collective orientation, because it has been found to positively affect coordination and performance in teams (Hagemann et al., 2021).

The Short Scale for Measuring Interpersonal Trust (KUSIV3) included three items (e.g., "In general, people can be trusted") rated on a five-point Likert scale ("strongly disagree" to "strongly agree") to measure an individual's disposition to trust and rely on other people (Beierlein et al., 2014). An investigation of its psychometric properties indicated good reliability (McDonald $\omega = .85$) as well as content and construct validity. As the final decision in the team task partially depended on whether participants trusted other members to adhere to the mutually agreed-upon solution, we included the KUSIV3 (see, e.g., Balliet & Van Lange, 2013).

The Big Five Inventory 10 (BFI-10) is a short version of the original 44-item scale to measure personality traits according to the five-factor model (Rammstedt & John, 2007). For each of the personality dimensions, participants answered two items (e.g., "I see myself as someone who is outgoing, sociable") rated on a five-point Likert scale ("strongly disagree" to "strongly agree"). With regard to the subscales, adequate to good reliability coefficients were obtained ($r_{tt} = .58$ to $.84$). Furthermore, several studies demonstrated its content, factorial, convergent, discriminant, and predictive validity (Rammstedt et al., 2014). We included the BFI-10 to test for potential confounding effects of personality traits on social gaze dynamics and team cooperation (see, e.g., Broz et al., 2012; Thielmann et al., 2020).

Post-Survey. As suggested by Salas et al. (2015), we operationalized team cohesion as a multifaceted construct including both task and social dimensions. Accordingly, we adopted appropriate items from three validated scales to measure belongingness, social cohesion, and task cohesion respectively. Similarly, Delfgaauw et al. (2022) measured social cohesion by including the respective dimension from the Group Environment Questionnaire by Carless and De Paola (2000).

Belongingness was measured using the Inclusion of Other in the Self scale (IOS; Aron et al., 1992). By selecting one of seven pictograms depicting increasingly overlapping circles, participants subjectively rated their relational closeness to the team. An extensive examination of the IOS' psychometric properties has proven it to be a highly reliable and valid tool for capturing the construct (Cronbach's $\alpha = .66$; Gächter et al., 2015). For instance, it was found to correlate strongly with a battery of related questionnaires and a principal component analysis-based index of relationship closeness (Spearman's $p = .85$, $p < .001$).

In order to measure social cohesion, we adopted the subdimension for cohesiveness from the Group Cohesiveness Scale (GCS; Wongpakaran et al., 2013). The subdimension consisted of two items ("I feel accepted by the team"; "In my team we trust each other") rated on a seven-point Likert scale ("strongly disagree" to "strongly agree"). The GCS showed a very good internal consistency (Cronbach's $\alpha = .87$) and evidence for construct and convergent validity. Despite being evaluated with psychiatric inpatients ($n = 96$), we decided to include the items due to their high face validity for assessing a team's social cohesion.

We measured task cohesion by including three items of the subdimension for task cohesion (Cronbach's $\alpha = .74$) from the Group Environment Questionnaire adapted for work teams (GEQ; Carless & De Paola, 2000). Items (e.g., "Our team is united in trying to reach its goals") were rated on a seven-point Likert scale ("strongly disagree" to "strongly agree"). The authors investigated the revised scale's construct and criterion validity with a sample of employees ($n = 120$) working in teams. Strong correlations were found between task cohesion and team effectiveness ($r = .67$, $p < .010$) as well as three subscales of the Work-Group Characteristics questionnaire by Campion et al. (1993): team spirit ($r = .72$, $p < .010$), social support ($r = .68$, $p < .010$), and communication/cooperation within the team ($r = .62$, $p < .010$).

In the second experiment, we additionally included the Networked Minds Questionnaire (NMQ) to measure social presence according to the well-established multifactorial conceptualization by Biocca et al. (2003). It contained six items rated on a seven-point Likert scale ("strongly disagree" to "strongly agree") for each of its six distinct dimensions: Co-Presence (e.g., "The presence of my team members was obvious to me"), Attentional Allocation (e.g., "My team members remained focused on me throughout our interaction"), Message Understanding (e.g., "Understanding my team members was difficult"), Affective Understanding (e.g., "I could tell how my team members felt"), Emotional Interdependence (e.g., "My team members' attitudes influenced how I felt"), and Behavioral Interdependence (e.g., "My behavior was often in direct response to my team members' behavior"). An investigation of the NMQ's psychometric properties showed that the six dimensions identified by confirmatory factor analysis are internally consistent with Cronbach's α coefficients ranging from 0.81 to 0.86 (Biocca et al., 2003). In addition, four dimensions were rated significantly higher in face-to-face interaction than in remote interaction, demonstrating criterion validity.

3.3.3 Data Preparation and Key Variables

Our key variables in this study were cooperation, self-reported team cohesion, and social gaze dynamics at the team level. In the following, we describe how we defined these variables as well as the steps that were required to prepare the data for statistical analyses. First, scores of the scales and corresponding subdimensions—CO, KUSIV3, BFI-10, IOS, GCS, GEQ, and NMQ—were calculated by taking the unweighted mean of their recoded items to operationalize *collective orientation*, *interpersonal trust*, *personality traits*, *belongingness*, *social cohesion*, *task cohesion*, and *social presence*.

Cooperation. Given the tension in our team task between maximizing personal gains and contributing to the team's utility, we measured the level of cooperation by the total amount of *individual contributions* to the team task—henceforth referred to as *team output.*

Team Cohesion. To compute *team cohesion* according to the conceptualization introduced earlier, we combined the values for *belongingness*, *social cohesion*, and *task cohesion* by calculating their unweighted mean for each participant and then determined the mean within teams.

Social Gaze Dynamics. The quantification of *mutual gaze*, *gaze aversion*, and *joint attention* included several steps. We used the open-source software Pupil Player (v3.5.1; Pupil Labs, 2023) to assign each participant's gaze points during the pre-play communication stage to one of the following areas of interest (AOIs): A, B, C, and Task. The AOIs A, B, and C refer to the respective team members to the left and right of each participant (e.g., C could look at team members A and B). The AOI Task referred to aspects within the visual scene that were directly related to the execution of the tangram task. In the first experiment, this included the payoff table and the task area in which the tangram pieces were arranged (see Appendix B: Figure B.1). In the second experiment, the AOI referred to the monitor on which the task was performed (see Appendix B: Figure B.2). The remaining gaze points outside these areas were defined as Else.

Further computations were conducted in R (R Core Team, 2023). First, each participant's time series of gaze points to the defined AOIs was cut into sequences, corresponding to the exact duration of the pre-play communication stage. Time series were synchronized between team members by using an annotation cue at the beginning and end of the pre-play

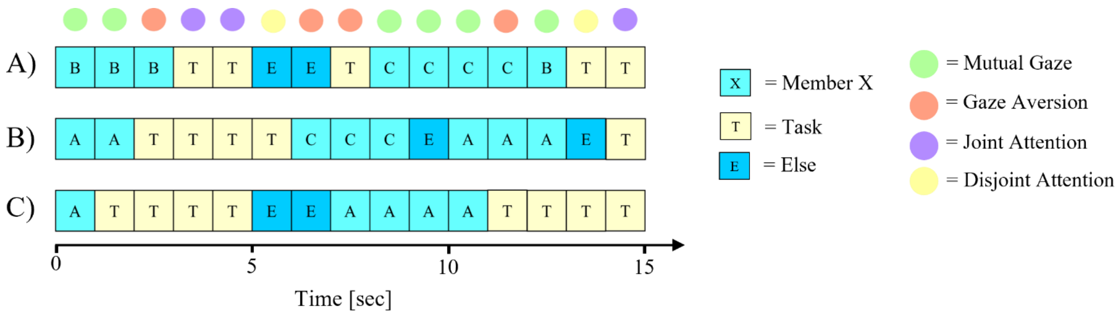

Figure 3.4: Exemplary time series of three team members with assigned areas of interest per interval and corresponding social gaze dynamics.

communication stage. Next, we cut each time series into one-second slices in the first experiment, and even finer-grained 100-millisecond slices in the second experiment. Subsequently, each slice was assigned the AOI that received the most gaze points during that period. Due to the high sampling rate of 200 gaze points per second, the described aggregation procedure was robust against missing values. Finally, building upon the paradigm by Vrzakova et al. (2021), we assigned each possible combination of AOIs within teams to one of the conceptualized social gaze dynamics: *mutual gaze*, *gaze aversion*, *joint attention*, and *disjoint attention* (see Figure 3.4).

We thus define:

- *Mutual Gaze*: Two team members look at each other simultaneously (e.g., $A_B \land B_A \land C_A$).
- *Gaze Aversion*: At least one participant looks at another team member while no one is looking at each other simultaneously (e.g., $A_B \land B_{Task} \land C_{Else}$).
- *Joint Attention*: All team members look at task-relevant aspects simultaneously ($A_{Task} \land B_{Task} \land C_{Task}$).
- *Disjoint Attention*: Remaining AOI combinations were defined as *disjoint attention* (e.g., $A_{Task} \land B_{Else} \land C_{Else}$).

Further, we calculated the proportion to which *mutual gaze*, *gaze aversion*, and *joint attention* occurred within teams during the pre-play communication stage. To do this, we simply divided the number of slices assigned to each social gaze dynamic by the total number of slices per team. Moreover, in the second experiment, we calculated an additional variable based on the proportion of *mutual gaze* and *gaze aversion*. Precisely, we operationalized the level of *attentional reciprocity* within teams as the ratio of *mutual gaze* to the number of cases in which at least one participant looked at another team member (i.e., the sum of *mutual gaze* and *gaze aversion*): $\frac{Mutual\ Gaze}{Mutual\ Gaze\ +\ Gaze\ Aversion}$. In other words, *attentional reciprocity* was defined as the extent to which looking at other members during the pre-play communication stage resulted in *mutual gaze* rather than *gaze aversion*.

3.4 Experiment 1: Social Gaze in Face-to-Face Meetings

In the first experiment, we sought to disentangle the differential role of *mutual gaze* and *gaze aversion* by examining their relationship with *team output* and *team cohesion*.[6] Therefore, teams performed the pre-play communication stage in a face-to-face meeting for ten minutes. Specifically, they were seated at a round table divided into three parts by partitions. The partitions contained rectangular cut-outs so that team members were able to see and communicate with each other despite being spatially separated (see Figure 3.5).

3.4.1 Sample

We recruited 33 students from the Karlsruhe Institute of Technology (KIT) via the KD2Lab subject pool using Hroot (Bock et al., 2014). Due to technical issues during one session, data of three participants had to be excluded from the analysis, resulting in a final sample of 30 participants aged between 20 and 28 years (M = 23.23, SD = 2.25, 50% female). Participants were randomly assigned to ten teams, consisting of either women or men only, and received earnings (EUR) according to the final decisions they and their team members made in the second stage of the team task (M = 14.78).

3.4.2 Main Hypotheses and Estimation Strategy

Previous research consistently indicated a positive relationship between the perception of *mutual gaze* and favorable interaction qualities, whereas *gaze aversion* was mainly associated with negative ones (see, e.g., Broz et al., 2012; Foddy, 1978; Kurzban, 2001; Vrzakova

[6] The experiment was preregistered at AsPredicted (#105022) and approved by the ethics committee of the KIT.

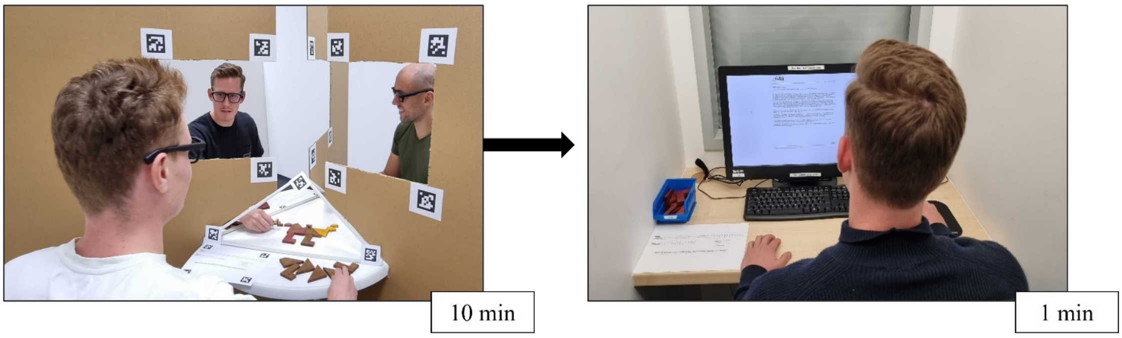

Figure 3.5: Face-to-face setting of the pre-play communication stage (left) and isolated cubicle in the second stage (right).

et al., 2021). Accordingly, we hypothesized the following correlations while controlling for the aggregated level of *collective orientation* within teams, as it may influence social gaze dynamics, *team output,* and *team cohesion*.

> **H1A.** *The level of mutual gaze within teams positively correlates with team output.*
>
> **H1B.** *The level of gaze aversion within teams negatively correlates with team output.*
>
> **H2A.** *The level of mutual gaze within teams positively correlates with team cohesion.*
>
> **H2B.** *The level of gaze aversion within teams negatively correlates with team cohesion.*

Estimation Strategy. After pre-processing the data, we conducted an initial analysis to report the sample's characteristics, pairwise correlations, and aggregated gaze patterns including the distribution of gaze among AOIs (Members, Task, and Else) and the proportion of each social gaze dynamic during the ten-minute pre-play communication stage.[7]

We tested our main hypotheses using ordinary least squares (OLS) regression analyses. Specifically, we regressed *team output* (**H1A**, **H1B**) and *team cohesion* (**H2A**, **H2B**) on *mutual gaze*, *gaze aversion*, and *collective orientation* at the team level. In addition, we

[7] We performed all statistical calculations in Stata (StataCorp., 2023).

performed Tobit regressions to compare our results regarding **H1A** and **H1B** because *team output* was limited to a number between 0 and 36.

We continued to test the robustness of our findings by adding further covariates at the individual level. Precisely, we performed step-wise OLS regressions with the participant's *individual contribution* to the team task and their *team cohesion* at the individual level as dependent variables. In the first model, we included all three social gaze dynamics—*mutual gaze*, *gaze aversion*, and *joint attention*—as explanatory variables. Next, we added *collective orientation* and *interpersonal trust* as social dispositions. The third model further contained demographics (*age*, *female*). Finally, we compared our results with those obtained using Tobit regressions because *individual contributions* were limited to a number between zero and twelve.

3.4.3 Results and Discussion

For a comprehensive overview of the summary statistics, see Appendix B: Table B.1 and Table B.2.

Social Gaze Dynamics. During the pre-play communication stage, participants (n = 30) spent more than two-thirds of the ten-minute period looking at aspects within the visual scene that were directly related to the execution of the task (e.g., shared task area for building the tangram; M = 67.66, SD = 11.23). However, they also looked at their team members for almost 18% of the time they were given to coordinate on a solution (M = 17.94, SD = 9.84). These findings are consistent with the results of similar eye-tracking studies in which the average proportion of gaze to other individuals ranged from 17% to 46% (see, e.g., Broz et al. 2012; Vrzakova et al., 2021). According to the gaze-cueing paradigm, looking at the faces of others enables individuals to infer their attentional focus by triggering reflexive gaze shifts to the same location (Frischen et al., 2007). Consistent with this, we observed similar gaze distributions within teams. These findings indicate that the real-effort task required team members not only to focus on arranging their tangram pieces but also to pool their resources by attending to each other. In doing so, teams coordinated their gaze, which ultimately resulted in substantial levels of social gaze dynamics.

Among social gaze dynamics within teams (n = 10), *joint attention* (M = 46.12, SD = 13.17) occurred most prominently, followed by *gaze aversion* (M = 21.96, SD = 7.08) and *mutual* *gaze* (M = 8.52, SD = 6.39). In previous studies, the proportion of *mutual gaze* in dyadic interactions ranged from 46% to 60% (Broz et al., 2012; Rogers et al., 2018). With about 15% to 41%, Capozzi et al. (2019) observed lower levels of *mutual gaze* during interactions involving more than two individuals. Given that the three-member teams in our study were not just participating in a conversation but also had to coordinate their gaze on a real-effort task, our findings line up well with these results. Furthermore, they support the assumption that the option to observe others' gaze—whether directed at oneself or averted—plays a crucial role by facilitating the coordination of attentional processes.

Team Output and Team Cohesion. Overall, we observed very high cooperation rates with an average *team output* of 33.60 pieces (SD = 4.30, Min = 24.00, Max = 36.00). Seven out of ten teams achieved to maximize team surplus, as 23 of 30 participants opted for the socially optimal contribution ($x_i^{TS} = 12$). Moreover, none of the participants showed purely selfish behavior, since the lowest *individual contribution* of eight pieces was considerably higher than the Nash equilibrium ($x_i^* = 4$). Given that team members were allowed to communicate in a face-to-face meeting before making their payoff-relevant decisions, our findings align with the typical finding that communication encourages cooperative behavior (Balliet, 2010; Sally, 1995).

Consistently, teams reported high levels of *team cohesion*. For instance, participants rated *belongingness* (n = 30, M = 5.50, SD = 1.43, Min = 2, Max = 7) on a level comparable to that of close friends, even though none of them knew their team members before participating in the experiment (Gächter et al., 2015). Moreover, average scores for *social cohesion* (M = 4.32, SD = 0.59, Min = 3, Max = 5) and *task cohesion* (M = 4.72, SD = 0.33, Min = 4, Max = 5) were close to the upper limit.

Taken together, these findings indicate that performing the real-effort task in a face-to-face meeting initiated the formation of *team cohesion* and led to high levels of cooperation. This interpretation is supported by the fact that our sample did not exhibit exceptionally altruistic characteristics per se, as the scores for *collective orientation*, *interpersonal trust*, and *personality traits* were similar to reference values for young adults aged between 20 and 28 (see Appendix B: Table B.1).

Testing the Main Hypotheses. Consistent with hypothesis **H1A**, OLS regression analysis showed a marginally significant positive correlation between *mutual gaze* and *team output*

Variable	(1) Team Output	(2) Team Output
Mutual Gaze	0.323	0.430*
	(0.218)	(0.198)
Gaze Aversion	-0.293	-0.394
	(0.336)	(0.280)
Collective Orientation		7.410
		(6.025)
Constant	37.290***	16.421
	(5.124)	(18.501)
R^2	0.246	0.376
Observations	10	10

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1: OLS regressions with *team output* as the dependent variable.

in the second model (p = .073; see Table 3.1). Tobit regressions yielded consistent findings, providing further evidence for a significant positive correlation between *mutual gaze* and *team output* (p = .033; see Appendix B: Table B.3).

These findings support our assumption that the level of *mutual gaze* within teams is taken into account when making strategic decisions. Consistent with this, Kurzban (2001) observed that participants increased their contribution to a public good when given the opportunity to look at each other simultaneously for three seconds before making a decision. Similarly, Mason et al. (2005) found that the perception of *mutual gaze* makes individuals feel more attracted to others than *gaze aversion*. Episodes of *mutual gaze* have also been shown to increase the probability of memorizing others (Frischen et al., 2007). Hence, the positive relationship between *mutual gaze* and *team output* aligns well with previous findings.

Variable	**(1)** **Team Cohesion**	**(2)** **Team Cohesion**
Mutual Gaze	0.064	0.069
	(0.052)	(0.067)
Gaze Aversion	0.058	0.054
	(0.079)	(0.064)
Collective Orientation		0.303
		(2.781)
Constant	-1.827	-2.681
	(2.100)	(9.539)
R^2	0.190	0.191
Observations	10	10

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: OLS regressions with *team cohesion* as the dependent variable.

Given that *gaze aversion* has previously been associated with competitive behavior and also naturally counteracts the dynamic of *mutual gaze*, we expected it to be negatively correlated with cooperation in teams (see, e.g., Foddy, 1978; Vrzakova et al., 2021). In contrast to **H1B**, however, we found no significant correlation between *gaze aversion* and *team output* in the second model (p = .210; see Table 3.1).

Furthermore, contrary to our hypotheses **H2A** and **H2B**, we observed no significant correlations between *team cohesion* and *mutual gaze* (p = .346) nor *gaze aversion* (p = .430) in the second model (see Table 3.2). Thus, the extent to which team members engaged in *mutual gaze* or *gaze aversion* during cooperation was not linked to the formation of *team cohesion* yet appeared to shape their cooperative behavior.

Variable	(1) Contribution	(2) Contribution	(3) Contribution
Mutual Gaze	0.082	0.098	0.016
	(0.077)	(0.076)	(0.084)
Gaze Aversion	-0.182	-0.182	-0.251**
	(0.135)	(0.130)	(0.101)
Joint Attention	-0.059	-0.048	-0.106
	(0.052)	(0.062)	(0.063)
Collective Orientation		1.014	1.093
		(0.951)	(1.006)
Interpersonal Trust		0.172	0.422
		(0.283)	(0.399)
Female			1.195
			(0.953)
Age			-0.041
			(0.104)
Constant	17.218***	12.899	16.979**
	(4.396)	(7.103)	(6.441)
R^2	0.245	0.296	0.371
Observations	30	30	30

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: OLS regressions with *individual contribution* as the dependent variable.

Further Analysis. Step-wise OLS regressions at the individual level showed a significant negative correlation between *gaze aversion* and the participants' *individual contributions* to the team task when considering the influence of each social gaze dynamic as well as social dispositions and demographics in the third model (p = .034; see Table 3.3). The results of Tobit regressions were qualitatively in line with those obtained from estimating OLS regressions (see Appendix B: Table B.4). Accordingly, teams in which the members were less responsive to each other's initiation of direct gaze—and thus exhibited higher levels of *gaze aversion*—generated lower *individual contributions* overall. This indicates that the perception of averted gaze not only allows team members to coordinate their visual attention as suggested by the gaze-cueing paradigm but also to obtain additional information that eventually shapes their economic behavior (Frischen et al., 2007). Similarly, recent findings from behavioral economics have shown that the option to observe others' (visualized) gaze in remote interaction enabled participants to maximize their payoff in simple coordination games and to estimate the prosocial motives of their counterparts in social dilemmas (Fischbacher et al., 2022; Hausfeld et al., 2021). Moreover, Bayliss and Tipper (2006) have previously demonstrated that individuals make inferences about the trustworthiness of others by observing their averted gaze. Beyond these findings, our results provide initial evidence that individuals adapt their economic behavior according to the level of *gaze aversion* experienced during face-to-face communication.

3.4.4 Conclusion

Taken together, our findings indicate that social gaze dynamics play a decisive role in teams. Specifically, our main results supported our first hypothesis, **H1A**, which proposed a positive relationship between *mutual gaze* and *team output*, whereas further analyses at the individual level hinted at a negative link with the perception of *gaze aversion*. Although these findings are consistent with our hypotheses, it remains unclear if there was a causal relationship between social gaze dynamics and (non-)cooperative behavior and, if so, whether it could be attributed to the level of *mutual gaze* or *gaze aversion* within teams. Given that both dynamics naturally counteract each other, it can be concluded that the reciprocation of eye-directed gaze within teams may foster cooperation. Overall, our findings underline the importance of nonverbal signals in face-to-face meetings. However, further research is needed to gain a broader understanding of the impact of social gaze in different settings such as video meetings, in which almost no information about the gaze of others is available.

Limitations. As in similar eye-tracking studies, the statistical power of our results was limited by the small number of observations. For this reason, we focused on statistically testing our main hypotheses at the team level and challenging the robustness of these results at the individual level. Furthermore, selfish behavior occurred very rarely in this experiment, which limited our ability to detect its correlation with *mutual gaze* and *gaze aversion*.

Although this was partly attributable to the opportunity for communication in face-to-face meetings before making decisions, we did not expect *individual contributions* to be as homogenous, converging at the upper boundary. As the tendency toward selfish money-maximizing behavior becomes more pronounced in larger teams (see, e.g., Barcelo & Capraro, 2015; Nosenzo et al., 2015), future studies might consider increasing group size. However, this adjustment would add to the complexity of adequately defining and measuring social gaze dynamics, as these mainly involve two individuals at a time. Hence, we rather propose to increase the incentive toward selfish behavior by emphasizing the stylized conflict between individual and collective interests.

In the second experiment, we addressed these limitations by substantially increasing the sample size and raising incremental costs for additional contributions to the team task. Moreover, to account for endogeneity issues—arising from the fact that we cannot externally manipulate social gaze dynamics without creating a highly artificial team setting—we employed two-stage least squares (2SLS) estimation to isolate the causal relationship between (non-)cooperative behavior and social gaze within teams.

3.5 Experiment 2: Attentional Reciprocity in Face-to-Face and Video Meetings

In the second experiment, we investigated the effect of *attentional reciprocity* (i.e., the extent to which looking at other members during the pre-play communication stage resulted in *mutual gaze* rather than *gaze aversion*; introduced in Section 3.3.3) on *team output* and *team cohesion*.[8] To accomplish this, we designed two experimentally randomized treatments that manipulated the option to exchange gaze information within teams. Notably, we also reduced the duration of the pre-play communication stage from ten minutes in the first experiment to five minutes in the second experiment to give more importance to the presence (and absence) of *attentional reciprocity* within teams. Below, we describe the setup of each treatment in detail.

[8] The experiment was preregistered at AsPredicted (#130545) and approved by the ethics committee of the KIT.

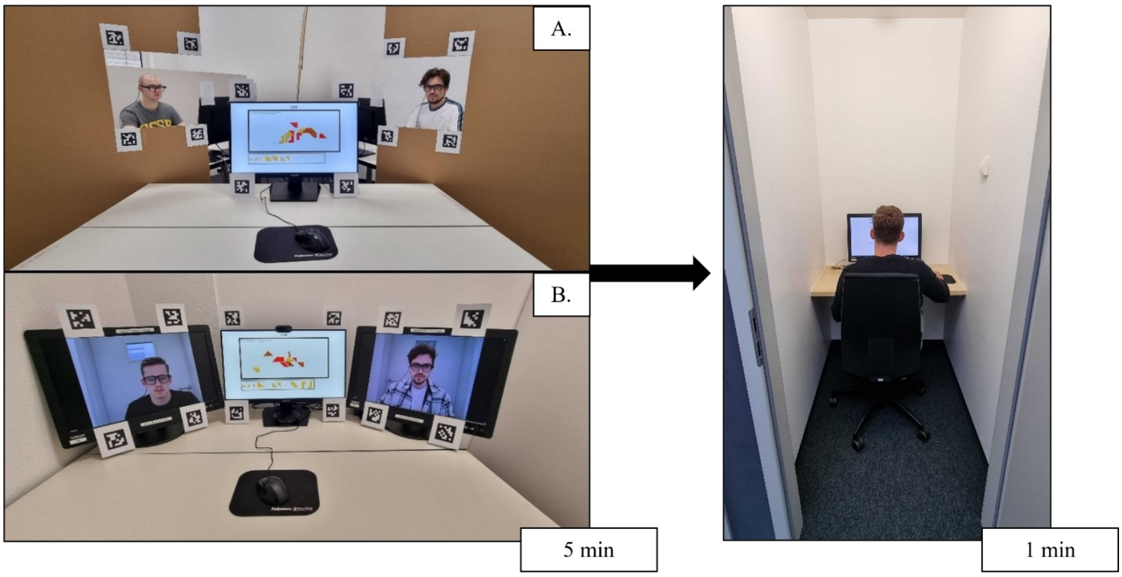

Figure 3.6: Pre-play communication stage from team member A's perspective in face-to-face (A) and video meeting setting (B; left), and the second stage in an isolated cubicle (right).

3.5.1 Treatments

Teams were randomly assigned to one of two treatments. These treatments only altered whether pre-play communication in the first stage of the team task took place in a *face-to-face meeting* (*FT*) or in a *video meeting* (*VT*). In both treatments, team members could see and verbally communicate with each other. In particular, the treatments only determined the option to perceive gaze information, without altering the access to other verbal and nonverbal signals. To rule out further treatment differences, the tangram puzzle task was performed digitally during the pre-play communication stage and participants could only see a square section of their team members' upper bodies in both treatments (see Figure 3.6).[9]

Treatment 1: Face-to-Face (FT). For the pre-play communication stage in *FT*, participants were led to a group room and then asked to take a seat at individual desks equipped with a computer and monitor to perform the tangram task together. The desks were separated from each other by three partitions. However, the partitions contained rectangular cut-

[9] The tangram puzzle task was programmed in oTree (v5.0.0a21; Chen et al., 2016) and deployed via Heroku (v22; Heroku, 2023). We used a locally hosted instance of BigBlueButton (v2.5) to set up the video meetings.

outs so that participants were able to see and verbally communicate with each other. To be as close as possible to *VT*, the cut-outs made sure that the participants could only see the upper part of each other.

Treatment 2: Video Meeting (VT). In *VT*, participants were led to individual rooms for the pre-play communication stage. In these rooms, they were asked to sit at a desk equipped with a computer and three monitors. While performing the team task on the central monitor, team members were displayed on the other two monitors so that the participants were able to see and verbally communicate with each other despite being spatially separated.

3.5.2 Sample

Overall, 231 students were recruited from the KD2Lab subject pool using Hroot (Bock et al., 2014) and received earnings (EUR) according to the payoff-relevant decisions they and their team members made in the second stage of the team task ($M = 13.69$). Due to technical issues during five team sessions, 15 individual observations had to be excluded from the analysis. According to the preregistered exclusion criteria, we also excluded four teams because they contained at least two members who knew each other before participation. Finally, we analyzed the data from 68 teams, including a total of 204 participants aged between 18 and 54 years ($M = 24.4$, $SD = 4.85$).[10] Gender-homogenous teams were randomly assigned to *FT* (50% female) and *VT* (56% female), resulting in 34 teams of three per treatment.

3.5.3 Main Hypotheses and Estimation Strategy

Previous research has shown that communication is pivotal for successful cooperation in teams (see, e.g., Babutsidze et al., 2021; Balliet, 2010; Cohn et al., 2022; Conrads & Reggiani, 2017; Sally, 1995). In particular, He et al. (2017) observed that individuals evaluate a variety of verbal and nonverbal signals to detect their team members' social type and adapt their economic behavior accordingly. Consistent with this, several studies have found that the mode of communication influences cooperation in social dilemmas because the

[10] The required sample size of 68 teams (204 participants) was calculated with G*Power (v3.1.9.7; Faul et al., 2009), using an alpha error probability of 0.05, a statistical power of 0.80, and assuming a medium effect size ($f^2 = 0.15$).

given nonverbal richness determines the amount of information that can be exchanged between team members (see, e.g., Bicchieri & Lev-On, 2007).

Building upon these findings, we aimed to understand the underlying mechanisms leading to differences in cooperation between two commonplace modes of team communication: face-to-face and video meeting settings. One of the most distinguishing factors between these settings is the absence of gaze information in the latter. While face-to-face communication encompasses the full range of nonverbal signals, conventional video meeting systems do not inform individuals about their team member's focus of gaze. Given that virtual team members cannot recognize whether they are looking at each other, our first hypothesis posited that the coordination of gaze is hampered in *VT*, resulting in relatively higher levels of *attentional reciprocity* in *FT*.

> **H1.** *The level of attentional reciprocity within teams is higher in FT compared to VT.*

Several studies revealed that the level of *mutual gaze* is linked to positive outcomes in social interactions, whereas *gaze aversion* is associated with negative outcomes (see, e.g., Broz et al., 2012; Foddy, 1978; Kurzban, 2001; Vrzakova et al., 2021). In addition, recent research indicates that individuals understand gaze information as a signal for prosocial motives and adapt their economic behavior accordingly (Fischbacher et al., 2022; Hausfeld et al., 2021). Thus, our second hypothesis proposed that higher levels of *attentional reciprocity* positively affect cooperative behavior, measured as *team output*.

> **H2.** *Higher levels of attentional reciprocity within teams positively affect team output.*

Moreover, previous research suggests that the perception of *mutual gaze* increases the probability of memorizing others, and makes individuals feel more attracted to others than *gaze aversion* (Frischen et al., 2007; Mason et al., 2005). Similarly, Kaiser et al. (2022) claimed that the absence of gaze information in video meetings interferes with the processing of nonverbal signals and thus hinders the formation of social relationships. Thus, given that team members in our experimental setup were strangers, our third hypothesis posited that higher levels of *attentional reciprocity* would positively affect their self-reported *team cohesion*.

H3. *Higher levels of attentional reciprocity within teams positively affect team cohesion.*

Estimation Strategy. After pre-processing the data, we conducted an initial analysis to report the sample's characteristics, pairwise correlations, and aggregated gaze patterns, including the distribution of gaze between AOIs (Members, Task, and Else) and the ratio of each respective social gaze dynamic.

We tested our hypotheses (**H1**, **H2**, and **H3**) using 2SLS regressions (for a comprehensive explanation of 2SLS estimation, see Appendix B.4) with the level of *attentional reciprocity* instrumented by our experimentally randomized treatment variable *face-to-face* (0 = *VT*, 1 = *FT*) and *team output* as well as *team cohesion* as dependent variables respectively. First, we examined if our experimentally randomized treatment variable *face-to-face* satisfied the (as if) randomness, exclusion, and relevance criterion to qualify as a valid instrument for the statistical testing of our hypotheses using 2SLS estimation (Bastardoz et al., 2023; Bound et al., 1995; Sajons, 2020; Wooldridge, 2010). Since we experimentally randomized teams to *FT* and *VT*, the (as if) randomness criterion was satisfied by design. Nevertheless, we performed a randomization check by calculating Pearson correlation coefficients between *face-to-face* and participants' individual characteristics as part of the summary statistics.

In addition, we performed further analyses using OLS regressions with *mutual gaze*, *gaze aversion*, and *joint attention* at the individual level as predictors for the participants' *individual contributions* to the team task. Notably, we also controlled for *face-to-face* and its interaction with *mutual gaze*, *gaze aversion*, and *joint attention*. Following a step-wise approach, we included *collective orientation* as well as *interpersonal trust* as social dispositions, *personality traits*, and demographics (*age*, *female*) to test if our findings are robust to adding further control variables at the individual level.

3.5.4 Results and Discussion

For an overview of the key variables' summary statistics and pair-wise correlations pooled across both treatments, see Appendix B: Table B.5 and Table B.6.

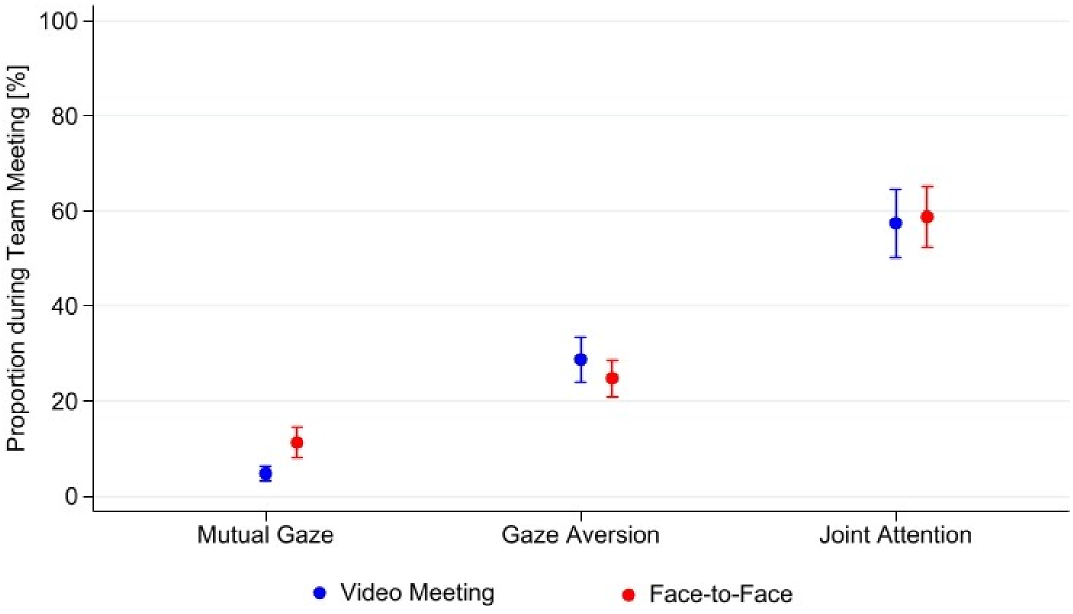

Figure 3.7: Proportion of each social gaze dynamic during the pre-play communication stage with dots indicating means and whiskers depicting 95% confidence intervals.

Attentional Reciprocity. In both treatments, individual participants (n = 204) predominantly looked at the task (M = 74.69, SD = 16.14) during the pre-play communication stage, followed by the AOIs of their team members (M = 19.22, SD = 13.11), and elsewhere (M = 6.09, SD = 6.62). Furthermore, participants allocated significantly more gaze to their team members in the *FT* (M = 21.62, SD = 14.30) compared to *VT* (M = 16.82, SD = 11.36), $t(202)$ = 2.65, p = .009, d = 0.37, and significantly less gaze to areas outside the defined AOIs in *FT* (M = 5.06, SD = 5.15) than *VT* (M = 7.13, SD = 7.70), $t(202)$ = 2.25, p = .026, d = 0.32. Thus, the option to exchange gaze information in *FT* helped team members to coordinate their gaze and to attend to each other more frequently. Overall, *joint attention* (M = 58.09, SD = 20.03) was the most prevalent among social gaze dynamics within teams (n = 68), succeeded by *gaze aversion* (M = 26.77, SD = 12.67) and *mutual gaze* (M = 8.03, SD = 7.98; see Figure 3.7).

Whereas *mutual gaze* was significantly higher in *FT* than *VT* (p < .001), we observed no significant differences in *gaze aversion* (p = .197) and *joint attention* (p = .797) between the treatments (see Table 3.4). Overall, our results suggest that the richness of gaze information in *FT* was essential for maintaining high levels of *mutual gaze*. Moreover, these findings indicate that the level of *gaze aversion* and *joint attention* did not depend on the

Variable	Video Meeting (n = 34) *M* (*SD*)	Face-to-Face (n = 34) *M* (*SD*)	$t(66)$	p	Cohen's d
Mutual Gaze	4.78 (4.52)	11.29 (9.34)	3.66	<.001***	0.89
Gaze Aversion	28.77 (13.86)	24.78 (11.21)	1.30	.197	0.32
Joint Attention	57.46 (21.15)	58.72 (19.13)	0.26	.797	0.06
Attentional Reciprocity	11.51 (8.02)	26.37 (14.57)	5.21	<.001***	1.26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Semi-parametric treatment comparisons (n = 68; two-sided t-tests) of each social gaze dynamic and *attentional reciprocity* by *FT* and *VT*.

option to exchange gaze information during communication. Given that *FT* had a positive effect on *mutual gaze*, while *gaze aversion* remained constant across treatments, we also found significantly higher levels of *attentional reciprocity* (i.e., $\frac{Mutual\ Gaze}{Mutual\ Gaze + Gaze\ Aversion}$) in *FT* than *VT* ($p < .001$; see Table 3.4).

Testing our first hypothesis (**H1**), first-stage 2SLS regressions provided strong evidence for the relevance of our experimentally randomized treatment variable *face-to-face* in the first model, $F(1,66) = 27.16$, $p < .001$, and the second model with *joint attention* as an additional control variable, $F(2,65) = 43.66$, $p < .001$ (see Table 3.5). Note that we decided to include *joint attention* in the second model due to several reasons. First, our initial results did not indicate any treatment effects on the level of *joint attention* ($p = .797$). Hence, adding *joint attention* as a control variable in the first stage did not add a bias to the estimated effect of *attentional reciprocity* in the second model. Second, the level of *joint attention* was inherently correlated with *attentional reciprocity*, as they are mutually exclusive dynamics (see Appendix B: Table B.6). Accordingly, the inclusion of *joint attention* added substantial information to the model. Third, a large body of literature demonstrates a close link between *joint attention* and collective performance, making it a highly relevant variable to control for in team settings (for a review, see Reuscher et al., 2023).

Variable	**(1)** **Attentional Reciprocity**	**(2)** **Attentional Reciprocity**
First-Stage 2SLS Regressions		
Face-to-Face	14.886***	15.292***
	(2.853)	(2.334)
Joint Attention		-0.337***
		(15.106)
Constant	11.508***	30.867***
	(1.375)	(4.025)
R^2	0.292	0.528
F-statistic	27.16	43.66
p-value	<.001	<.001
Observations	68	68

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: First-stage 2SLS regressions with *attentional reciprocity* as the dependent variable.

In support of **H1**, we observed a significant positive effect of *face-to-face* on the level of *attentional reciprocity* within teams in the first ($p < .001$) and second model ($p < .001$; see Table 3.5). These findings show that the coordination of attentional processes between team members was effectively impaired by our treatment manipulation. As expected, the absence of gaze information in *VT* has led to a substantial decrease in *attentional reciprocity*, most likely because gaze could not be recognized. Furthermore, the results revealed that our experimentally randomized treatment variable *face-to-face* satisfied the criteria for a valid instrument in 2SLS estimation. First, it met the **relevance criterion**, evidenced by the significant first-stage *F*-statistic (see Table 3.5), which indicates a strong predictive value for *attentional reciprocity*. Second, the **exclusion restriction** held, as we designed *face-to-face* to influence *team output* and *team cohesion* only through its impact on *attentional* *reciprocity*.[11] Finally, given that we randomly assigned teams to either *FT* or *VT*, the **random assignment criterion** was naturally supported. Accordingly, we continued to calculate the second-stage regressions with *team output* and *team cohesion* regressed on the instrumented level of *attentional reciprocity*.

Cooperation. Overall, we observed a medium level of cooperation as *team output* averaged 17.84 pieces (n = 68, SD = 6.90, Min = 3, Max = 36), with only nine teams successfully maximizing team surplus. The most frequent decision made by individual participants (n = 204, M = 5.95, SD = 2.80, Min = 0, Max = 12) was an *individual contribution* of three pieces (n = 38). This aligned with the Nash equilibrium (x_i^* = 3), which risk-neutral, money-maximizing participants were predicted to choose. Notably, a large share of participants also selected to contribute nine pieces (n = 33), which would have maximized team surplus if chosen by all members (x_i^{TS} = 9). Whereas *individual contributions* consistent with the Nash equilibrium were approximately equally frequent between *FT* (n = 21) and *VT* (n = 17), 73% of participants who opted for the team surplus maximizing decision belonged to *FT*. Thus, if a participant decided to deviate from purely selfish money-maximizing behavior, the extent of that deviation was higher after pre-play communication in *FT* than in *VT*. In line with this finding, *team output* was descriptively higher in *FT* (M = 18.65, SD = 6.83) as compared to *VT* (M = 17.03, SD = 6.98; see Figure 3.8). Note that we did not hypothesize a significant effect of *face-to-face* on *team output*. Instead, we designed the treatment variable to serve as an experimentally randomized instrument within 2SLS estimation to correct for the correlation between *attentional reciprocity* and the error term in our models (Sajons, 2020).

To test the second hypothesis (**H2**), we proceeded with our estimation strategy. Accordingly, we computed the second stages of the 2SLS models including *joint attention* as a control variable, then tested for endogeneity, and finally compared our results to those

[11] First and foremost, face-to-face and video meetings differ in the physical distance between team members: in face-to-face meetings, team members are located in the same room, whereas in video meetings, they are spatially separated. This change in physical distance could, in addition to affecting the availability of gaze information, also influence levels of perceived social presence. To test if social presence operates as an alternative channel through which our treatments might impact outcome variables, we conducted two-sided t-tests with six distinct dimensions of social presence (Biocca et al., 2003) and found no evidence of a treatment effect on any of these dimensions (see Appendix B: Table B.7).

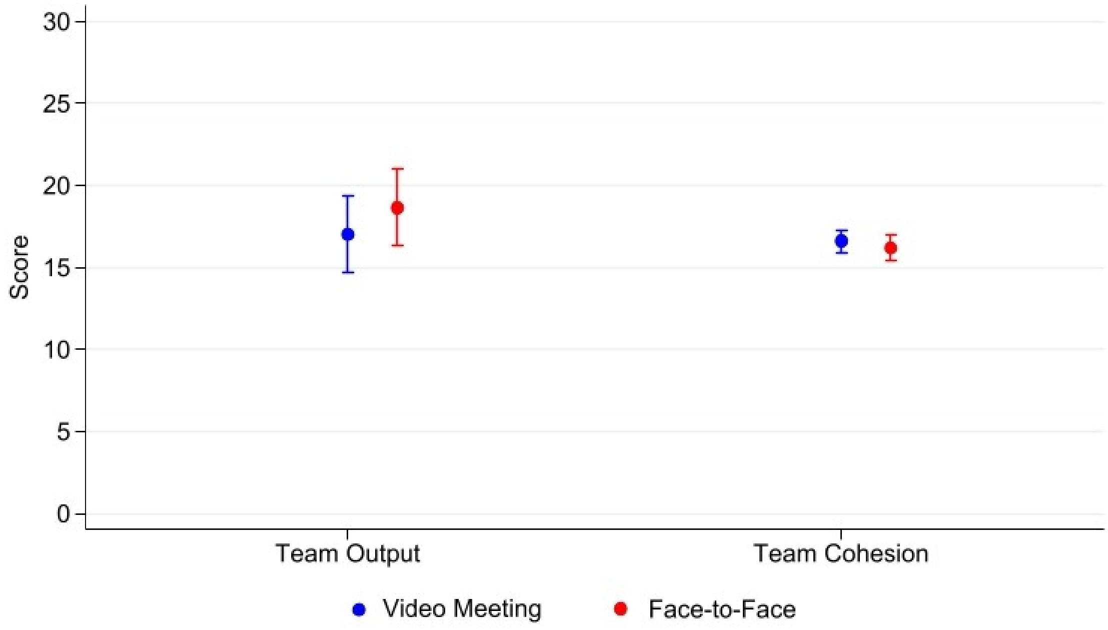

Figure 3.8: Scores of *team output* and *team cohesion* with dots indicating means and whiskers depicting 95% confidence intervals.

obtained using OLS as an efficient estimator. Contrary to **H2**, second-stage 2SLS regressions revealed no significant effects of the instrumented level of *attentional reciprocity* on *team output* in the first (p = .330) and second models (p = .332; see Table 3.6).[12]

We took advantage of 2SLS estimation to address endogeneity concerns regarding the level of *attentional reciprocity* within teams and, thus, to examine its causal relationship with *team output*. However, post-hoc testing for endogeneity using Wooldridge's robust scores revealed strong evidence that we did not face a problem with endogeneity in both the first (χ^2 = 20.344, p = .558) and second models (χ^2 = 0.524, p = .469). Following not only practical (Bastardoz et al., 2023; Sajons, 2020) but also theoretical guidelines (Bound et al., 1995; Wooldridge, 2010) for 2SLS estimation, we therefore re-estimated the equations using OLS.

In support of **H2**, OLS regressions indicated a significant positive relationship between *attentional reciprocity* and *team output* in the second model (p = .031; see Table 3.7). Notably, however, this effect was only significant when *joint attention* was included as a

[12] The addition of *joint attention* as a covariate increased the explained variance from less than 1% in the first model, $\chi2(1)$ = 0.95, p = .330, to over 15% in the second model, $\chi2(2)$ = 8.88, p = .012.

Variable	(1) Team Output	(2) Team Output
Second-Stage 2SLS Regressions		
Attentional Reciprocity	0.109	0.098
	(0.112)	(0.101)
Joint Attention		0.132***
		(0.046)
Constant	15.777***	8.314**
	(2.294)	(4.132)
R^2	0.000	0.152
χ^2-statistic	0.95	8.88
p-value	.330	.012
Observations	68	68

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Second-stage 2SLS regressions with *attentional reciprocity* instrumented by *face-to-face* and *team output* as the dependent variable.

control variable. As previously discussed, this could be attributed to the fact that *joint attention* and *attentional reciprocity* are mutually exclusive dynamics and, thus, were inherently correlated. Therefore, interpreting the effects of *attentional reciprocity* was most meaningful when both variables were included. Additionally, *joint attention* contributed valuable information to the model, as highlighted by the increase in explained variance from approximately 1% in the first model, $F(1,66) = 0.63$, $p = .431$, to about 16% in the second model, $F(2,65) = 7.16$, $p = .002$. Yet, when controlling for *face-to-face* and its interaction with *attentional reciprocity* in the third model, the positive relationship between *attentional reciprocity* and *team output* was rendered insignificant ($p = .684$; see Table 3.7). This suggests that in *VT*, where gaze information was absent, *attentional reciprocity* did not contribute to *team output*. Notably, however, two-sided *F*-tests of the linear hypothesis

Variable	(1) Team Output	(2) Team Output	(3) Team Output
Attentional Reciprocity	0.055	0.157**	0.075
	(0.069)	(0.071)	(0.184)
Joint Attention		0.151***	0.157***
		(0.041)	(0.049)
Face-to-Face			-3.566
			(3.097)
Face-to-Face* Attentional Reciprocity			0.146
			(0.190)
Constant	16.805***	6.067*	7.129*
	(1.377)	(3.146)	(4.068)
R^2	0.012	0.163	0.181
F-statistic	0.63	7.16	3.52
p-value	.431	.002	.012
Observations	68	68	68

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: OLS regressions with *team output* as the dependent variable.

attentional reciprocity + *face-to-face***attentional reciprocity* revealed that in *FT*, where gaze information was available, *attentional reciprocity* showed a significant positive relationship with *team output*, $F(1,63) = 4.59$, $p = .036$. These findings highlight that simply attending to each other in *VT* was not sufficient to establish successful cooperation. Thus, for *attentional reciprocity* to enhance cooperation within teams, it must be recognizable. Consistent with this, previous studies on social gaze showed that speakers tend to divide their gaze evenly among listeners, likely to assess whether they are paying attention during communication (see, e.g., Capozzi et al., 2019).

In summary, our 2SLS regressions did not reveal a causal relationship between *attentional reciprocity* and *team output*. Consequently, we rejected our second hypothesis (**H2**), positing that *attentional reciprocity* would universally promote team cooperation across different meeting modes. However, the results of our OLS regressions provided initial evidence that *attentional reciprocity* might serve as a key signal for type detection in face-to-face communication. Aligning with He et al. (2017), this mechanism appeared vital for successful team cooperation. Thus, future research should further investigate the contextual factors and underlying processes that enable *attentional reciprocity* to enhance cooperative behavior, particularly in computer-mediated communication, where gaze information is absent.

Team Cohesion. In general, we observed high levels of *team cohesion* (n = 68, M = 16.41, SD = 2.21, Min = 8.94, Max = 19). However, in contrast to the cohesion-performance literature (see, e.g., Delfgaauw et al., 2022; Gächter et al., 2024), we found no significant relationship between *team cohesion* and *team output* (p = .309; see Appendix B: Table B.6). Moreover, our summary statistics showed no considerable difference in *team cohesion* between *FT* (M = 16.19, SD = 2.38) and *VT* (M = 16.62, SD = 2.05; see Figure 3.8).

Contrary to our third hypothesis (**H3**), second-stage 2SLS regressions revealed no significant effect of *attentional reciprocity* on *team cohesion* in the first (p = .447) and second model (p = .442; see Table 3.8). When testing for endogeneity in a further step, Wooldridge's robust scores indicated a high likelihood of endogeneity in the first (χ^2 = 3.129, p = .077) and the second model (χ^2 = 5.008, p = .025), suggesting that *attentional reciprocity* was indeed correlated with the error term in both models. Given that OLS does not account for the correlation between endogenous regressors and the error term, we did not compare our 2SLS estimation results with those obtained using OLS. Consequently, we rejected **H3**, proposing that higher levels of *attentional reciprocity* would positively impact *team cohesion*.

Individual Cooperation in the Absence of Gaze Information. Given that teams met and communicated in the first stage of the team task, our observations were correlated between team members at the individual level. For example, a participant's *individual contribution* was likely influenced by the behavior of their team members during pre-play communication: if two team members verbally committed to contributing a large number of pieces to

Variable	(1) Team Cohesion	(2) Team Cohesion
Second-Stage 2SLS Regressions		
Attentional Reciprocity	-0.028	-0.028
	(0.037)	(0.036)
Joint Attention		-0.008
		(0.018)
Constant	16.942***	17.384***
	(0.713)	(1.622)
R^2	0.000	0.000
χ^2-statistic	0.58	0.61
p-value	.447	.738
Observations	68	68

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8: Second-stage 2SLS regressions with *attentional reciprocity* instrumented by *face-to-face* and *team cohesion* as the dependent variable.

the tangram task, the third might have also chosen a higher number of pieces (Fischbacher et al., 2001; He et al., 2017). Hence, to ensure a robust examination of our main hypotheses, we tested them at the team level. However, to gain additional insights, we conducted further analyses on the relationship between *individual contribution* and the level of *mutual gaze*, *gaze aversion*, and *joint attention* at the individual level.

A key adjustment involved the inclusion of each social gaze dynamic as a separate regressor, rather than combining *mutual gaze* and *gaze aversion* into a single metric of *attentional reciprocity*. When testing our main hypotheses at the team level, we included *attentional reciprocity* as a combined metric to address the issue of underidentification in 2SLS estimation (Bastardoz et al., 2023; Sajons, 2020; Wooldridge, 2010), as we had only one experimentally randomized instrumental treatment variable—*face-to-face*—to account for two potentially endogenous regressors: *mutual gaze* and *gaze aversion*. By using *attentional reciprocity* as a combined metric, we were able to include both dynamics in the models, allowing for a more streamlined analysis within the constraints of 2SLS estimation. Moreover, our main results suggested no significant evidence of endogeneity issues, indicating that 2SLS was not the appropriate approach to measure the relationship between social gaze dynamics and *team output*. Thus, within further analyses at the individual level, we employed OLS as an efficient estimator, allowing us to include *mutual gaze* and *gaze aversion* as separate regressors. This adjustment enabled a more precise assessment of each dynamic's effect on *individual contribution*.

Our results showed that *individual contribution* was negatively influenced by the level of *gaze aversion* in *VT*, where gaze information was absent (see Table 3.9). This negative effect remained (marginally) significant when including several control variables in the fourth model (p = .050), suggesting that *individual contribution* declined in *VT* when participants frequently attended to their team members without receiving attention in return. Notably, we also found a significant positive interaction between *face-to-face* and *gaze aversion* (p = .010), indicating that the availability of gaze information in *FT* changed the effect that *gaze aversion* had on *individual contributions*. Contrary to the negative influence in *VT*, two-sided F-tests of the linear hypothesis *gaze aversion* + *face-to-face***gaze aversion* revealed a (marginally) significant positive relationship between *gaze aversion* and *individual contribution* in *FT*, $F(1,67) = 3.54$, $p = .064$. This suggests that while *gaze aversion* was detrimental in *VT*, potentially indicating that team members were not adequately attending to each other, it became a valuable signal that enabled individuals to coordinate their attention in *FT*, as suggested by the gaze-cueing paradigm (Frischen et al., 2007). In support of this assumption, team members engaged in *mutual gaze* for 11.51% of the pre-play communication in *VT* compared to 26.37% in *FT*, whereas the level of *gaze aversion* remained constant across treatments. Thus, the option to observe other team members' averted gaze might have supported the establishment of *attentional reciprocity*. Furthermore, two-sided F-tests of the linear hypothesis *mutual gaze* + *face-to-face***mutual gaze* revealed that, unlike in *VT*, *mutual gaze* showed a (marginally) significant positive relationship with *individual contribution* in *FT*, $F(1,67) = 3.05$, $p = .086$.

Variable	**(1) Contribution**	**(2) Contribution**	**(3) Contribution**	**(4) Contribution**
Mutual Gaze	0.048	0.059	0.063	0.091
	(0.125)	(0.124)	(0.128)	(0.132)
Gaze Aversion	-0.063*	-0.079**	-0.080**	-0.076*
	(0.035)	(0.037)	(0.039)	(0.038)
Joint Attention	0.041*	0.034	0.033	0.035
	(0.025)	(0.026)	(0.028)	(0.028)
Face-to-Face	-3.126	-3.783	-3.911	-4.070
	(4.210)	(4.063)	(3.988)	(3.956)
Face-to-Face*Mutual Gaze	0.070	0.053	0.055	0.027
	(0.148)	(0.146)	(0.143)	(0.144)
Face-to-Face*Gaze Aversion	0.127**	0.151**	0.149**	0.154**
	(0.056)	(0.057)	(0.058)	(0.058)
Face-to-Face*Joint Attention	0.018	0.024	0.026	0.028
	(0.046)	(0.044)	(0.044)	(0.044)
Constant	3.430	-0.089	0.624	-0.451
	(2.142)	(2.974)	(3.524)	(3.563)
Social Dispositions	✗	✓	✓	✓
Big Five Factors	✗	✗	✓	✓
Demographics	✗	✗	✗	✓
R^2	0.107	0.129	0.147	0.162
F-statistic	3.05	2.71	1.84	2.02
p-value	.008	.009	.051	.024
Observations	204	204	204	204

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: OLS regressions with *individual contribution* as the dependent variable.

Overall, our findings at the individual level indicate that higher levels of *gaze aversion* reflected a lack of attention among team members in *VT*. However, consistent with the gaze-cueing paradigm (Frischen et al., 2007), the perception of *gaze aversion* appeared to become a crucial mechanism in *FT* by enabling teams to establish and recognize higher levels of *mutual gaze*, which eventually enhanced cooperative behavior. Taken together with our findings at the team level, these results further substantiate the notion that individuals incorporate gaze information to judge their team members' cooperative type and adapt their strategic decisions accordingly, which aligns well with previous findings on type detection and gaze as a signal for prosocial motives (Fischbacher et al., 2022; Hausfeld et al., 2021; He et al., 2017).

3.5.5 Conclusion

Our findings provide valuable insights into the role of nonverbal signals in team communication, the relationship between social gaze dynamics and (non-)cooperative behavior, and the potential impact of missing gaze information in computer-mediated communication. Unlike previous studies, our setup allowed us to capture participants' eye movements during communication in face-to-face and video meeting settings. This enabled us to detect differences in *attentional reciprocity* between these two settings and examine their effects on *team output* and *team cohesion*.

Supporting our first hypothesis, **H1**, we found that *attentional reciprocity* differed significantly between *FT* and *VT*. Whereas direct gaze was reciprocated about 11% of the time in *VT*, this likelihood more than doubled to around 26% in *FT*, where gaze information was available.

Regarding our second hypothesis, **H2**, 2SLS estimation did not reveal that higher levels of *attentional reciprocity* universally promoted cooperation across both *FT* and *VT*. However, OLS regressions provided a more detailed perspective. Consistent with the 2SLS results, we observed no significant relationship between *attentional reciprocity* and *team output* in *VT*. Conversely, in *FT*, where individuals could observe each other's gaze, we identified a significant positive relationship between *attentional reciprocity* and *team output*. In accordance with previous findings (Fischbacher et al., 2022; He et al., 2017), these results suggest that higher levels of *attentional reciprocity* may enhance cooperation, but only when team members are able to visually perceive them during face-to-face communication. Similarly, analyses at the individual level revealed a negative link between *gaze aversion* and *individual contributions* in *VT*, potentially reflecting a lack of attention among team members. In contrast, in *FT*, *gaze aversion* appeared to function as a valuable signal that promoted cooperative behavior, possibly by enabling individuals to coordinate their gaze and, thus, establish higher levels of *attentional reciprocity*. Overall, our results did not support **H2**, which proposed that *attentional reciprocity* would positively affect team cooperation across both meeting modes. Nevertheless, they provide initial evidence that *attentional reciprocity* may promote cooperation when it can be recognized as a nonverbal signal in face-to-face communication.

Finally, we observed no effect of *attentional reciprocity* on *team cohesion*, which contradicted our third hypothesis, **H3**. Consequently, while cooperative behavior may indeed be influenced by the extent to which direct gaze is reciprocated within teams, the formation of *team cohesion* might not be affected.

Limitations. Although our total sample size of 204 participants exceeded that of comparable eye-tracking studies (see, e.g., Fiedler et al., 2013; Fischbacher et al., 2022; Hausfeld et al., 2021), concerns about the statistical power of our findings remain. This limitation is particularly pertinent as we tested our hypotheses at the team level, with each observation comprising three participants. Specifically, with 34 teams per treatment, we fell short of the recommended sample size of at least 50 independent observations per treatment for 2SLS estimation (Bastardoz et al., 2023; Sajons, 2020). This typical recommendation was grounded on two main considerations. First, smaller sample sizes exacerbate finite-sample bias in 2SLS estimates (Bound et al., 1995). The relationship between an experimentally randomized instrument and the endogenous variable in first-stage models is estimated with greater variability in smaller samples, leading to potential biases toward zero and underestimation of true effects. Second, due to the additional layer of estimation involved, 2SLS generally produces estimates with larger standard errors compared to OLS (Wooldridge, 2010). In smaller samples, this loss of precision is even more pronounced, which may explain why we observed a significant positive effect of *attentional reciprocity* on *team output* when using OLS, but not when estimating second-stage 2SLS regressions with the instrumented level of *attentional reciprocity*.

Furthermore, our experimental procedure enabled participants to discuss various strategies related to their payoff-relevant decisions because they received comprehensive instructions on the team task and payoff structure before entering the pre-play communication stage. Thus, participants could have made explicit commitments regarding their *individual contributions* to the team task. Although this was possible in both treatments, we cannot entirely rule out systematic differences in the effect of commitments between *FT* and *VT*. Given that commitments are known to have a large positive effect on cooperative behavior (see, e.g., He et al., 2017), future studies should consider delaying game-relevant instructions until after communication to prevent confounding effects.

3.6 General Discussion and Conclusion

Overall, our two experiments offered valuable insights into the relationship between social gaze dynamics and team cooperation, as well as the potential consequences of missing gaze information in video meetings. In contrast to previous studies, our novel setup enabled us to capture the participants' eye movements during a natural team setting that paralleled the characteristics of a social dilemma, allowing us to test the relationship between social gaze dynamics and economic behavior in teams. We found initial evidence that cooperation rates in social dilemmas might hinge on the extent to which looking at others during collaboration results in *mutual gaze* or *gaze aversion*. In the first experiment, we observed that *team output* increased with the duration of *mutual gaze*. Moreover, further analysis at the individual level revealed a negative correlation between *gaze aversion* and *individual contributions* to the team task. These results are consistent with previous research, which showed that higher levels of *mutual gaze* were typically linked to positive qualities in social interaction, whereas *gaze aversion* had opposite effects (see, e.g., Broz et al., 2012; Foddy, 1978; Kurzban, 2001; Vrzakova et al., 2021). Building upon these findings, in the second study, we further investigated the relationship between cooperative behavior and the extent of *attentional reciprocity* within teams. By experimentally manipulating the participants' option to exchange gaze information, we found initial evidence that team cooperation is positively associated with the level of *attentional reciprocity* in face-to-face communication. In contrast, neither of the two experiments indicated a relationship between social gaze dynamics and *team cohesion*.

Hence, in accordance with He et al. (2017), our results partially support the assumption that communication in face-to-face settings fosters team cooperation by enabling members to recognize one another's cooperativeness. Similarly, recent eye-tracking studies demonstrated that individuals were capable of incorporating gaze information when making strategic decisions, understanding it as a signal of prosocial motives (Fischbacher et al., 2022; Hausfeld et al., 2021). Since individuals cannot exchange gaze information in video meeting settings, our findings highlight the negative consequences of increasingly shifting team meetings to the virtual space.

General Limitations and Future Research. The introduction of our novel multiparty eye-tracking setup provided valuable insights into the role of social gaze dynamics in teams. However, it was also accompanied by certain limitations.

The controlled meeting setups, while necessary to ensure precise and comparable measurements, diverged from naturalistic team settings. For example, the face-to-face setting included physical barriers with cutouts that allowed participants to only see each other's upper half, creating an artificial environment compared to typical on-site meetings, where individuals share an open space. Similarly, the video meeting setup displayed each team member on separate monitors to ensure consistent and equal visibility among participants. While this configuration allowed for controlled comparisons between face-to-face and video meeting settings, it did not fully replicate the layout of conventional video meeting systems, where participants are typically displayed together on a single screen.

Furthermore, the reliance on QR codes to track the defined AOIs added another layer of artificiality to the setup. Although this method was a practical and necessary solution for accurately quantifying social gaze dynamics, it may have limited the generalizability of the findings. Recently, advancements in AI-driven eye-tracking technologies enabled the identification of AOIs without relying on QR-based image recognition, paving the way for more naturalistic experimental designs (Pupil Labs, 2023). Thus, future studies employing such methods could preserve methodological rigor while enhancing the ecological validity of findings, offering deeper insights into the role of social gaze dynamics in real-world team settings.

Beyond these design limitations, we could not establish causal conclusions about the relationship between *attentional reciprocity* and team cooperation, as 2SLS estimation did not reveal significant effects. Although this approach is generally effective in testing causality, it did not allow for differentiating effects between our treatments *FT* and *VT*. In contrast, OLS regressions provided this distinction, indicating that social gaze dynamics during face-to-face communication were associated with subsequent cooperative behavior. Based on these findings, future research could prioritize measuring social gaze dynamics during face-to-face communication, where gaze information is naturally available, to evaluate whether higher levels of *attentional reciprocity* act as a signal for prosocial motives and, in turn, promote cooperation. To achieve this, however, researchers need to develop an instrumental variable for 2SLS estimation that directly influences the level of *attentional reciprocity* without restricting access to gaze information. This approach would allow for a more precise evaluation of its role in fostering cooperative behavior while eliminating confounding factors arising from differences between meeting settings.

An alternative direction for future research could involve exploring the causal effects of social gaze dynamics in remote settings, where gaze information is naturally limited. Video meeting systems offer a unique opportunity to test whether introducing or enhancing the visibility of social gaze dynamics influences cooperative behavior within a controlled environment, rather than comparing face-to-face and computer-mediated communication. For example, a video meeting system could be designed to visualize episodes of bidirectional direct gaze between team members, allowing participants to observe and adjust their behavior according to the level of *attentional reciprocity*. Comparing the effects of such a system with a baseline—representing a conventional video meeting system—could offer valuable insights into the role of social gaze dynamics in enhancing team cooperation. In particular, it would deepen our understanding of whether and how the option to observe the level of *attentional reciprocity* functions as a signal of prosocial motives in team settings.

CHAPTER 4

The Eyes Speak Louder Than Words: Visualizing Gaze Contact in Virtual Teams

Abstract

Driven by the rise of remote work arrangements, video meeting systems have become an essential tool for facilitating collaboration across geographically distributed teams. Due to their visual component, they allow individuals to see one another, enriching computer-mediated communication with a broad spectrum of nonverbal signals. However, video meetings still lack the richness of nonverbal signals inherent to face-to-face communication, with the absence of gaze information remaining their most notable limitation. In this study, we conducted a laboratory experiment to examine the impact of a gaze-adaptive video meeting system that bridges this gap between computer-mediated and face-to-face communication. Specifically, we designed two treatments in which teams got to know each other in a video meeting before participating in a repeated Weakest Link Game. In the Baseline treatment, we used a conventional video meeting system that enabled team members to see and hear each other. In the Gaze Contact treatment, the system additionally indicated when team members were simultaneously looking at each other's video feeds. Our results suggest that the option to perceive gaze contact in video meetings has the potential to increase team cooperation—possibly by enhancing interpersonal trust, as indicated by further analyses at the individual level. In contrast, we observed no significant effects on team coordination. With these findings, we offer theoretical insights into the role of social gaze in facilitating type detection and provide practical implications for improving remote work practices.

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4.1 Introduction

Collaboration is fundamental to organizational success as it allows team members to leverage their unique skills, optimize resource utilization, and create a cohesive environment that enhances commitment to shared objectives (Balliet & Van Lange, 2013; Delfgaauw et al., 2022; Fischbacher & Gächter, 2010; Gächter et al., 2024). In the modern workplace, video meetings have been established as an efficient alternative to face-to-face meetings, enabling collaboration across geographically distributed teams (see, e.g., Standaert et al., 2021). However, concerns about the negative consequences of increasingly relying on virtual team collaboration persist, prompting organizations to reconsider their remote work policies and, in some cases, to mandate a full-time return to office-based work (see, e.g., Jassy, 2024).

Although remote work arrangements offer notable benefits (see, e.g., Angelici et al., 2023; Chatterjee et al., 2022; Choudhury et al., 2021), a return to office-based work could still be the right choice, as empirical research has consistently shown that face-to-face communication produces higher cooperation rates than computer-mediated communication (Balliet, 2010; Sally, 1995). A central mechanism driving this effect is type detection—the ability to infer others' prosocial motives by interpreting both verbal and nonverbal communication signals (He et al., 2017). Whereas verbal signals are present in both face-to-face and computer-mediated communication, the richness of nonverbal signals sets them apart (Daft & Lengel, 1986; Bicchieri & Lev-On, 2007).

Video meetings—a commonplace mode of computer-mediated communication in the modern workplace (Standaert et al., 2021)—have narrowed this gap by conveying a broad range of nonverbal signals, such as gestures and facial expressions. However, a key factor differentiating them from face-to-face meetings is the absence of gaze information (Bohannon et al., 2013). We might be able to see each other's eyes during a video meeting, but we cannot experience the profound moment when our eyes meet, henceforth referred to as gaze contact. The role of gaze contact in social interactions has previously been examined by social psychologists, leading to the formulation of the Cooperative Eye Hypothesis (Tomasello et al., 2007). Most notably, its perception is known to evoke positive emotional responses in cooperative settings (Hietanen, 2018; Kaiser et al., 2022) and enables individuals to coordinate their actions (Hessels, 2020; Grossmann, 2017; Kleinke, 1986; Pfeiffer et al., 2013). However, robust conclusions about the causal relationship between gaze contact and collaborative success have yet to be drawn.

In this study, we employed state-of-the-art eye-tracking technology to investigate how the option to perceive gaze contact affects cooperation and coordination in virtual teams. Specifically, we designed two treatments that allowed teams of three to communicate in a pre-play video meeting before performing a repeated Weakest Link Game (WLG; Brandts & Cooper, 2006). Notably, game-relevant information was provided only after pre-play communication, and the treatments—*Baseline* and *Gaze Contact*—differed solely in regard to the video meeting system featured. In the *Baseline* treatment, a conventional video meeting system enabled team members to see and talk to each other. In the *Gaze Contact* treatment, we used a gaze-adaptive video meeting system that, in addition, processed eye movement data to visualize episodes of gaze contact in real time. Specifically, we continuously informed the team members whether they were simultaneously looking at each other's video feeds or not. Overall, our findings indicate that the option to perceive gaze contact during pre-play communication has the potential to enhance team cooperation. However, we found no evidence for a relationship between gaze contact and team coordination. Further analyses at the individual level supported the robustness of our team-level results and further indicated that the (marginally) positive effect of the *Gaze Contact* treatment on cooperative behavior was driven by an increase in interpersonal trust among team members.

These findings contribute to several strands of literature and hold important practical implications. First, within behavioral economics, our results deepen the understanding of how communication affects economic behavior in teams by identifying gaze contact as a potential type detection mechanism. Second, we advanced methodological concepts for exploring the role of gaze in social interaction by introducing a novel framework, leveraging gaze-adaptive video meeting systems, to systematically manipulate and analyze specific gaze dynamics. This approach provides researchers with a powerful tool to study gaze behavior in highly controlled environments. Third, from an information systems perspective, we addressed a significant challenge in computer-mediated communication by designing an adaptive video meeting system that compensates for the lack of gaze information. This is particularly relevant in the modern workplace, where video meeting systems—despite lacking the nonverbal richness of face-to-face communication—have become essential to facilitate virtual team collaboration. Taken together, this study offers theoretical insights into the role of gaze as a type detection mechanism as well as practical implications for maintaining successful collaboration in virtual teams.

The remainder of this paper is structured as follows. Section 4.2 provides a literature review that highlights the specific research gaps we aimed to address. Section 4.3 presents our study design, main hypotheses, and estimation strategy. Section 4.4 details our findings. Finally, Section 4.5 provides an overall conclusion, outlines the limitations of our study, and proposes avenues for future research.

4.2 Literature Review

4.2.1 Cooperation and Coordination in Social Dilemmas

In experimental economics, the level of cooperation and coordination is typically assessed in controlled settings using social dilemma games (for reviews, see Kollock, 1998; Pletzer et al., 2018; Van Lange et al., 2013). These games create scenarios where individual interests conflict with collective welfare, creating a tension between maximizing personal gains and contributing to the team's utility (Capraro, 2013). One widely used social dilemma game is the WLG (Brandts & Cooper, 2006; Gächter et al., 2024), which elicits cooperation and coordination within teams by requiring participants to decide how much effort to contribute to a joint project. While contributions to the joint project incur individual costs, the team's overall utility depends on the lowest contribution, incentivizing participants to align their efforts with the rest of the team. Any strategy profile in which all participants contribute the same effort constitutes a Nash equilibrium. These equilibria can be Pareto-ranked, with the equilibrium involving the highest contribution Pareto-dominating other strategies. Despite the clear benefits of cooperation and coordination in the WLG, empirical evidence suggests that teams often fail to achieve the Pareto-dominant equilibrium, as choosing the highest option entails substantial risk for individual members (Riedl et al., 2016). Since participants are generally not allowed to observe the effort levels chosen by their team members, opting for the lowest effort level becomes the safest strategy to minimize personal losses. Consequently, selecting higher options reflects an individual's belief that other team members will reciprocate by contributing at least the same level of effort to the joint project.

4.2.2 The Communication Effect

Previous research has consistently shown that communication promotes cooperative behavior in social dilemmas. In particular, opportunities to communicate before or during decision-making significantly increased cooperation rates in social dilemma games by up to 40% (Balliet, 2010; Sally, 1995). While many studies have focused on the verbal content of team communication as a driver of cooperative behavior, recent work suggests that nonverbal signals may play an even more critical role. In particular, He et al. (2017) found that verbalized commitments during communication only accounted for 26.3% of the increase in cooperation rates. The majority of the positive effect (73.7%) was attributed to type detection—the ability to discern cooperative from noncooperative individuals by evaluating nonverbal signals. These findings suggest that the option to exchange nonverbal communication signals is essential to collaborative success.

Consistent with these findings, it has previously been shown that the effectiveness of communication in promoting cooperation and coordination depends on the richness of nonverbal signals in remote settings (Brosig & Weimann, 2003). Although verbal commitments can be made through various modes of computer-mediated communication—whether it takes place via chat, audio, or video-based channels—cooperation rates vary significantly between them (Bicchieri & Lev-On, 2007). The key factor influencing the effectiveness of communication between these channels is the richness of nonverbal signals (Daft & Lengel, 1986; Kahai & Cooper, 2003). Nonverbal signals, such as gestures and facial expressions, enrich communication by providing contextual information that verbal messages alone cannot convey. The more nonverbal signals a channel provides, the greater its potential to foster cooperation (see, e.g., Babutsidze et al., 2021; Cohn et al., 2022; Conrads & Reggiani, 2017; Rockmann & Northcraft, 2008).

Video meeting systems provide the richest form of computer-mediated communication, as they are capable of conveying a broad spectrum of nonverbal signals. Accordingly, video meetings have been shown to produce significantly higher cooperation rates than chats or audio-based channels (see, e.g., Brosig & Weimann, 2003). Nevertheless, conventional video meeting systems still fall short of incorporating the full range of nonverbal signals inherent to face-to-face communication, with the absence of gaze information remaining their greatest shortcoming (Bohannon et al., 2013). This deficit deprives team members of the option to perceive episodes of gaze contact—a nonverbal signal known to play a crucial role in social interactions (Grossmann, 2017; Hietanen, 2018; Kleinke, 1986).

4.2.3 Gaze Contact and Cooperation

According to the Cooperative Eye Hypothesis (Tomasello et al., 2007), the unique morphology of human eyes, such as their high visibility compared to other primates, evolved because it offered a crucial advantage in cooperation and coordination among individuals. This phylogenetic assumption is supported by numerous studies demonstrating that gaze contact fulfills several key functions that form the foundation for successful collaboration (for a comprehensive review, see Grossmann, 2017). More specifically, Hietanen (2018) claims that gaze contact fosters prosocial behavior by automatically triggering positive emotional responses in cooperative settings. In accordance with that finding, a growing body of research shows that the perception of (artificial) gaze contact can significantly enhance cooperation rates in economic games. Specifically, known as the "watching eyes effect," the mere presence of eye images has been found to increase cooperative behavior in both laboratory and real-world environments (see, e.g., Burnham & Hare, 2007; Ernest-Jones et al., 2011; Haley & Fessler, 2005). Additional studies showed that gaze contact plays an important role in facilitating coordination during decision-making. For instance, Wyman et al. (2013) found that the opportunity to engage in gaze contact enabled 4-year-old children to coordinate their actions with an adult in a Stag Hunt game, highlighting the role of direct gaze between individuals as a strategic signal even from an early age.

However, to the best of our knowledge, there have been no studies examining how the option to perceive gaze contact affects economic behavior in virtual teams. This gap in research is especially compelling since video meetings have become a commonplace mode of computer-mediated communication and are not capable of transmitting gaze information. Given that most individuals are conditionally cooperative (i.e., generally willing to reciprocate if they assume their counterpart will cooperate; Fischbacher et al., 2001), the difficulty in distinguishing between cooperative and noncooperative individuals in the absence of gaze information bears negative consequences for successful collaboration in virtual teams (He et al., 2017). As a result, an increasing body of research has begun to investigate potential solutions to compensate for the absence of gaze contact in video meetings.

4.2.4 Integration of Gaze Contact in Video Meetings

One common recommendation to mitigate the lack of gaze information in video meetings is to actively look into the camera during video meetings (Basch et al., 2021; Bohannon et al., 2013). However, this solution poses another challenge, as it prevents individuals from attending the screen, where they can see their team members or the task at hand. Further strategies to overcome this problem include optimizing conventional video meeting setups by positioning the camera at eye level or relying on innovative setups that create the illusion of gaze contact. For instance, Kaiser et al. (2022) found that such a solution improved the feeling of interpersonal connection between individuals. The authors concluded that the inability to perceive episodes of gaze contact in video meetings disrupts the natural processing of nonverbal signals, thereby diminishing the sense of social cohesion.

However, despite potential advantages over conventional video meeting practices, these approaches overlooked the fact that they simulate constant gaze contact, which does not mirror the natural dynamics of gaze in social interactions. In face-to-face communication, gaze contact typically alternates with periods of gaze aversion and joint attention (see, e.g., Emery, 2000; Pfeiffer et al., 2013). Prolonged, unbroken episodes of gaze contact could even have adverse effects, as they have previously been associated with social dominance and competitive behavior (Jarick & Kingstone, 2015). In cooperative settings, gaze contact generally occurs in relatively brief episodes of a few seconds. Moreover, the simulation of constant gaze contact becomes especially uninformative in team settings involving multiple individuals, where it is unclear who is actually being visually attended to, causing the signal to be effectively lost.

More advanced approaches to integrating gaze contact into video meetings utilize adaptive information systems. For instance, Schuessler et al. (2024) explored a system employing six cameras to create the illusion of gaze contact by visualizing each team member's head and dynamically adjusting its rotation to match the focus of visual attention. While this solution represents a significant step toward replicating the natural dynamics of social gaze in remote settings, its implementation requires a complex and resource-intensive setup. Furthermore, simulating gaze contact by displaying only the head and its direction excludes the visibility of other nonverbal signals, such as body language, which are essential for capturing the full richness of face-to-face communication. Kumar et al. (2024), on the other hand, introduced a system designed to convey gaze information as a signal of visual attention without compromising access to other nonverbal signals. Specifically, their system recorded and visualized the eye movement data from multiple participants in real time to display the team members' names within circular bubbles in the upper right corner of each participant's video feed. In particular, this visualization indicated for each video feed who was currently directing their visual attention to it. This solution was integrated into the familiar interface of conventional video meeting systems, balancing the need for gaze awareness with the preservation of other nonverbal signals. However, it did not convey the natural signal of gaze contact. While indicating when someone was being looked at, participants had to shift their gaze away from others to their own video feed to determine who was paying attention to them, disrupting the natural flow of communication.

Reuscher et al. (2024) further advanced this concept by developing a gaze-adaptive system that relies on real-time eye movement data from multiple individuals to visualize episodes of gaze contact. Specifically, when two team members simultaneously looked at each other during the video meeting, an eye symbol appeared on their respective video feeds. This allowed participants to infer whether others were paying attention to them by simply looking at their team member's video feeds, replicating the communicative function of gaze contact in face-to-face communication. Although this gaze-adaptive video meeting system was generally perceived as beneficial by participants, the visualization via an explicit eye symbol introduced certain challenges. In particular, the eye symbol in the lower-right corner of the video feed distracted participants from the conversation by causing them to shift their gaze back and forth between the symbol and their team members.

Based on these insights, we adapted the system by replacing the eye symbol with a green frame around the video feed of the team members engaging in gaze contact. This subtle yet salient signal allowed participants to easily recognize when gaze contact was established, bridging the gap between computer-mediated and face-to-face communication. By using the system to experimentally manipulate the option to perceive gaze contact, we aimed to further understand the mechanisms of the communication effect and, especially, the role of gaze contact for cooperation and coordination in virtual teams.

4.3 Study Design and Methods

To examine how the option to perceive gaze contact affects cooperation and coordination in virtual teams, we conducted a controlled laboratory study on a three-player WLG with (not game-related) pre-play communication (Brandts & Cooper, 2006).[13] The study consisted of a two-stage team task, followed by a post-experimental survey. Each session included three participants who formed a team. In the first stage, teams engaged in pre-play communication for eight minutes via video meetings, in which we experimentally manipulated the option to perceive gaze contact between two treatments (see Section 4.3.2). In the second stage, participants received the instructions for the WLG, with all information being common knowledge (see Appendix C.2), before proceeding to perform ten consecutive rounds with their team.[14]

4.3.1 Procedure

Below, we outline the procedure, encompassing the two-stage team task and post-experimental survey, for both treatments in detail.

Stage 1: Pre-Play Communication. In the first stage, participants were informed about the general process of the team task before engaging in pre-play communication. In particular, they learned that they would form a team with two other participants and get to know them in an eight-minute video meeting. Next, they were shown a short tutorial presenting the user interface and functionality of the video meeting system. Depending on the treatment, this tutorial also demonstrated the system's capability to visualize gaze contact. Moreover, we used an established method to promote conversational flow between participants during pre-play communication by asking them to indicate their preferences

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[13] The experiment was preregistered at AsPredicted (#176471) and approved by the ethics committee of the KIT.

[14] We used oTree (v5.10.4; Chen et al., 2016) to code the experiment. Video meetings were facilitated using a locally hosted instance of the open-source platform Jitsi, integrated into oTree via its iFrame API (Jitsi Meet, 2024).

regarding six different types of holidays and to discuss them during the video meeting (see, e.g., Kaiser et al., 2022; Koudenburg et al., 2013). This approach enabled us to control the content of communication and the potential effects of similar preferences within teams.

Stage 2: Weakest Link Game. Following the pre-play communication stage, participants entered the second stage, where they received further instructions and performed the WLG with their team. Drawing on the paradigm established by Brandts and Cooper (2006), participants were asked to imagine themselves as team members of a firm, with each of the ten rounds of the WLG representing a work week. During each round, they were required to allocate 40 work hours between a team project A and an individual project B. Specifically, each of three participants', $i = 1, 2, 3$, contribution of work hours was denoted by $x_i \in \{0,10,20,30,40\}$, with remaining hours allocated to the individual project B. In order to capture additional efforts of working on a joint team project instead of an individual project, contributing work hours to the team project A, x_i, created additional costs, with a cost factor $\mathrm{c} = 5$. Participants also received a bonus depending on the "success" of the team project A. This bonus was determined by the lowest contribution of work hours to the team project A in a given round, $\min(x_1, \dots, x_i)$, and a bonus rate $B = 6$. Accordingly, each participant's payoff was determined as follows:

$$\pi_i = 200 - c(x_i) + B(\min(x_1, \dots, x_i)) = 200 - 5(x_i) + 6(\min(x_1, \dots, x_i))$$

Similar to Gächter et al. (2024), participants also stated their beliefs about their team members' lowest contribution and rated their confidence in these beliefs on a scale from 1 ("not confident at all") to 7 ("completely confident") in the first and final rounds of the WLG. After each round, participants were informed about their own contribution, the lowest contribution made within their team, and their resulting payoff.

Post-Experimental Survey. After completing the team task, participants answered a post-experimental survey that included the Inclusion of Other in the Self scale (IOS; Aron et al., 1992) and We scale (Cialdini et al., 1997) to assess team cohesion as suggested by Gächter et al. (2024). Next, they completed three scales measuring their feeling of psychological safety, availability, and engagement (May et al., 2004) experienced during pre-play communication. Furthermore, the post-experimental survey included a combination of selected items from the global preference survey (Falk et al., 2018; 2023) and the interpersonal trust scale (Beierlein et al., 2014) to elicit risk and social preferences. Finally, we collected gaze anxiety scores (Domes et al., 2016), demographic information (age, gender, ethnicity, field of study, previous participation in experimental study, familiarity within teams), and self-assessments of attractiveness (Ebner et al., 2010; Kemper et al., 2014).[15]

4.3.2 Treatments and Eye-Tracking Setup

We designed two treatments—*Baseline* and *Gaze Contact*—between which we only manipulated the option to perceive gaze contact. In both treatments, participants communicated in a (not game-related) pre-play video meeting. In the *Baseline* treatment, team members used a conventional video meeting system, where they could see and talk to each other, thereby having access to both verbal and nonverbal signals. In the *Gaze Contact* treatment, team members used a gaze-adaptive video meeting system that additionally processed gaze information to visualize episodes of gaze contact in real time, enriching the communication with gaze information compared to the *Baseline* treatment. In particular, we informed the participants when they were looking at each other's video feeds simultaneously by highlighting their respective video feeds with a green frame (see Figure 4.1).

To achieve this, we tracked the eye movements of each participant using desktop-mounted Tobii 4C eye-tracking devices with a sampling rate of 90Hz (Tobii, 2024; see Appendix C: Figure C.1). In order to visualize episodes of gaze contact, we developed a gaze-adaptive video meeting system that synchronized eye movement data among multiple participants. Specifically, the system continuously determined what the individual team members were looking at within their respective screens. This data was used to determine, for each team member, which specific area of the video meeting interface—categorized as the video feed of team members A, B, C, or elsewhere on the screen—contained the most gaze points during the last second. If two team members had looked at each other's video feed for the

[15] Previous research has revealed a strong relationship between physical attractiveness and economic behavior (see, e.g., Hansson et al., 2024; Voit et al., 2023). Physically attractive individuals are typically perceived as more cooperative and trustworthy, a phenomenon known as the "beauty premium" effect (Andreoni & Petrie, 2008). However, individuals also face a "beauty penalty" if they fail to meet the high expectations associated with their appearance (Wilson & Eckel, 2006). These findings underscore the importance of controlling for physical attractiveness when investigating non-anonymous team collaboration.

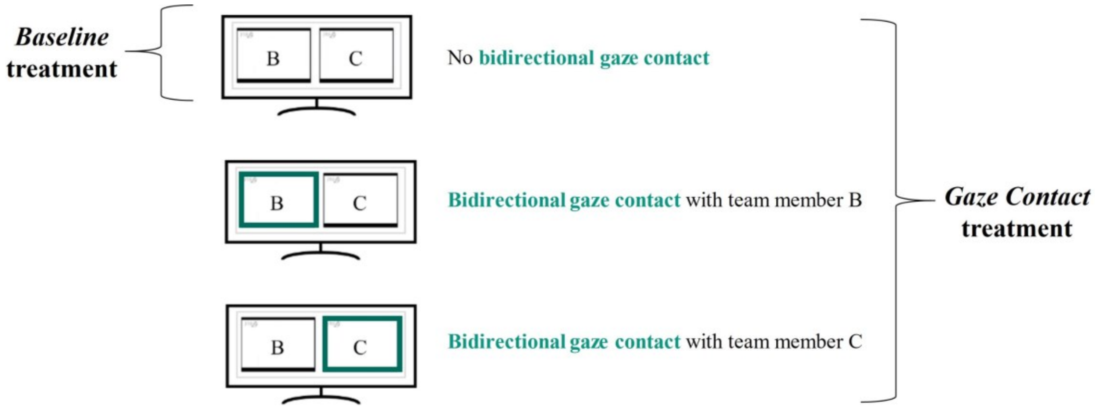

Figure 4.1: Possible interface adaptations from team member A's perspective in the *Baseline* and the *Gaze Contact* treatments.

majority of the previous second, the gaze contact visualization was triggered for the next second. Accordingly, the visualization remained for prolonged episodes of gaze contact (see Figure 4.2).[16] After extensive pre-testing, we decided to conduct the study in a local network to minimize latency and ensure smooth and real-time visualization. Moreover, we validated the system's technical feasibility in a pilot study with 36 participants (Reuscher et al., 2024).

4.3.3 Sample

We conducted the study at the KD2Lab. Participants were recruited from the corresponding KD2Lab subject pool using ORSEE (Greiner, 2015). Participation required advanced proficiency in German (C1/C2 level) as well as normal or corrected-to-normal vision and hearing. Upon providing informed consent, participants engaged in the 45-minute study and received €9 for their participation, €3 for careful completion of the post-survey (i.e., no more than one failed attention check), and an additional amount of up to €7.20 based on their payoff in a randomly selected round of the WLG (M = 14.62).

[16] Since we aimed to visualize episodes of bidirectional gaze contact, we qualitatively analyzed if the gaze points triggering the visualization (i.e., those within the defined area of the video feed) indeed corresponded to participants looking at each other's faces, rather than other parts of the image such as the upper body or background. The resulting heatmap confirmed that participants (n = 156) primarily directed their gaze at their team members' faces when looking at the video feeds (see Appendix C: Figure C.2).

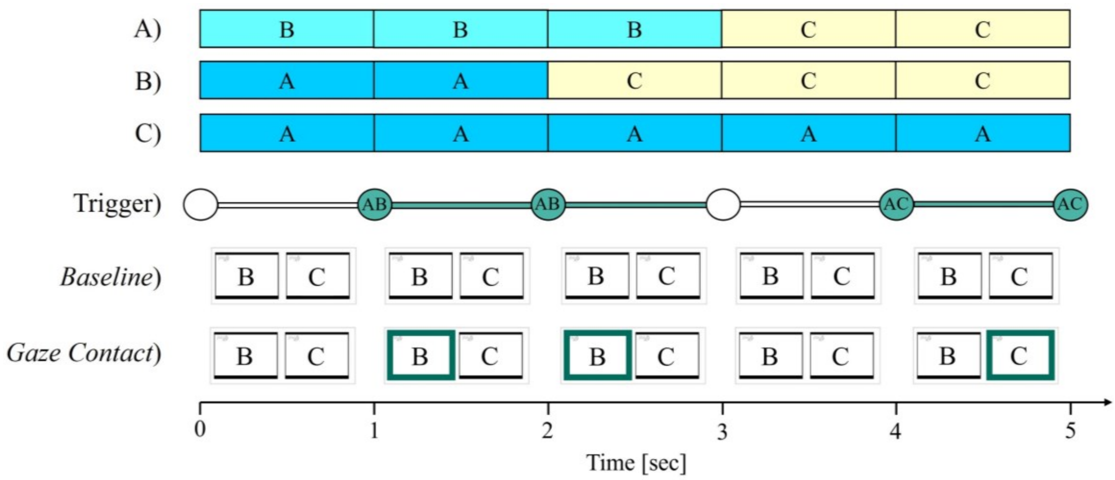

Figure 4.2: Three exemplary sequences of gaze to the areas of interest captured over one-second intervals, along with the corresponding visualizations from team member A's perspective in the *Baseline* and the *Gaze Contact* treatments.

In total, 156 participants (46% female), aged between 18 and 42 years (M = 23.82, SD = 3.99), were included in the study.[17] We randomly assigned them to teams of three, with each team comprising at least one male and one female to ensure gender diversity and, thus, enhance the generalizability of our findings (for potential effects of varying gender compositions, see Hardt et al., 2024). The teams were then randomly allocated to either the *Baseline* or the *Gaze Contact* treatments. Finally, each treatment encompassed 26 gender-mixed teams.

4.3.4 Data Preparation and Key Variables

To prepare our data for statistical analyses, we first calculated the scores for the included scales according to their respective manuals. Moreover, we dichotomized the following variables for inclusion in our additional analyses at the individual level: *gender*, *ethnicity*, *field of study*, and *familiarity* within teams (see Appendix C: Table C.1).

Cooperation and Coordination. To examine how our treatments influenced cooperation and coordination in teams, we analyzed their effects on three well-established metrics

[17] Power analysis with G*Power (v3.1.9.7; Faul et al., 2009) yielded a required sample size of 92 teams, using an alpha error probability of 0.05, a statistical power of 0.80, and a low effect size (f^2 = 0.10). However, constraints in the subject pool limited data collection to 52 teams (156 participants).

derived from the aggregation of individual decisions in the WLG: *Minimum effort*, *average effort*, and *wasted effort* (see, e.g., Brandts & Cooper, 2006; Gächter et al., 2024). *Minimum effort* and *average effort* served as measures of cooperation within teams. Whereas *minimum effort* was defined as the lowest contribution within a team that determined the team's bonus, the *average effort* depicted the mean contribution made by all team members, thereby indicating the team's overall level of cooperation. In addition to examining the level of cooperation, *wasted effort* served as a measure of coordination within teams. It was defined as the sum of effort that exceeded the *minimum effort* in a given round of the WLG. For example, if three team members contributed 10, 20, and 30 work hours to the team project A, the *wasted effort* would have amounted to 30 work hours in this round.

Team Cohesion and Homophily. We calculated *team cohesion* in two procedural steps, following the guidelines of Gächter et al. (2024). Thus, we first averaged the IOS and We scale scores to compute the level of *oneness* at the individual level (Cialdini et al., 1997). Second, we averaged these individual *oneness* scores within each team.

Gächter et al. (2024) also accounted for the effects of *homophily* within teams, arguing that team members exhibit high levels of *team cohesion* when sharing similar socio-demographic characteristics. Following their approach, we first transformed each variable of interest—*gender*, *age*, *ethnicity*, *attractiveness*, and *field of study*—into more nuanced, discrete categories (see Appendix C: Table C.1).[18] In a further step, we computed five subindices at the team level by identifying the most frequent category for each variable within teams, and then calculating the proportion of team members belonging to this dominant category (e.g., if a team consists of three members, with two being female and one male, the subindex for *gender* would be 0.67, indicating that two-thirds of the team shares the same gender identity). Finally, we computed overall *homophily* scores for each team by averaging the five subindices.

[18] Note that some categories differ from those of the control variables used in our main analysis (e.g., econ-related field of study: 0 = not economics-related; 1 = economics-related), as the goal here was to assess the degree of *homophily* within teams across multiple distinct categories. For instance, the field of study was divided into more specific groups: 1 = engineering, 2 = mathematics/physics/informatics, 3 = natural sciences, and 4 = arts/education. This more nuanced categorization allowed for an examination of team similarities across various dimensions.

4.3.5 Main Hypotheses and Estimation Strategy

Previous research has consistently shown that communication is critical in facilitating cooperation within teams, particularly in contexts involving social dilemmas (for reviews, see Balliet, 2010; Sally, 1995). A key mechanism underlying this effect is type detection (He et al., 2017). This mechanism is particularly important for conditionally cooperative individuals, who are more likely to contribute effort when they believe that others will do the same (Fischbacher et al., 2001). Therefore, the ability to accurately detect these prosocial motives should influence team cooperation. In face-to-face communication, gaze contact serves as a powerful signal known to naturally trigger positive emotional responses in cooperative settings (Hietanen, 2018; Ho et al., 2015; Grossmann, 2017; Kleinke, 1986; Pfeiffer et al., 2013). However, conventional video meeting systems fall short in conveying gaze information. Therefore, a gaze-adaptive video meeting system that visualizes gaze contact in real time might support type detection by enriching the depth of information that can be exchanged between team members (see, e.g., Fischbacher et al., 2022; Hausfeld et al., 2021). Given the importance of type detection in social dilemmas, we expected that the option to perceive gaze contact via a gaze-adaptive video meeting system positively affects cooperation and coordination in teams when compared to a conventional video meeting system.

Cooperation. Specifically, we hypothesized that teams using the gaze-adaptive video meeting system during pre-play communication would exhibit higher *minimum effort* levels in the WLG compared to those using the conventional video meeting system. We proposed that the option to perceive gaze contact would enable participants to better assess the social type of their team members, reducing uncertainty about other's contributions. As a result, we anticipated that even the least contributing member would exert more effort toward the team project A, thereby raising the *minimum effort* observed within teams.

> **H1.** *The minimum effort within teams is higher in the Gaze Contact treatment than in the Baseline treatment.*

Similarly, we hypothesized that the *average effort* would be higher in teams using the gaze-adaptive system during pre-play communication as compared to those using the conventional video meeting system. We argued that the improved richness of communication through the inclusion of gaze information would facilitate a more accurate evaluation of team members' prosocial motives, encouraging all members to contribute more effort. Accordingly, we expected that the cumulative effect of each team member's increased cooperativeness would be reflected in higher *average effort* levels in the *Gaze Contact* treatment than in the *Baseline* treatment.

> **H2.** *The average effort within teams is higher in the Gaze Contact treatment than in the Baseline treatment.*

Coordination. Furthermore, we hypothesized that teams using the gaze-adaptive system would waste less effort in the process of allocating their work hours to either the team project A or the individual project B. Although higher *minimum effort* and *average effort* levels were desirable, we suggested that they must be achieved through efficient coordination among team members to maximize their team's utility. Specifically, we expected that the gaze-adaptive video meeting system would enhance type detection, thereby reducing instances in which effort is misaligned or excessive.

> **H3.** *The wasted effort within teams is lower in the Gaze Contact treatment than in the Baseline treatment.*

Estimation Strategy. To test our hypotheses (**H1**, **H2**, and **H3**), we first conducted non-parametric (two-sided Mann-Whitney U tests) and semi-parametric (two-sided t-tests) analyses to identify treatment differences between our key variables—*minimum effort*, *average effort*, and *wasted effort*.[19] These tests were performed using data from the first round, aggregated data across all rounds, and specific blocks of rounds (1 to 5, and 6 to 10) of the WLG. This initial analysis provided insights into the effects of the *Gaze Contact* treatment during different stages of the game without imposing strict assumptions about the data's distribution.

Subsequently, to test the robustness of our first hypothesis (**H1**) while appropriately accounting for the ordinal nature of *minimum effort* (0, 10, 20, 30, or 40), we employed ordered probit regressions with clustering at the team level, following Gächter et al. (2024). We analyzed behavior both in the first round and across all rounds. Focusing on the first round allowed us to isolate the treatment effect since participants had not yet been

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[19] We performed all statistical calculations in Stata (StataCorp., 2023).

influenced by prior interactions within the WLG. Conversely, analyzing all rounds enabled us to capture the treatment's impact on behavior over time, revealing patterns of adaptation and learning. Both approaches provided complementary insights into the effects of the *Gaze Contact* treatment on cooperation and coordination. In extending our analyses to include data from all rounds, we applied ordered probit panel regressions (random effects) to account for the repeated measurements over time. Since decisions made in consecutive rounds were not independent, we included round dummies (relative to round 1) in all panel models to control for time-specific effects and address potential intercorrelations between rounds. To test the robustness of our findings regarding the second hypothesis (**H2**) and the third hypothesis (**H3**), we repeated this estimation strategy using OLS regressions.

Notably, we employed a step-wise approach to include the following team-level control variables in our regression analyses: demographics (*male-dominant ratio*, *average age*), *team cohesion*, and *homophily*. Recognizing that *team cohesion* and some of the variables used to compute homophily (e.g., self-rated *attractiveness*) were endogenous, we first tested whether these control variables were affected by our treatments using non-parametric and semi-parametric tests. We found no significant treatment effects on these variables (see Appendix C: Table C.2 and Table C.3), suggesting that including them as control variables did not introduce considerable bias due to endogeneity.

In addition, we conducted further robustness checks at the individual level focusing on *individual effort* and *beliefs* about *minimum effort* levels in the WLG. Following the same approach used for testing our main hypotheses, we began by conducting non-parametric and semi-parametric tests to explore differences in *individual effort* and *beliefs* between our treatments. We then applied ordered probit regressions to test the robustness of our findings by adding further control variables at the individual level. Finally, we extended this analysis to cover all rounds using ordered probit panel regressions, including round dummies (relative to round 1) and clustering at the team level to address intercorrelations between rounds and within teams. By systematically applying these methods, we ensured a comprehensive examination of the treatment effects, accounting for both initial and dynamic behavioral responses throughout the rounds of the WLG, while addressing potential statistical concerns related to our data structure and endogenous variables.

4.4 Results and Discussion

As a first step, we conducted randomization checks to ensure comparability across treatments. Both non-parametric (two-sided Mann-Whitney U tests) and semi-parametric (two-sided t-tests) tests revealed no significant differences in socio-demographic and team characteristics between *Baseline* and *Gaze Contact* (see Appendix C: Table C.2 and Table C.3). These findings indicate that the randomization process was successful, providing a solid foundation for analyzing our hypotheses. For additional information on the summary statistics and pairwise correlations at both the individual and team levels pooled across treatments, please refer to Appendix C: Table C.4 and Table C.5.

4.4.1 Cooperation

In this section, we present and discuss the results pertaining to our **first and second hypotheses** regarding the effects of the *Gaze Contact* treatment on team cooperation within the WLG. Specifically, we examined whether the option to perceive gaze contact during pre-play communication positively affected cooperation measured as *minimum effort* (**H1**) and *average effort* (**H2**).

Minimum Effort. Overall, the level of cooperation in the WLG was relatively low, as evidenced by a mean *minimum effort* of 12.12 in the first round (n = 52, SD = 7.76, Min = 0, Max = 30), and 10.69 (n = 520, SD = 10.23, Min = 0, Max = 40) across all rounds. Throughout the ten rounds, only five teams achieved a *minimum effort* of 30 or higher, with four of these five teams belonging to the *Gaze Contact* treatment. Conversely, six of eight teams that failed to raise *minimum effort* levels above zero were part of the *Baseline* treatment.

In line with these findings, mean *minimum effort* levels were descriptively higher in the *Gaze Cont*act treatment compared to the *Baseline* treatment throughout all ten rounds of the WLG (see Figure 4.3). However, despite these descriptive differences between treatments, non-parametric and semi-parametric tests revealed no significant treatment effects on *minimum effort* when considering the first round, the averages across all rounds, or the averages of the first and second halves of the rounds (see Table 4.1).

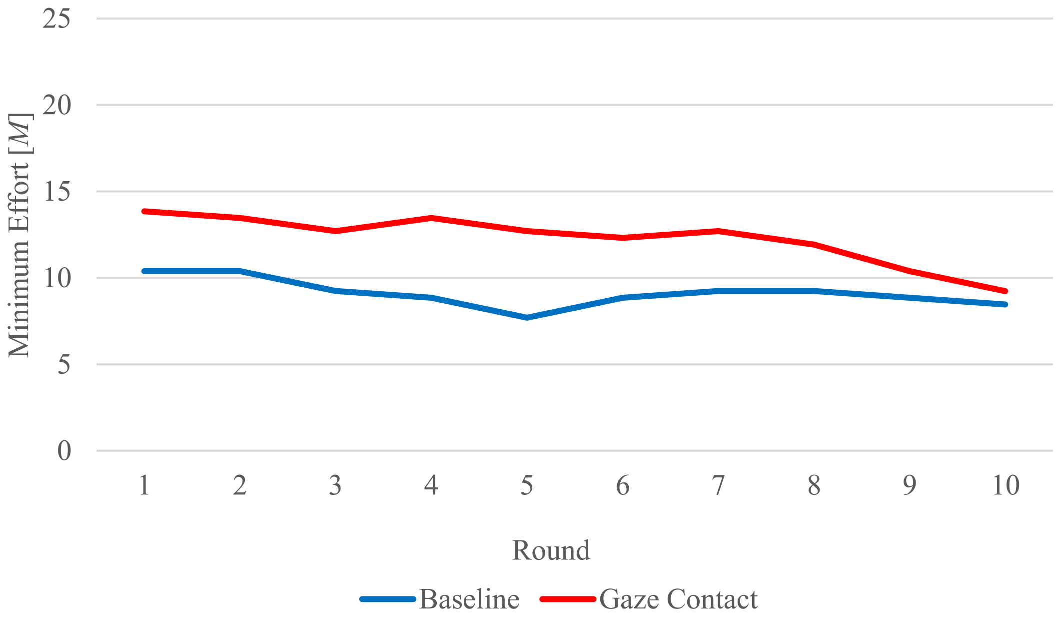

Figure 4.3: Progression of the mean *minimum effort* throughout the ten rounds of the Weakest Link Game.

	Baseline (n = 26)	**Gaze Contact (n = 26)**	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Minimum Effort	***M* (*SD*)**	***M* (*SD*)**	***z***	***p***	***t*(50)**	***p***
First round	10.38 (8.24)	13.85 (6.97)	1.44	.149	1.64	.108
All rounds	9.12 (8.45)	12.27 (10.11)	1.23	.218	1.22	.228
Rounds 1-5	9.31 (8.04)	13.23 (9.33)	1.52	.130	1.62	.111
Rounds 6-10	8.92 (9.07)	11.31 (11.36)	0.79	.431	0.84	.407

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.1: Non-parametric and semi-parametric treatment comparisons (n = 52) of *minimum effort* in the first round, across all rounds, as well as the first and second halves of the rounds by *Baseline* and *Gaze Contact*.

In contrast, ordered probit regressions revealed a marginally significant positive effect of the *Gaze Contact* treatment on *minimum effort* in the first round (p = .088; see Table 4.2). This effect remained robust when adding further control variables in a step-wise approach. Specifically, when adding *male-dominant ratio* as well as *average age* in the second (p = .052), *team cohesion* in the third (p = .065), and *homophily* in the fourth models (p = .050), the positive effect of the *Gaze Contact* treatment on *minimum effort* persisted at a marginally significant level.[20] Although these effects were only marginally significant, they suggest that the option to perceive gaze contact during pre-play communication may have positively influenced team cooperation. However, the evidence is not strong enough to draw definitive conclusions. Given that we did not achieve the required sample size of 92 teams, our study might have lacked the power to detect the *Gaze Contact* treatment's effects with statistical significance below the conventional 5% threshold. Therefore, additional data is warranted to validate the robustness of our findings.

Examining marginal effects based on the estimates from the fourth model provided deeper insights into the impact of the *Gaze Contact* treatment on team cooperation. The analyses indicated that the *Gaze Contact* treatment significantly increased the likelihood of teams attaining a *minimum effort* of 20 by 16% (z = 2.07, p = .038), while marginally significantly decreasing the probability of opting for the lowest *minimum effort* of zero by 13% (z = -1.83, p = .068). This pattern suggests that enabling the option to perceive gaze contact during pre-play communication not only enhanced participants' willingness to opt for a medium level of cooperation but also reduced the chances of minimal cooperative engagement in the first round of the WLG.

In a further step, we expanded our analyses to include all rounds using ordered probit panel regressions. When considering only the round dummies (relative to round 1) as control variables, the treatment effect was not statistically significant (p = .187; see Table 4.3). However, we observed marginally significant positive treatment effects on *minimum effort* in the first (p = .095), second (p = .056), and third models (p = .059). Testing the marginal effects based on the estimates from the fourth model revealed that the *Gaze Contact*

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[20] Importantly, since the control variables did not differ significantly between treatments (see Appendix C: Table C.2), it is unlikely that their inclusion introduced endogeneity bias into the estimated treatment effects.

Dep. Var.: Minimum Effort	**(1) First Round**	**(2) First Round**	**(3) First Round**	**(4) First Round**
Gaze Contact	0.510*	0.579*	0.547*	0.582*
	(0.300)	(0.298)	(0.296)	(0.297)
Male-dominant Ratio		0.439	0.267	0.338
		(0.310)	(0.312)	(0.315)
Average Age		-0.014	0.000	0.014
		(0.066)	(0.066)	(0.068)
Team Cohesion			0.434***	0.415***
			(0.141)	(0.145)
Homophily				-3.544
				(2.724)
Log-pseudolikelihood	-57.112	-56.116	-50.974	-49.922
Pseudo R^2	0.024	0.041	0.129	0.147
χ^2-statistic	2.90	5.94	14.55	18.92
p-value	.088	.114	.129	.002
Observations	52	52	52	52

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.2: Ordered probit regressions with *minimum effort* in the first round as the dependent variable.

treatment marginally significantly increased the probability of teams achieving a *minimum effort* of 20 by 7% ($z = 1.88$, $p = .061$), while marginally significantly decreasing the likelihood of exhibiting a *minimum effort* of zero by 10% ($z = -1.80$, $p = .072$).

These results align with our findings on *minimum effort* in the first round, further supporting the notion that the option to perceive gaze contact had a persistent yet subtle influence on cooperative behavior, as proposed by our first hypothesis (**H1**). However, it is important to note that the treatment effects remained only marginally significant, limiting the strength

Dep. Var.: Minimum Effort	**(1) All Rounds**	**(2) All Rounds**	**(3) All Rounds**	**(4) All Rounds**
Gaze Contact	1.059	1.256*	0.763*	0.767*
	(0.803)	(0.752)	(0.400)	(0.406)
Male-dominant Ratio		1.643**	0.774**	0.787**
		(0.780)	(0.376)	(0.354)
Average Age		-0.072	-0.014	-0.012
		(0.169)	(0.087)	(0.087)
Team Cohesion			1.558***	1.554***
			(0.217)	(0.220)
Homophily				-0.611
				(3.187)
Log-pseudolikelihood	-384.107	-381.513	-357.301	-357.283
Pseudo R^2	0.002	0.009	0.072	0.072
χ^2-statistic	25.44	32.24	105.42	106.14
p-value	.005	<.001	<.001	<.001
Observations	520	520	520	520

Cluster-robust standard errors in parentheses; round dummies (relative to 1) always included
$^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Table 4.3: Ordered probit panel regressions (random effects) with *minimum effort* across all rounds as the dependent variable.

of our conclusions. This underscores the need for cautious interpretation and further investigation to better understand the conditions under which gaze contact may enhance team cooperation.

Average Effort. In contrast to the relatively low *minimum effort* in the WLG, the *average effort* was at a medium level. Specifically, teams exhibited a mean *average effort* of 21.86 in the first round (n = 52, SD = 6.81, Min = 6.67, Max = 36.67). When considering all rounds, *average effort* remained moderate with a mean of 15.17 (n = 520, SD = 10.14, Min = 0, Max = 40). Similar to the pattern observed for *minimum effort*, mean *average effort*

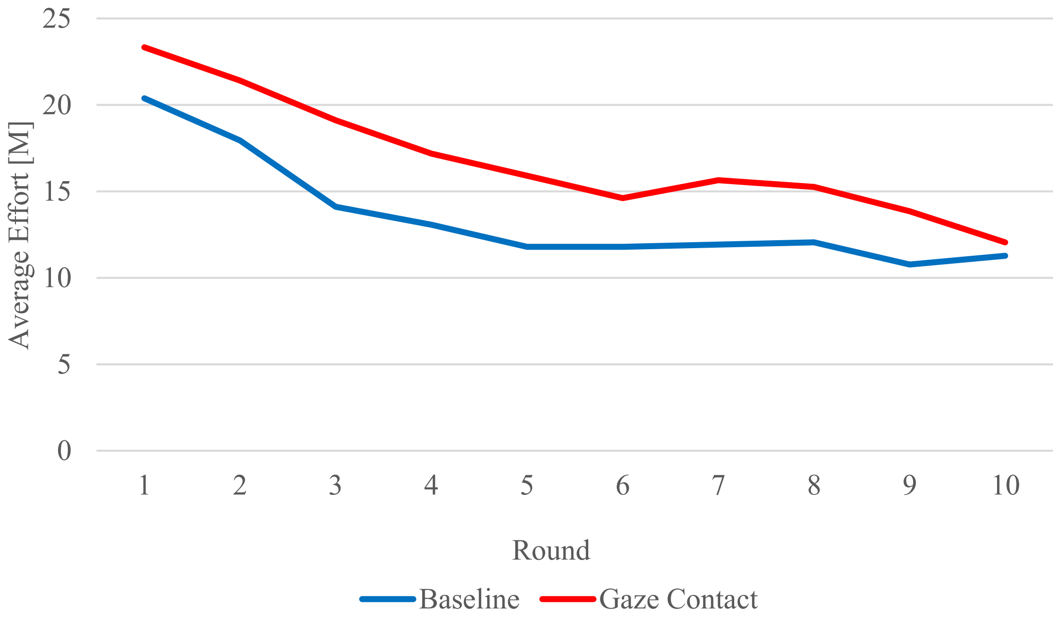

Figure 4.4: Progression of the mean *average effort* throughout the ten rounds of the Weakest Link Game.

levels were descriptively higher in the *Gaze Cont*act treatment compared to the *Baseline* treatment throughout all ten rounds of the WLG (see Figure 4.4). However, two-sided t-tests only revealed a marginally significant positive treatment effect on *average effort* when specifically examining data from the first five rounds combined (p = .082; see Table 4.4).

Since two-sided t-tests examining the first round, all rounds, and the second half of rounds did not yield significant effects, the observed treatment effect in the first half of rounds of the WLG was likely a statistical artifact due to multiple hypothesis testing rather than robust evidence of an early-round treatment effect. Consistent with this assumption, non-parametric Mann-Whitney U tests also showed no significant treatment differences (see Table 4.4). Although these results strengthen the notion that the marginal significant finding may be a statistical artifact, it is important to note that non-parametric tests did not account for differences in the variance of *average effort* between treatments. Given that *average effort* consistently exhibited higher standard deviations in the *Gaze Contact* treatment, non-parametric tests may have lacked the sensitivity to detect significant differences. This limitation could explain the discrepancy between our non-parametric and semi-parametric test results. Nevertheless, the overall evidence does not support our assumption that the option to

	Baseline (n = 26)	**Gaze Contact (n = 26)**	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Average Effort	***M* (*SD*)**	***M* (*SD*)**	z	p	$t(50)$	p
First round	20.38 (6.55)	23.33 (6.86)	1.55	.122	1.58	.119
All rounds	13.51 (7.91)	16.83 (9.63)	1.08	.280	1.36	.180
Rounds 1-5	15.46 (7.09)	19.38 (8.74)	1.59	.113	1.77	.082*
Rounds 6-10	11.56 (9.07)	14.28 (10.93)	0.72	.469	0.98	.333

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 4.4: Non-parametric and semi-parametric treatment comparisons (n = 52) of *average effort* in the first round, across all rounds, as well as the first and second halves of the rounds by *Baseline* and *Gaze Contact*.

perceive gaze contact during pre-play communication influenced *average effort*, which contradicts our second hypothesis (**H2**).

In a further step, we employed OLS regressions to test the *Gaze Contact* treatment's effect on *average effort* while controlling for potentially confounding variables. In the first model, we found no significant treatment effect on *average effort* in the first round of the WLG (p = .119; see Table 4.5). However, when considering further control variables, we observed marginally significant positive treatment effects in the second (p = .075), third (p = .094), and fourth models (p = .095). The observed treatment effects on *average effort* in the first round align with our previous findings on *minimum effort*, indicating a consistent, though subtle, influence of the *Gaze Contact* treatment on cooperative behavior. Hence, although only marginally significant, these effects align with our second hypothesis (**H2**). Including not only the first but all rounds of the WLG in the analyses, using OLS panel regressions, further highlighted the potential benefits of enabling gaze content during pre-play communication. Consistent with **H2**, we observed marginally significant positive treatment effects on *average effort* in the second (p = .085), third (p = .054), and fourth models (p = .056; see Table 4.6).

Dep. Var.: Average Effort	**(1) First Round**	**(2) First Round**	**(3) First Round**	**(4) First Round**
Gaze Contact	2.949	3.442*	3.024*	3.056*
	(1.861)	(1.894)	(1.774)	(1.796)
Male-dominant Ratio		2.476	1.513	1.675
		(1.940)	(2.025)	(2.034)
Average Age		-0.369	-0.315	-0.276
		(0.416)	(0.404)	(0.406)
Team Cohesion			1.660**	1.585**
			(0.781)	(0.815)
Homophily				-8.923
				(14.524)
Constant	20.385***	27.345***	20.681*	26.184*
	(1.285)	(9.892)	(10.381)	(14.673)
R^2	0.048	0.104	0.192	0.200
F-statistic	2.51	1.52	2.65	2.28
p-value	.119	.221	.043	.061
Observations	52	52	52	52

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: OLS regressions with *average effort* in the first round as the dependent variable.

Overall, these findings suggest that the gaze-adaptive video meeting system helped team members recognize each other’s prosocial motives. Since individuals are generally more willing to cooperate when they expect others to do the same (Fischbacher et al., 2001), one possible explanation is that the option to perceive gaze contact facilitated type detection (He et al., 2017). We further explored potential mechanisms by conducting additional analyses at the individual level (see Section 4.3.3).

Dep. Var.: Average Effort	**(1) All Rounds**	**(2) All Rounds**	**(3) All Rounds**	**(4) All Rounds**
Gaze Contact	3.321	4.151*	2.900*	2.894*
	(2.443)	(2.412)	(1.503)	(1.516)
Male-dominant Ratio		5.580**	2.697*	2.665**
		(2.324)	(1.443)	(1.344)
Average Age		-0.331	-0.172	-0.180
		(0.472)	(0.297)	(0.301)
Team Cohesion			4.972***	4.986***
			(0.626)	(0.611)
Homophily				1.747
				(12.021)
Constant	20.199***	24.138***	4.183	3.106
	(1.445)	(11.591)	(7.884)	(10.773)
R^2	0.122	0.204	0.557	0.557
χ^2-statistic	90.91	117.64	343.27	344.61
p-value	<.001	<.001	<.001	<.001
Observations	520	520	520	520

Cluster-robust standard errors in parentheses; round dummies (relative to 1) always included
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: OLS panel regressions (random effects) with *average effort* across all rounds as the dependent variable.

4.4.2 Coordination

Next, we discuss the results related to our third hypothesis (**H3**), concerning the effects of the *Gaze Contact* treatment on team coordination within the WLG. In particular, we investigated whether the option to perceive gaze contact during pre-play communication influenced the participant's ability to align their effort levels, operationalized as *wasted effort*.

Wasted Effort. Summary statistics revealed a high mean *wasted effort* level of 29.23 in the first round (n = 52, SD = 15.95, Min = 0, Max = 60), suggesting that teams initially struggled to coordinate on a uniform effort level, thereby deviating from one of the Nash equilibria. However, when considering all rounds, *wasted effort* decreased substantially to 13.44 on average (n = 520, SD = 13.67, Min = 0, Max = 60), indicating that teams learned to coordinate more efficiently as they gained information about their *minimum effort* in previous rounds. However, unlike the patterns observed for *minimum effort* and *average effort*, there were no consistent descriptive differences in *wasted effort* between the *Gaze Contact* and *Baseline* treatments across the ten rounds of the WLG (see Figure 4.5). This suggests that the option to perceive gaze contact during pre-play communication did not influence the teams' ability to coordinate their efforts. Consistent with these findings, both non-parametric and semi-parametric tests revealed no significant treatment effects on *wasted effort*, contradicting **H3** (see Table 4.7).

Similarly, OLS regressions showed no significant treatment effects on *wasted effort* in the first round (see Table 4.8). These results persisted when examining all rounds using OLS panel regressions (see Appendix C: Table C.6), further suggesting that the option to perceive gaze contact during pre-play communication did not affect team coordination.

4.4.3 Individual Effort and Beliefs

Due to the inherent correlation of individual observations within teams, we tested our main hypotheses (**H1**, **H2**, and **H3**) at the team level.[21] Nevertheless, we conducted further analyses at the individual level to challenge the robustness of our team-level results. In particular, we examined the *Gaze Contact* treatment's effects on *individual effort* and *beliefs* about the *minimum effort* in the first and last rounds of the WLG.

[21] Since team members communicated via video meetings, they had the opportunity to adapt their choices in the ensuing WLG based on each other's behaviors. Additionally, throughout the WLG, teams were informed about their *minimum effort* levels, allowing individuals to adjust their decisions accordingly. Therefore, analyses at the team level were the most appropriate approach to assess whether the option to perceive gaze contact within teams affected their level of cooperation and coordination.

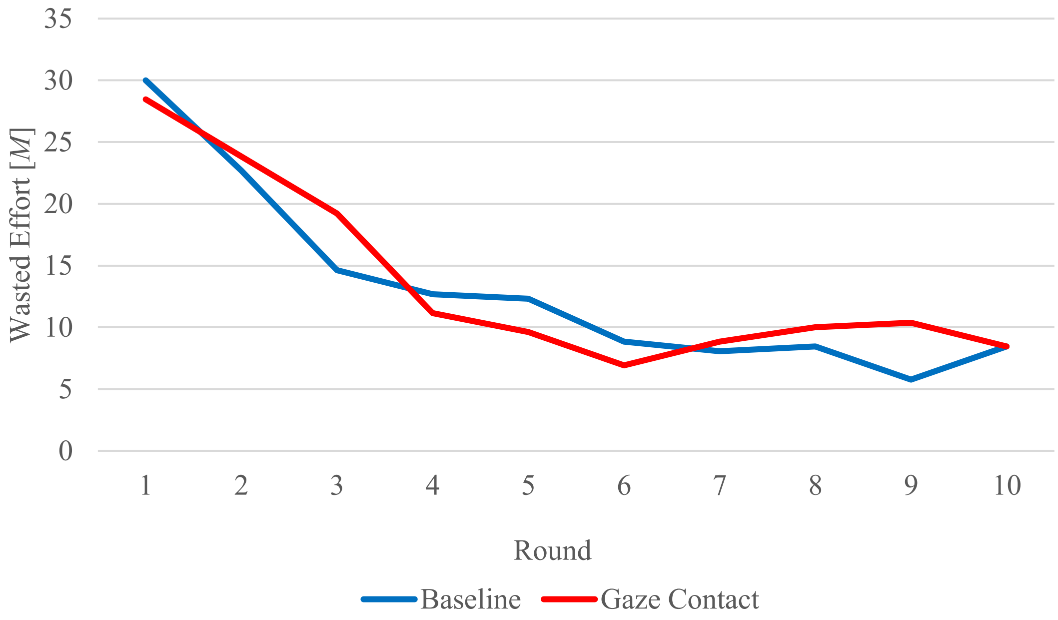

Figure 4.5: Progression of the mean *wasted effort* throughout the ten rounds of the Weakest Link Game.

	Baseline (n = 26)	**Gaze Contact (n = 26)**	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Wasted Effort	***M* (*SD*)**	***M* (*SD*)**	z	p	$t(50)$	p
First round	30.00 (16.00)	28.46 (16.17)	0.48	.635	0.34	.731
All rounds	13.19 (6.18)	13.69 (5.92)	0.73	.463	0.30	.767
Rounds 1-5	18.46 (6.68)	18.46 (7.07)	0.48	.632	0.00	.999
Rounds 6-10	7.92 (8.03)	8.92 (7.16)	0.87	.386	0.47	.638

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Non-parametric and semi-parametric treatment comparisons (n = 52) of *wasted effort* in the first round, across all rounds, as well as the first and second halves of the rounds by *Baseline* and *Gaze Contact*.

Dep. Var.: Wasted Effort	**(1) First Round**	**(2) First Round**	**(3) First Round**	**(4) First Round**
Gaze Contact	-1.538	-1.214	-0.535	-0.669
	(4.462)	(4.462)	(4.473)	(4.492)
Male-dominant Ratio		-1.280	0.285	-0.396
		(4.966)	(4.763)	(4.818)
Average Age		-0.837	-0.924	-1.091
		(0.899)	(0.877)	(0.897)
Team Cohesion			-2.698	-2.380
			(1.767)	(1.762)
Homophily				37.652
				(28.627)
Constant	30.000***	50.594**	61.422**	38.200
	(3.138)	(22.267)	(23.052)	(28.351)
R^2	0.002	0.019	0.061	0.086
F-statistic	0.12	0.31	0.79	0.99
p-value	.732	.815	.536	.431
Observations	52	52	52	52

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: OLS regressions with *wasted effort* in the first round as the dependent variable.

Before assessing the robustness of our findings by including additional control variables such as risk and social preferences at the individual level, we conducted randomization checks to determine whether these variables were equally balanced across treatments. The results revealed that participants in the *Gaze Contact* treatment exhibited significantly lower *gaze anxiety* and significantly higher levels of *negative reciprocity* as well as *interpersonal trust* (see Table 4.9). Although these measures were intended to capture stable traits and thus should be exogenous, the observed significant treatment differences suggest endogeneity issues. This concern is further heightened by the fact that our randomization

	Baseline (***n*** **= 78)**	**Gaze Contact** (***n*** **= 78)**	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Variable	***M*** **(*SD*)**	***M*** **(*SD*)**	*z*	***p***	***t*****(154)**	***p***
Gaze Anxiety	0.82 (0.38)	0.67 (0.35)	2.57	.010**	2.58	.012**
Risk Taking	5.21 (2.22)	5.64 (2.21)	1.34	.181	1.23	.221
Altruism	0.08 (0.82)	-0.08 (0.78)	1.03	.302	1.32	.190
Pos. Reciprocity	0.03 (0.68)	-0.03 (0.79)	0.02	.986	0.54	.593
Neg. Reciprocity	-0.13 (0.70)	0.13 (0.80)	1.65	.099*	2.12	.036**
Interpersonal Trust	-0.16 (0.82)	0.16 (0.75)	2.51	.012**	2.62	.010***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9: Non-parametric and semi-parametric treatment comparisons (n = 156) of gaze anxiety scores, risk, and social preferences by *Baseline* and *Gaze Contact*.

checks with inherently exogenous variables, such as *gender*, *age*, and *ethnicity*, showed no significant differences between treatments (see Appendix C: Table C.3), indicating that our experimental randomization process was successful.

One possible explanation is that participants' responses to these trait measures were shaped by the *Gaze Contact* treatment. For instance, the scale to assess *gaze anxiety* (Domes et al., 2016) included items directly related to the video meeting context (e.g., "Speaking in a discussion with a few people"). Participants in the *Gaze Contact* treatment may have referenced the gaze-adaptive video meeting system when responding, leading to significantly different scores compared to the *Baseline* treatment. Although the scales were not designed to capture state variations, previous research has demonstrated that treatment manipulations targeting specific constructs can also influence responses to related trait measures (see, e.g., Naef & Schupp, 2009). Given that we designed the *Gaze Contact* treatment to enhance the ability to recognize each other's cooperativeness, it could have influenced participants' responses to the *interpersonal trust* scale by Beierlein et al. (2014; e.g., "You can't rely on anyone these days"). Similarly, the observed treatment differences may have shaped subsequent responses to the items assessing *negative reciprocity* (Falk et al., 2018; 2023; e.g., "If I am treated very unjustly, I will take revenge at the first opportunity, even if there is a cost to do so"), especially since decisions in the WLG were continually shaped by the knowledge of *minimum effort* levels in previous rounds.

In summary, these limitations must be considered when interpreting the results of our additional analyses at the individual level, including *gaze anxiety*, *interpersonal trust*, and *negative reciprocity* as control variables. The imbalances in these trait measures may have introduced endogeneity bias, potentially confounding our estimates.

Individual Effort. First, we examined whether the option to perceive gaze contact during pre-play communication shaped *individual effort*. Both non-parametric ($p = .039$) and semi-parametric tests ($p = .008$) showed a significant positive effect of the *Gaze Contact* treatment on *individual effort* during the first five rounds (see Table 4.10). In addition, semi-parametric t-tests revealed a significant positive treatment effect on *individual effort* when considering all rounds ($p = .025$). However, when focusing on the second half of the rounds, we observed only a marginally significant positive treatment effect ($p = .098$). Notably, the estimated standard deviations of *individual effort* were consistently higher in the *Gaze Contact* treatment compared to the *Baseline* treatment (see Table 4.10). This increased variability may explain why non-parametric tests, which do not account for differences in variance between treatments, failed to detect a significant effect, whereas the semi-parametric tests did.

Furthermore, ordered probit regressions revealed a marginally significant positive effect of the *Gaze Contact* treatment on *individual effort* in the first round ($p = .100$; see Appendix C: Table C.7). This effect remained robust when including *oneness* ($p = .098$), *age* as well as *gender* ($p = .066$), and *gaze anxiety* ($p = .053$) as individual-level control variables in the models. However, the addition of risk and social preferences rendered the treatment effect insignificant ($p = .242$). On the one hand, these results suggest that the option to perceive gaze contact during pre-play communication did not significantly impact *individual effort* once risk and social preferences were appropriately controlled for. On the other hand, they further highlight potential limitations due to endogeneity issues regarding the self-rated levels of *negative reciprocity* and *interpersonal trust*, as discussed above (see Table 4.9).

	Baseline (n = 78)	**Gaze Contact** (n = 78)	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Individual Effort	M (SD)	M (SD)	z	p	t(154)	p
First round	20.38 (11.67)	23.33 (11.70)	1.35	.178	1.58	.117
All rounds	13.51 (8.25)	16.83 (9.98)	1.56	.119	2.27	.025**
Rounds 1-5	15.46 (8.28)	19.38 (9.82)	2.07	.039**	2.70	.008**
Rounds 6-10	11.56 (9.17)	14.28 (11.16)	0.96	.335	1.66	.098*

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10: Non-parametric and semi-parametric treatment comparisons (n = 156) of *individual effort* in the first round, across all rounds, as well as the first and second halves of the rounds by *Baseline* and *Gaze Contact*.

This is particularly concerning because the fifth model revealed a significant positive relationship between *interpersonal trust* and *individual effort* (p < .001; see Appendix C: Table C.7). When considering all rounds in ordered probit panel regressions, the positive effect of the *Gaze Contact* treatment on *individual effort* reached statistical significance below the 5% threshold in the third (p = .045) and fourth models (p = .037; see Appendix C: Table C.8). However, consistent with the results on *individual effort* in the first round, including global preferences in the fifth model rendered the *Gaze Contact* treatment's effect insignificant (p = .081).

Testing marginal effects, conducted as a further step to deepen the interpretation of the fifth model's estimates, revealed more nuanced insights into the influence of the *Gaze Contact* treatment on *individual effort* across all ten rounds. Specifically, we found that the *Gaze Contact* treatment marginally significantly reduced the likelihood of participants choosing *individual effort* levels of zero by 8% (z = -1.73, p = .084) and ten by 2% (z = -1.76, p = .078). In contrast, the *Gaze Contact* treatment marginally significantly increased the probability of selecting higher *individual effort* levels, such as 20 by 4% (z = 1.85, p = .064) and 30 by 3% (z = 1.75, p = .079). Considering that we did not achieve the required sample size of 92 teams, these marginally significant positive results indicate that the *Gaze Contact* treatment may have fostered cooperative behavior by reducing preferences for safer, yet

	Baseline (n = 78)	Gaze Contact (n = 78)	Two-sided Mann-Whitney U		Two-sided t-test	
Beliefs	***M*** **(*SD*)**	***M*** **(*SD*)**	z	p	$t(154)$	p
First round	16.41 (11.39)	20.26 (11.84)	1.89	.059*	2.07	.040**
Final round	9.36 (9.31)	11.28 (12.10)	0.59	.558	1.11	.268

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11: Non-parametric and semi-parametric treatment comparisons (n = 156) of *beliefs* about the minimum effort level in the first and final rounds by *Baseline* and *Gaze Contact*.

less cooperative decisions by encouraging team members to adopt strategies that involve greater risk but enhance the potential for greater collective gains.

Beliefs. Consistent with our findings on *individual effort*, semi-parametric tests revealed a positive treatment effect on participants' *beliefs* about their team's *minimum effort* in the first round (p = .040; see Table 4.11). This result suggests that the option to perceive gaze contact heightened expectations regarding their team members' cooperativeness. However, results regarding *beliefs* in the final round of the WLG showed that these elevated expectations diminished substantially throughout the rounds. By the final round, *beliefs* about the minimum effort no longer differed between the *Gaze Contact* and *Baseline* treatments. A possible explanation for this finding is that participants may have recalibrated their expectations based on the information about their team's *minimum effort* in earlier rounds.

Using ordered probit regressions to challenge the robustness of these findings yielded similar results as our analyses on *individual effort* (see Appendix C: Table C.9). Specifically, the positive effect of the *Gaze Contact* treatment remained robust when adding *oneness* (p = .044), *age* as well as *gender* (p = .031), and *gaze anxiety* (p = .039) as individual-level control variables to the models, while the inclusion of global preferences in the fifth model diminished its statistical significance (p = .186). Moreover, the fifth model revealed a significant positive relationship between *interpersonal trust* and *beliefs* (p = .002), paralleling the results obtained for *individual effort* in the first and across all rounds. Considering the positive effect of the *Gaze Contact* treatment on *interpersonal trust* (see Table 4.9), we

	Baseline (n = 78)	**Gaze Contact (n = 78)**	**Two-sided Mann-Whitney U**		**Two-sided t-test**	
Psych. Condition	***M* (*SD*)**	***M* (*SD*)**	***z***	***p***	***t*(154)**	***p***
Safety	4.21 (0.70)	4.53 (0.60)	2.78	.006***	3.08	.002***
Availability	4.23 (0.55)	4.27 (0.47)	0.22	.825	0.53	.598
Engagement	3.58 (0.53)	3.58 (0.60)	0.44	.661	0.01	.989

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Non-parametric and semi-parametric treatment comparisons (n = 156) of *psychological safety, availability*, and *engagement* by *Baseline* and *Gaze Contact*.

proceeded to investigate its role as a potential mediator between the option to perceive gaze contact during pre-play communication and *beliefs* in the first round of the WLG.

The Mediating Role of Interpersonal Trust. Across all regression models at the individual level, we identified a significant positive effect of *interpersonal trust*. This finding aligns with prior research on the WLG, which suggests that teams often fail to coordinate on the payoff-dominant equilibrium (i.e., all team members allocating the highest possible effort to the team project) because achieving this equilibrium requires overcoming substantial risks of losing individual earnings (see, e.g., Riedl et al., 2016). This conflict was amplified in our study by the implementation of a harsh payoff structure adapted from Brandts and Cooper (2006). Specifically, participants who contributed more effort than their team's *minimum effort* level incurred significant penalties in a given round. As a result, each participant's level of *interpersonal trust* likely played a critical role in shaping their *beliefs*. In line with this assumption, non-parametric and semi-parametric treatment comparisons of relevant psychological conditions (May et al., 2004) revealed that participants in the *Gaze Contact* treatment reported significantly higher levels of *psychological safety* (see Table 4.12).

Given these findings, we took advantage of 2SLS estimation (for a comprehensive explanation of 2SLS estimation, see Appendix B.4) to test the causal relationship between *interpersonal trust* and *beliefs* in the first round of the WLG. This approach enabled us to test whether variations of *interpersonal trust* induced by the *Gaze Contact* treatment influenced

Dep. Var.: Beliefs	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Interpersonal Trust	11.716*	12.254*	12.214**	13.378*	11.838*
	(6.079)	(6.625)	(5.956)	(7.079)	(6.809)
Oneness		-1.059	-0.548	-0.615	-0.362
		(1.046)	(0.839)	(0.910)	(0.868)
Constant	18.333***	22.298***	25.409***	22.697***	20.933**
	(0.998)	(3.985)	(7.542)	(8.563)	(8.886)
Demographics	✗	✗	✓	✓	✓
Gaze Anxiety	✗	✗	✗	✓	✓
Global Preferences	✗	✗	✗	✗	✓
R^2	0.043	0.102	0.142	0.157	0.187
χ^2-statistic	3.72	4.00	21.60	20.51	29.57
p-value	.054	.136	.010	.025	.009
Observations	156	156	156	156	156

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: Second-stage 2SLS regressions with *interpersonal trust* instrumented by *Gaze Contact* and *beliefs* about the minimum effort level in the first round as the dependent variable.

the participants' *beliefs* about the minimum effort level in the first round. Consistent with non-parametric and semi-parametric tests (see Table 4.11), first-stage 2SLS regressions showed a significant positive effect of the *Gaze Contact* treatment on *interpersonal trust* (p = .006; see Appendix C: Table C.10). Notably, this positive treatment effect remained robust across all model specifications. Second-stage 2SLS regressions revealed a marginally positive effect of *interpersonal trust* on *beliefs* (p = .054), which also remained robust across all models (see Table 4.13). Overall, these findings indicate that the level of *interpersonal trust* played a key role in shaping participants' expectations about their team members' cooperativeness.

4.5 Conclusion

Taken together, our findings suggest that the option to perceive gaze contact during video meetings has the potential to foster team cooperation while having no discernible effects on team coordination. Regarding our first and second hypotheses, initial non-parametric and semi-parametric tests did not indicate that the *Gaze Contact* treatment enhanced cooperative behavior. However, more comprehensive regression analyses, including relevant control variables, yielded marginally significant positive effects of the *Gaze Contact* treatment on both *minimum effort* and *average effort*. Further analyses at the individual level supported the robustness of these team-level findings. In particular, participants in the *Gaze Contact* treatment exhibited significantly higher levels of *individual effort* and more optimistic *beliefs* about their team's *minimum effort* in the first round of the WLG. Moreover, 2SLS estimation at the individual level provided initial evidence that the *Gaze Contact* treatment may have fostered cooperative behavior by promoting the formation of *interpersonal trust* among team members. While interpretations at the individual level must be treated with caution due to potential intercorrelations within teams, these findings provide partial support for our first and second hypotheses. In summary, they indicate that enabling team members to perceive gaze contact during video meetings may promote their subsequent cooperative behavior by strengthening feelings of *interpersonal trust* and, in turn, elevating expectations about one another's cooperativeness. In contrast, we found no support for our third hypothesis, which posited that gaze contact would enhance team coordination.

Overall, our findings contribute to the broader literature on how communication shapes economic behavior in virtual teams. More specifically, they underscore the importance of gaze contact as a subtle yet powerful nonverbal signal in team collaboration, which yields several practical implications. For certain team projects—particularly those where team members must individually decide how much effort to contribute—scheduling meetings that enable the perception of gaze contact may be beneficial. For example, when unfamiliar individuals are assigned to a joint project, employing gaze-adaptive video meeting systems or simply conducting face-to-face meetings, in which gaze information is naturally available, might help team members recognize each other's prosocial motives and, in turn, promote their cooperative behavior. Similarly, the option to perceive gaze contact could prove beneficial in meetings aiming at conflict resolution. By signaling prosocial motives, the option to perceive gaze contact could foster a more cooperative atmosphere, encouraging team members to approach each other. In conclusion, whenever building trust or resolving conflicts within teams is critical, organizations might consider leveraging the power of gaze contact.

Limitations and Future Research. Despite these insights, our study was subject to certain limitations. First, due to constraints in the subject pool, we were unable to achieve the required sample size of 92 teams (see Section 4.3.3). This limitation could have contributed to the positive treatment effects on cooperation remaining only marginally significant. To address this, we will conduct a follow-up study involving the remaining 40 teams to evaluate if our results reach statistical significance below the conventional 5% threshold. Second, our study focused on measuring the impact of gaze contact on subsequent cooperative behavior, specifically to test its role as a type detection mechanism. As a result, we were unable to examine how the option to perceive gaze contact might influence ongoing strategic interactions. Future investigations might consider incorporating the team task directly into the video meeting to examine potential effects during the decision-making process itself. Finally, we exclusively examined the impact of gaze contact in video meetings to control for other aspects that differentiate it from face-to-face meetings. Accordingly, future studies could examine whether the effects of a gaze-adaptive video meeting system visualizing episodes of gaze contact in real time are similar to those observed in face-to-face meetings. While our study advances the understanding of how gaze contact affects cooperation and coordination in virtual teams, addressing these limitations in future research is essential for drawing more robust and generalizable conclusions.

CHAPTER 5

Discussion

5.1 Summary and Theoretical Insights

This dissertation contributes to the literature on the communicative function of gaze in team collaboration by precisely measuring social gaze dynamics across different settings and testing their impact on subsequent team collaboration. As organizations increasingly rely on video meetings to facilitate communication among geographically distributed team members, understanding how the absence of gaze information—compared to face-to-face meetings—affects cooperation and coordination has become crucial for maintaining effective collaboration in virtual teams. Despite the well-established dual function of gaze in social interaction (see, e.g., Gobel et al., 2015), experimental evidence on its role in supporting type detection and its impact on economic behavior remains scarce (Fischbacher et al., 2022; Hausfeld et al., 2021). To fill this gap, this dissertation was guided by four interrelated research questions (see Section 1.3). Building on the insights from our systematic literature review and three controlled laboratory experiments, we were able to provide comprehensive answers to these questions.

Regarding the first research question (RQ1) on how multiparty eye-tracking can be utilized to measure, operationalize, and analyze gaze dynamics in team collaboration, our systematic literature review highlighted several methodological considerations for studying social gaze dynamics. To ensure valid comparisons among participants, researchers must standardize the visual environment (e.g., maintaining consistent setups for all team members) and assign equal operating roles during collaboration to prevent systematic biases in gaze. Because highly specialized tasks (e.g., pair programming) may limit generalizability, future research could benefit from employing more controlled tasks, such as economic games. Furthermore, relying on video meetings rather than text-based communication helps avoid the confounding effects of reading or typing on gaze patterns and is necessary for capturing social gaze dynamics, as team members must see each other. Finally, the review identified several research gaps, such as the need to examine the role of gaze in larger groups beyond dyadic interactions. Overall, multiparty eye-tracking setups, coupled with advanced analytical methods such as MdRQA, promise a more comprehensive understanding of the spatiotemporal dynamics of social gaze, including mutual gaze and gaze aversion.

Turning to the second research question (RQ2), how social gaze dynamics affect team collaboration, our findings showed that higher levels of mutual gaze during face-to-face communication were marginally significantly associated with increased team output, whereas higher levels of gaze aversion undermined cooperative behavior at the individual level. These results highlight the importance of social gaze dynamics in facilitating type detection during face-to-face communication and underscore the potential consequences of missing gaze information in virtual teams. Our findings contribute to the literature on the communicative function of gaze, supporting and extending prior research conducted in artificial settings. Earlier studies using pictures of faces displaying direct or averted gaze demonstrated that the perception of mutual gaze enhances the likelihood of memorizing others and fosters greater interpersonal attraction compared to gaze aversion (Frischen et al., 2007; Mason et al., 2005). By situating these findings and their implications within the context of social gaze dynamics in teams and their impact on economic behavior, our methodological approach—employing multiparty eye-tracking—substantially enhanced the ecological validity of foundational assumptions on the dual function of gaze.

Addressing the third research question (RQ3) on the emergence and impact of social gaze in face-to-face versus video meeting settings, we observed that team members reciprocated each other's direct gaze more than twice as often when gaze information was available due to physical copresence. In addition, we found that higher levels of attentional reciprocity during face-to-face communication significantly promoted subsequent cooperation, potentially because the reciprocation of direct gaze was consciously recognized as a signal of prosocial motives. In contrast, we observed no effects when teams got to know each other in a video meeting, where gaze information was absent. Our results revealed that both the emergence and impact of social gaze dynamics differ considerably between face-to-face and video meeting settings, raising concerns about increasingly shifting team communication into the virtual space. With these findings, we contribute to the broader literature on the effects of communication on cooperative behavior, supporting the notion that individuals evaluate nonverbal signals to discern between cooperative and noncooperative team members (Fischbacher et al., 2001; He et al., 2017). Furthermore, to the best of our knowledge, this study provides initial evidence of the isolated effects of social gaze dynamics on economic behavior. By shedding light on the specific role of attentional reciprocity in fostering cooperation, our findings deepen the understanding of the subtle yet crucial role of nonverbal signals in team collaboration.

Finally, by examining the effects of an adaptive video meeting system that bridges the gap between face-to-face and computer-mediated communication by visualizing gaze information in real time, we gained valuable insights into the role of gaze contact in team collaboration (RQ4). Specifically, our findings indicate that enabling individuals to perceive gaze contact during video meetings marginally significantly promoted team cooperation by strengthening interpersonal trust and positively shifting beliefs about one another's effort at the individual level. However, no significant effects on team coordination emerged, suggesting distinct underlying mechanisms. Overall, these findings contribute to understanding the nuanced role of nonverbal communication in collaborative settings. By focusing on gaze contact as a specific social gaze dynamic—underscored as particularly important in previous research (see, e.g., Grossmann, 2017; Hietanen, 2018; Kleinke, 1986)—our study provided a more detailed analysis of its effects on cooperation and the formation of interpersonal trust. In particular, our results supported the Cooperative Eye Hypothesis (Tomasello et al., 2007), suggesting that gaze contact plays a fundamental role in social interaction by examining its implications for economic behavior in team settings. Moreover, by moving beyond qualitative approaches (see, e.g., Kaiser et al., 2022), we provided experimental evidence that the option to perceive gaze contact in video meetings may be a pivotal factor for maintaining successful collaboration in virtual teams.

5.2 Practical Implications

The rise of remote work policies has sparked ongoing debates about the optimal modes of team communication, particularly in the context of virtual teams that rely solely on computer-mediated communication (see, e.g., Standaert et al., 2021). The theoretical insights from this dissertation offer valuable guidance for organizations seeking to sustain successful team collaboration in the modern workplace and offer potential strategies for fostering cooperative behavior within virtual teams.

Our findings suggest that organizations could benefit from prioritizing face-to-face meetings during the initial stages of team formation to establish interpersonal trust and promote subsequent cooperative behavior. In a broader sense, enabling the exchange of gaze information might prove especially advantageous for activities that require recognizing prosocial motives, such as team building and conflict resolution. While not explicitly examined in this dissertation, the relevance of social gaze dynamics in fostering cooperative behavior may extend to critical tasks requiring exceptionally high levels of cooperation (e.g., challenging projects with the risk of no rewards). Nevertheless, these implications should not be construed to advocate a full-time return to office-based work, as mandated by some major organizations like Amazon (Jassy, 2024), since remote work offers numerous benefits (see, e.g., Angelici et al., 2023; Chatterjee et al., 2022; Choudhury et al., 2021).

For instance, Bloom et al. (2024) found that a hybrid schedule, with two days of remote work per week, did not harm organizational performance while improving job satisfaction and reducing quit rates by 33%. Thus, organizations could take advantage of these benefits without compromising cooperation due to the absence of gaze information by scheduling face-to-face meetings on days when all team members are physically present. Moreover, establishing consistent in-office days across the organization could facilitate periodic face-to-face meetings between team members from different departments. These strategies would enable organizations to harness the advantages of remote work policies while maintaining successful team collaboration.

For virtual teams that rely solely on computer-mediated communication, improving virtual meeting practices is crucial. Encouraging team members to activate their video feeds during meetings and ensuring their webcams are positioned directly in front of them enhances the richness of nonverbal communication (Bicchieri & Lev-On, 2007). Although gaze information is absent in video meetings, gestures such as nodding or open body language may help compensate for this limitation, fostering attentional reciprocity among team members. To further boost cooperative behavior in virtual teams, organizations may consider implementing gaze-adaptive video meeting systems. Recent advancements in eye-tracking technology, particularly the increasing precision of webcam-based methods (see, e.g., Kumar et al., 2024), appear to eliminate the need for complex setups and expensive hardware, thereby paving the way for the widespread adoption of gaze-adaptive video meeting systems. In the future of work, such systems might feature gaze-adaptive capabilities that can be enabled for specific meeting types, ultimately enhancing collaboration in virtual teams.

Finally, organizations may also invest in training programs to educate team members on the impact of their gaze as a nonverbal communication signal. These programs could provide guidelines to encourage gaze contact in face-to-face meetings and emphasize the use of verbal reassurances to compensate for the lack of gaze information in computer-mediated communication. A special consideration must be given to neurodiverse teams, which may include individuals with Attention Deficit Hyperactivity Disorder (ADHD) or Autism Spectrum Disorder (ASD). These individuals often face challenges in maintaining gaze contact or using their gaze as a signal of visual attention in the same way as neurotypical individuals (Frick et al., 2023; Madipakkam et al., 2017; Senju & Johnson, 2009). Educating employees about these differences could foster a more inclusive work environment. For instance, organizations should advise team members to interpret gaze aversion with caution in neurodiverse teams, understanding that it does not necessarily indicate a lack of prosocial motives.

5.3 Methodological Contributions

Beyond answering the research questions, which provided theoretical insights and practical implications, this dissertation makes several methodological contributions that equip researchers with the means to explore the communicative function of gaze in greater depth.

In particular, we introduced a comprehensive framework for effectively employing multiparty eye-tracking as a diagnostic method in experimental settings. Our systematic literature review specifically details how to collect, process, and analyze eye movement data of multiple individuals to operationalize social gaze dynamics in a rigorous way. By providing a comprehensive overview, this multiparty eye-tracking framework lays the foundation for future research on the role of social gaze dynamics.

Furthermore, this dissertation expands the study of social gaze by advancing its conceptualization to encompass interactions among at least three individuals. Previous research has predominantly focused on attentional processes between two individuals, framing social gaze dynamics as strictly dyadic (e.g., defining gaze aversion as one person looking at another who looks away). To address more complex interactions, such as those involving teams, we introduced a novel approach to conceptualizing the core processes of social gaze—mutual gaze, gaze aversion, and joint attention (Emery, 2000; Pfeiffer et al., 2013)—

within triadic and larger interactions. For example, we redefined gaze aversion as a team-level dynamic in which one member looks at another who neither reciprocates that direct gaze nor engages in mutual gaze with another team member at the same time (see Section 3.3.3). In addition, we proposed the concept of attentional reciprocity, quantifying the extent to which direct gaze is reciprocated within a team. This expanded conceptualization broadens the scope of social gaze research, offering new avenues to explore how interdependent attentional processes affect team collaboration and related constructs.

Another methodological contribution lies in the integration of multiparty eye-tracking into behavioral economic experiments. Typically, incentivized social dilemma games—such as the Public Goods Dilemma or the Weakest Link Game—are highly controlled and require individuals to make payoff-relevant decisions privately (see, e.g., Brandts & Cooper, 2006; Gächter et al., 2024; Nalbantian & Schotter, 1997; Riedl et al., 2016). In contrast, capturing social gaze dynamics in a meaningful way necessitates free-form communication (Hessels, 2020), which introduces opportunities to infer others' intentions. To resolve these conflicting prerequisites, we designed a pre-play communication stage that was structured around a payoff-irrelevant real-effort task, mirroring the key elements of the ensuing dilemma. This approach allowed us to measure social gaze dynamics during free-form communication while maintaining the private, payoff-relevant decision-making stage. Specifically, the tangram task—employed in the experiments detailed in Chapter 3—required team members to decide how many of their own pieces to contribute, paralleling the numeric decision made in various social dilemma games. This design created a versatile experimental platform for investigating the impact of social gaze dynamics on economic behavior. For broader application in experimental research, the oTree code for the interactive tangram task can be made available upon request.

Finally, this dissertation introduced a novel experimental framework to examine the effects of specific social gaze dynamics. Instead of comparing face-to-face and video meetings—which may involve variations beyond the availability of gaze information—our approach, detailed in Chapter 4, directly contrasted communication via a conventional video meeting system with a gaze-adaptive one. Manipulating only the social gaze dynamic of interest while keeping the meeting mode constant enabled us to isolate and examine the impact of gaze contact. Beyond our focus on the role of gaze contact in virtual teams, this experimental framework provides a valuable research method to examine social gaze dynamics in a highly controlled environment.

5.4 Limitations and Future Research

Despite adhering to scientific standards, the research presented in this dissertation is subject to certain limitations. By acknowledging these, we sought to provide a transparent account of potential challenges and aimed to identify promising directions for future research.

Statistical Power. Although our findings on the role of social gaze in team collaboration are largely consistent and align well across the distinct experiments, some results were only marginally significant, failing to reach the conventional threshold of 5%. This suggests that our laboratory experiments, despite relatively large sample sizes of up to 204 participants, may have been influenced by random variation or lacked sufficient statistical power.[22] This issue was particularly pronounced because our main analyses were conducted at the team level to account for intercorrelations among team members. This substantially reduced the number of independent observations as three participants forming one team were treated as a single interdependent unit. Consequently, our findings warrant further investigation through follow-up studies to determine whether the observed relationships are robust or spurious.

Future research employing multiparty eye-tracking should proactively address such power issues arising from interdependent observations at the individual level. The logistical challenges inherent to laboratory eye-tracking studies—such as the dependence on available equipment and limited capacity for simultaneous sessions—further exacerbate this issue. To address these challenges in ensuring statistical power, researchers could adopt several strategies. Collaboration across multiple laboratories could provide access to larger and

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[22] In our first experiment, an exploratory approach with ten teams revealed a marginally significant relationship between mutual gaze and team cooperation. Based on these findings, we anticipated a medium effect size ($f^2 = 0.15$) for attentional reciprocity in the second experiment. While OLS regressions partially supported our hypothesis on the relationship between attentional reciprocity and team cooperation, 2SLS estimation—known for underestimating true effects (Bound et al., 1995; Wooldridge, 2010)—did not. Based on these results, we anticipated a lower effect size ($f^2 = 0.10$), which guided the power analysis for the third experiment, ultimately resulting in an estimated requirement of 92 teams. However, constraints in the subject pool allowed us to recruit only 52 teams, which limited the statistical power and robustness of our findings.

more diverse subject pools, enhancing the robustness of findings. Alternatively, scalable solutions such as webcam-based eye-tracking methods could be utilized, enabling experiments to be conducted on online platforms like Amazon Mechanical Turk (Aguinis et al., 2020) and Prolific (Palan & Schitter, 2018), thereby expanding the feasibility of data collection.

Endogeneity and Causality. When conducting analyses at the team level, social gaze dynamics are inherently endogenous because they emerge from reciprocal interactions, where gaze serves as both a driver of and response to collaborative processes. This creates the potential for correlations between gaze variables and the models' error term due to unaccounted factors and reverse causation (Bound et al., 1995; Wooldridge, 2010). For example, unobserved characteristics at the individual and team levels may simultaneously influence both social gaze dynamics and economic behavior, leading to omitted variable bias. Additionally, social gaze dynamics are intertwined with the collaborative processes during communication (e.g., a team member looking at an object of interest may prompt others to discuss it, while the discussion itself may redirect gaze), introducing simultaneity bias. To address these endogeneity issues, we took advantage of 2SLS estimation to isolate the exogenous component of attentional reciprocity that was uncorrelated with the error term (Bastardoz et al., 2023; Bound et al., 1995; Sajons, 2020; Wooldridge, 2010). However, while OLS regressions revealed a significant relationship between attentional reciprocity during face-to-face communication and subsequent team cooperation, 2SLS estimates did not yield significant effects. Thus, although our findings highlight a correlation, we could not draw causal inferences. This limitation underscores the need to disentangle the causal pathways linking attentional reciprocity with cooperative behavior. Besides 2SLS estimation, alternative econometric techniques, such as structural equation modeling (Hair et al., 2019), may aid in establishing causal evidence on the relationship between social gaze dynamics and team collaboration.

Generalizability. Our experimental studies focused on the impact of social gaze dynamics in teams consisting of three members, raising questions about the extent to which these findings can be generalized to larger teams. We decided to examine three-member teams for two key reasons. First, previous research showed that cooperation is typically high in pairs but tends to decline as group size increases (see, e.g., Barcelo & Capraro, 2015;

Nosenzo et al., 2015). Anticipating this decline in team cooperation allowed us to detect differences in cooperative behavior between our treatments. If cooperation had already been maximized in the baseline, potential differences between treatments would have been obscured. Second, it simplified the analysis of social gaze dynamics, which become increasingly complex when more than three individuals are involved. In larger teams, the impact of mutual gaze or gaze aversion—redefined as multiparty constructs involving two members while only being passively perceived by the remaining—may be harder to detect. Although our proposed conceptualization could theoretically extend to larger teams, its validity in these contexts remains untested and may yield less precise insights. Therefore, future research should explore more robust conceptualizations, such as attentional reciprocity, to better capture the dynamics of visual attention in larger teams. Taken together, these implications underscore the importance of carefully considering group size when designing experiments on the role of social gaze dynamics in team collaboration. When appropriately addressing their increasing complexity, future studies could investigate whether the exchange of gaze information helps to mitigate noncooperative behavior in larger teams.

Furthermore, we specifically examined the impact of social gaze dynamics in newly formed teams where unfamiliar members interacted in a single meeting before making their payoff-relevant decisions in private. This setup mirrored scenarios in organizations with newly constituted teams but may not reflect dynamics in established teams with a history of interaction. Future research should explore how social gaze dynamics influence collaboration among team members with pre-existing relationships. For instance, experimental designs may include multiple communication stages to examine whether periodic opportunities to exchange gaze information increase cooperation stability over consecutive rounds of a social dilemma game. This would enhance generalizability to real-world scenarios in which team members are often familiar with one another. Alternatively, researchers could conduct a field experiment to test the impact of a gaze-adaptive video meeting system in real organizational settings. Such an approach would provide insights into the role of social gaze in authentic workplace environments, offering a broader understanding of their practical implications.

Cultural Norms and Neurodiverse Teams. Although we controlled for ethnicity in our experiments, potential effects of cultural norms on social gaze dynamics warrant a deeper investigation. For example, while sustained gaze contact during communication is typically encouraged and perceived as pleasant in Western cultures, it may convey dominance or competitive intent in Eastern cultures (see, e.g., Akechi et al., 2013; Uono & Hietanan, 2015). Examining how cultural norms affect the relationship between social gaze dynamics and economic behavior would deepen our understanding of their contextual variability. This research holds particularly important implications for virtual team collaboration, which connects geographically distributed employees.

Additionally, the impact of social gaze dynamics within neurodiverse teams presents an underexplored yet critical area for future research. For instance, individuals with ASD often struggle to use and interpret gaze, which can influence both their individual behavior and the team as a whole (Madipakkam et al., 2017; Senju & Johnson, 2009). While we controlled for personality traits (Rammstedt et al., 2014), global preferences (Beierlein et al., 2014; Falk et al., 2018; 2023), and gaze anxiety scores (Domes et al., 2016) to account for individual differences in social gaze dynamics, a more comprehensive investigation is necessary to understand their impact. Future studies could explore tailored interventions or adaptive information systems that address these challenges, ensuring inclusivity and optimizing collaboration in neurodiverse teams.

Interplay between Nonverbal Signals. By only manipulating the availability of gaze information between treatments, our experimental designs allowed us to isolate the effects of social gaze dynamics. However, this approach limited our ability to control for the broader, synergistic interplay between nonverbal signals. Nonverbal signals such as social gaze, facial expressions, and gestures often interact in complex ways—amplifying, complementing, or counterbalancing each other (for a review, see Hessels, 2020). For example, gaze contact has been shown to elicit smiling responses, which, in turn, could have fostered cooperative behavior in our experiments (Hietanen & Peltola, 2020). Moreover, Kaiser et al. (2022) demonstrated that the absence of gaze information in video meetings disrupts the processing of other nonverbal signals, ultimately diminishing social cohesion. By narrowing our research focus on the isolated effect of social gaze, we were unable to explore these interdependencies, leaving a gap that needs to be addressed by future research.

While a detailed examination of this interplay between nonverbal signals was beyond the scope of this dissertation, the recordings of team meetings collected in our third experiment provide several opportunities for further investigation. Future studies could also integrate multiparty eye-tracking with physiological measures such as heart rate, skin conductance, or EEG (see, e.g., Pfeiffer et al., 2013). The perception of gaze contact has previously been linked to positive affective responses (Hietanen, 2018). As such, multimodal approaches offer a promising avenue for uncovering the mechanisms behind the relationship between social gaze dynamics and economic behavior in teams.

CHAPTER 6

Conclusion

The widespread adoption of video meetings in the modern workplace presents organizations with both opportunities and challenges. While video meeting systems facilitate collaboration among geographically distributed teams, they deprive individuals of the option to perceive social gaze dynamics. Although previous studies have shown that the absence of nonverbal signals can undermine cooperative behavior, experimental studies specifically addressing the impact of social gaze dynamics were lacking. Guided by this research gap, we conducted a systematic literature review and three controlled laboratory experiments to illuminate the role of social gaze dynamics for successful team collaboration and, in particular, to disentangle how differences in these dynamics between face-to-face and video meeting settings affect cooperation and coordination.

By conducting the systematic literature review, we established a conceptual framework for synchronously capturing the eye movements of multiple individuals engaged in team collaboration and offered a comprehensive overview of established procedures for quantifying social gaze dynamics. In the first experiment, we examined the emergence and impact of social gaze in face-to-face meetings, revealing that higher levels of mutual gaze enhanced team cooperation. In line with this finding, the second experiment demonstrated that the degree to which team members reciprocated each other's direct gaze during face-to-face meetings significantly promoted cooperative behavior. However, the absence of gaze information in video meetings negated this positive effect, raising concerns about increasingly shifting team communication to the virtual space. Building upon these results, in the third experiment, we explored the impact of a gaze-adaptive video meeting system and found that enabling the option to perceive gaze contact in video meetings promoted subsequent team cooperation, highlighting its potential to bridge the gap between face-to-face and computer-mediated communication.

Taken together, the research presented in this dissertation significantly advances the literature on the communicative function of gaze by identifying social gaze dynamics as critical nonverbal signals in team collaboration (1), developing a framework to measure these dynamics across face-to-face and video meeting settings (2), and providing initial evidence of their relationship with cooperative behavior (3). Overall, these contributions offer valuable guidance for optimizing team collaboration in the modern workplace.

REFERENCES

Abdullah, A., Kolkmeier, J., Lo, V., & Neff, M. (2021). Videoconference and Embodied VR: Communication Patterns across Task and Medium. *Proceedings of the ACM on Human-Computer Interaction*, *5*(2), 1-29. https://doi.org/10.1145/3479597

Aguinis, H., Villamor, I., & Ramani, R. S. (2021). MTurk Research: Review and Recommendations. *Journal of Management*, *47*(4), 823-837. https://doi.org/10.1177/0149206320969787

Akechi, H., Senju, A., Uibo, H., Kikuchi, Y., Hasegawa, T., & Hietanen, J. K. (2013). Attention to Eye Contact in the West and East: Autonomic Responses and Evaluative Ratings. *PloS One*, *8*(3), e59312. https://doi.org/10.1371/journal.pone.0059312

Andreoni, J., & Petrie, R. (2008). Beauty, gender and stereotypes: Evidence from laboratory experiments. *Journal of Economic Psychology, 29*(1), 73-93. https://doi.org/10.1016/j.joep.2007.07.008

Angelici, M., & Profeta, P. (2024). Smart Working: Work Flexibility Without Constraints. *Management Science*, *70*(3), 1680-1705. https://doi.org/10.1287/mnsc.2023.4767

Aron, A., Aron, E. N., & Smollan, D. (1992). Inclusion of Other in the Self Scale and the Structure of Interpersonal Closeness. *Journal of Personality and Social Psychology*, *63*(4), 596-612. https://doi.org/10.1037/0022-3514.63.4.596

Babutsidze, Z., Hanaki, N., & Zylbersztejn, A. (2021). Nonverbal content and trust: An experiment on digital communication. *Economic Inquiry, 59*(4), 1517-1532. https://doi.org/10.1111/ecin.12998

Balliet, D. (2010). Communication and Cooperation in Social Dilemmas: A Meta-Analytic Review. *Journal of Conflict Resolution, 54*(1), 39-57. https://doi.org/10.1177/0022002709352443

Balliet, D., & Van Lange, P. A. (2013). Trust, Conflict, and Cooperation: A Meta-Analysis. *Psychological Bulletin*, *139*(5), 1090-1112. https://doi.org/10.1037/a0030939

Balliet, D., Wu, J., & De Dreu, C. K. (2014). Ingroup Favoritism in Cooperation: A Meta-Analysis. *Psychological Bulletin*, *140*(6), 1556-1581. https://doi.org/10.1037/a0037737

Baltes, B. B., Dickson, M. W., Sherman, M. P., Bauer, C. C., & LaGanke, J. S. (2002). Computer-Mediated Communication and Group Decision Making: A Meta-Analysis. *Organizational Behavior and Human Decision Processes*, *87*(1), 156-179. https://doi.org/10.1006/obhd.2001.2961

Barcelo, H., & Capraro, V. (2015). Group size effect on cooperation in one-shot social dilemmas. *Scientific Reports*, *5*, e7937. https://doi.org/10.1038/srep07937

Barrero, J. M., Bloom, N., & Davis, S. J. (2023). The Evolution of Work from Home. *Journal of Economic Perspectives*, *37*(4), 23-49. https://doi.org/10.1257/jep.37.4.23

Basch, J. M., Melchers, K. G., Kurz, A., Krieger, M., & Miller, L. (2021). It Takes More Than a Good Camera: Which Factors Contribute to Differences Between Face-to-Face Interviews and Videoconference Interviews Regarding Performance Ratings and Interviewee Perceptions?. *Journal of Business and Psychology*, *36*, 921-940. https://doi.org/10.1007/s10869-020-09714-3

Bastardoz, N., Matthews, M. J., Sajons, G. B., Ransom, T., Kelemen, T. K., & Matthews, S. H. (2023). Instrumental variables estimation: Assumptions, pitfalls, and guidelines. *The Leadership Quarterly*, *34*, e101673. https://doi.org/10.1016/j.leaqua.2022.101673

Bayliss, A. P., & Tipper, S. P. (2006). Predictive Gaze Cues and Personality Judgments: Should Eye Trust You?. *Psychological Science*, *17*(6), 514-520. https://doi.org/10.1111/j.1467-9280.2006.01737.x

Bednarik, R., & Kauppinen, M. (2013). Unravelling the interaction strategies and gaze in collaborative learning with online video lectures. *Proceedings of the 6th Workshop on Eye Gaze in Intelligent Human Machine Interaction: Gaze in Multimodal Interaction – GazeIn '13*, 57-62. https://doi.org/10.1145/2535948.2535959

Beierlein, C., Kemper, C., Kovaleva, A. J., & Rammstedt, B. (2014). *Interpersonales Vertrauen (KUSIV3)*. ZIS. https://doi.org/10.6102/zis37

Belenky, D., Ringenberg, M., Olsen, J., Aleven, V., & Rummel, N. (2014). Using Dual Eye-Tracking to Evaluate Students' Collaboration with an Intelligent Tutoring System for Elementary-Level Fractions. *Proceedings of the 36th Annual Meeting of the Cognitive Science Society – CogSci '14*, 1-6. https://files.eric.ed.gov/fulltext/ED556498.pdf

Bicchieri, C., & Lev-On, A. (2007). Computer-mediated communication and cooperation in social dilemmas: An experimental analysis. *Politics, Philosophy & Economics, 6*(2), 139-168. https://doi.org/10.1177/1470594X07077267

Biocca, F., Harms, C., & Burgoon, J. K. (2003). Toward a More Robust Theory and Measure of Social Presence: Review and Suggested Criteria. *Presence: Teleoperators and Virtual Environments*, *12*(5), 456-480. https://doi.org/10.1162/105474603322761270

Bloom, N., Han, R., & Liang, J. (2024). Hybrid working from home improves retention without damaging performance. *Nature*, *630*, 920-925. https://doi.org/10.1038/s41586-024-07500-2

Bock, O., Baetge, I., & Nicklisch, A. (2014). Hroot: Hamburg Registration and Organization Online Tool. *European Economic Review*, *71*, 117-120. https://doi.org/10.1016/j.euroecorev.2014.07.003

Bohannon, L. S., Herbert, A. M., Pelz, J. B., & Rantanen, E. M. (2013). Eye contact and video-mediated communication: A review. *Displays, 34*(2), 177-185. https://doi.org/10.1016/j.displa.2012.10.009

Borghoff, U. M., & Schlichter, J. H. (2000). *Computer-Supported Cooperative Work: Introduction to Distributed Applications*. Springer, Berlin. https://doi.org/10.1007/978-3-662-04232-8_2

Bound, J., Jaeger, D. A., & Baker, R. M. (1995). Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak. *Journal of the American Statistical Association*, *90*(430), 443-450. https://doi.org/10.1080/01621459.1995.10476536

Brandts, J., & Cooper, D. J. (2006). A change would do you good.... An experimental study on how to overcome coordination failure in organizations. *American Economic Review, 96*(3), 669-693. https://doi.org/10.1257/aer.96.3.669

Brosig, J., & Weimann, J. (2003). The effect of communication media on cooperation. *German Economic Review, 4*(2), 217-241. https://doi.org/10.1111/1468-0475.00080

Broz, F., Lehmann, H., Nehaniv, C. L., & Dautenhahn, K. (2012). Mutual Gaze, Personality, and Familiarity: Dual Eye-Tracking during Conversation. *Proceedings of the 2012 IEEE 21st International Symposium on Robot and Human Interactive Communication*, 858-864. https://doi.org/10.1109/ROMAN.2012.6343859

Brucks, M. S., & Levav, J. (2022). Virtual communication curbs creative idea generation. *Nature*, *605*, 108-112. https://doi.org/10.1038/s41586-022-04643-y

Burnham, T. C., & Hare, B. (2007). Engineering Human Cooperation. *Human Nature*, *18*, 88-108. https://doi.org/10.1007/s12110-007-9012-2

Çakır, M. P., & Uzunosmanoğlu, S. D. (2014). An Interactional Analysis of Gaze Coordination during Online Collaborative Problem Solving Activities. *Proceedings of the 11th International Conference of the Learning Sciences – ICLS '14*, 1112-1116. https://repository.isls.org//handle/1/945

Camerer, C. F. (2011). *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton University Press, New Jersey.

Campion, M. A., Medsker, G. J., & Higgs, A. C. (1993). Relations between Work Group Characteristics and Effectiveness: Implications for Designing Effective Work Groups. *Personnel Psychology*, *46*(4), 823-847. https://doi.org/10.1111/j.1744-6570.1993.tb01571.x

Capozzi, F., Beyan, C., Pierro, A., Koul, A., Murino, V., Livi, S., Bayliss, A. P., Ristic, J., & Becchio, C. (2019). Tracking the Leader: Gaze Behavior in Group Interactions. *iScience*, *16*, 242-249. https://doi.org/10.1016/j.isci.2019.05.035

Capraro, V. (2013). A Model of Human Cooperation in Social Dilemmas. *PLoS One, 8*(8), e72427. https://doi.org/10.1371/journal.pone.0072427

Carless, S. A., & De Paola, C. (2000). The Measurement of Cohesion in Work Teams. *Small Group Research*, *31*(1), 71-88. https://doi.org/10.1177/104649640003100104

Carletta, J., Hill, R. L., Nicol, C., Taylor, T., De Ruiter, J. P., & Bard, E. G. (2010). Eye-tracking for Two-Person Tasks with Manipulation of a Virtual World. *Behavior Research Methods*, *42*, 254-265. https://doi.org/10.3758/BRM.42.1.254

Carnevale, J. B., & Hatak, I. (2020). Employee adjustment and well-being in the era of COVID-19: Implications for human resource management. *Journal of Business Research*, *116*, 183-187. https://doi.org/10.1016/j.jbusres.2020.05.037

Casey-Campbell, M., & Martens, M. L. (2009). Sticking it All Together: A Critical Assessment of the Group Cohesion–Performance Literature. *International Journal of Management Reviews*, *11*(2), 223-246. https://doi.org/10.1111/j.1468-2370.2008.00239.x

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2022). Does remote work flexibility enhance organization performance? Moderating role of organization policy and top management support. *Journal of Business Research*, *139*, 1501-1512. https://doi.org/10.1016/j.jbusres.2021.10.069

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree—An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance, 9*, 88-97. https://doi.org/10.1016/j.jbef.2015.12.001

Cherubini, M., Nüssli, M. A., & Dillenbourg, P. (2008). Deixis and gaze in collaborative work at a distance (over a shared map): A computational model to detect misunderstandings. *Proceedings of the 2008 Symposium on Eye Tracking Research & Applications – ETRA '08*, 173-180. https://doi.org/10.1145/1344471.1344515

Cherubini, M., Nüssli, M. A., & Dillenbourg, P. (2010). This is it!: Indicating and looking in collaborative work at distance. *Journal of Eye Movement Research*, *3*(5), 1-20. https://doi.org/10.16910/jemr.3.5.3

Chiocchio, F., & Essiembre, H. (2009). Cohesion and Performance: A Meta-Analytic Review of Disparities between Project Teams, Production Teams, and Service Teams. *Small Group Research*, *40*(4), 382-420. https://doi.org/10.1177/1046496409335103

Choudhury, P., Foroughi, C., & Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. *Strategic Management Journal*, *42*(4), 655-683. https://doi.org/10.1002/smj.3251

Cialdini, R. B., Brown, S. L., Lewis, B. P., Luce, C., & Neuberg, S. L. (1997). Reinterpreting the empathy–altruism relationship: When one into one equals oneness. *Journal of Personality and Social Psychology,* *73*(3), 481-494. https://doi.org/10.1037/0022-3514.73.3.481

Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Frontiers in Psychology*, *5*, e510. https://doi.org/10.3389/fpsyg.2014.00510

Cohn, A., Gesche, T., & Maréchal, M. A. (2022). Honesty in the Digital Age. *Management Science, 68*(2), 827-845. https://doi.org/10.1287/mnsc.2021.3985

Conrads, J., & Reggiani, T. (2017). The effect of communication channels on promise-making and promise-keeping: experimental evidence. *Journal of Economic Interaction and Coordination, 12*, 595-611. https://doi.org/10.1007/s11403-016-0177-9

Daft, R. L., & Lengel, R. H. (1986). Organizational Information Requirements, Media Richness and Structural Design. *Management Science*, *32*(5), 554-571. https://doi.org/10.1287/mnsc.32.5.554

Dale, R., Kirkham, N. Z., & Richardson, D. C. (2011). The dynamics of reference and shared visual attention. *Frontiers in Psychology*, *2*, e355. https://doi.org/10.3389/fpsyg.2011.00355

Dalmaijer, E. S., Mathôt, S., & Van der Stigchel, S. (2014). PyGaze: An open-source, cross-platform toolbox for minimal-effort programming of eyetracking experiments. *Behavior Research Methods*, *46*, 913-921. https://doi.org/10.3758/s13428-013-0422-2

D'Angelo, S., & Schneider, B. (2021). Shared Gaze Visualizations in Collaborative Interactions: Past, Present and Future. *Interacting with Computers*, *33*(2), 115-133. https://doi.org/10.1093/iwcomp/iwab015

Delfgaauw, J., Dur, R., Onemu, O., & Sol, J. (2022). Team Incentives, Social Cohesion, and Performance: A Natural Field Experiment. *Management Science, 68*(1), 230-256. https://doi.org/10.1287/mnsc.2020.3901

Domes, G., Marx, L., Spenthof, I., & Heinrichs, M. (2016). The German version of the Gaze Anxiety Rating Scale (GARS): reliability and validity. *PLoS One*, *11*(3), e0150807. https://doi.org/10.1371/journal.pone.0150807

Duchowski, A. T. (2007). *Eye Tracking Methodology: Theory and Practice*. Springer, London. https://link.springer.com/chapter/10.1007/978-1-84628-609-4_5

Ebner, N. C., Riediger, M., & Lindenberger, U. (2010). FACES—A database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior Research Methods*, *42*, 351-362. https://doi.org/10.3758/BRM.42.1.351

Eckel, C. C., & Petrie, R. (2011). Face Value. *American Economic Review*, *101*(4), 1497-1513. https://doi.org/10.1257/aer.101.4.1497

Emanuel, N., & Harrington, E. (2024). Working remotely? Selection, Treatment, and the Market for Remote Work. *American Economic Journal: Applied Economics*, *16*(4), 528-559. https://doi.org/10.1257/app.20230376

Emery, N. J. (2000). The eyes have it: the neuroethology, function and evolution of social gaze. *Neuroscience & Biobehavioral Reviews, 24*(6), 581-604. https://doi.org/10.1016/S0149-7634(00)00025-7

Ernest-Jones, M., Nettle, D., & Bateson, M. (2011). Effects of eye images on everyday cooperative behavior: a field experiment. *Evolution and Human Behavior, 32*(3), 172-178. https://doi.org/10.1016/j.evolhumbehav.2010.10.006

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global evidence on economic preferences. *Quarterly Journal of Economics, 133*(4), 1645–1692. https://doi.org/10.1093/qje/qjy013

Falk, A., Becker, A., Dohmen, T., Huffman, D., & Sunde, U. (2023). The preference survey module: A validated instrument for measuring risk, time, and social preferences. *Management Science, 69*(4), 1935-1950. https://doi.org/10.1287/mnsc.2022.4455

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149-1160. https://doi.org/10.3758/BRM.41.4.1149

Fiedler, S., Glöckner, A., Nicklisch, A., & Dickert, S. (2013). Social Value Orientation and information search in social dilemmas: An eye-tracking analysis. *Organizational Behavior and Human Decision Processes, 120*(2), 272-284. https://doi.org/10.1016/j.obhdp.2012.07.002

Fındık-Coşkunçay, D., & Çakır, M. P. (2022). An investigation of the relationship between joint visual attention and product quality in collaborative business process modeling: A dual eye-tracking study. *Software and Systems Modeling*, *21*, 2429-2460. https://doi.org/10.1007/s10270-022-00974-6

Fischbacher, U., & Gächter, S. (2010). Social Preferences, Beliefs, and the Dynamics of Free Riding in Public Goods Experiments. *American Economic Review*, *100*(1), 541-556. https://doi.org/10.1257/aer.100.1.541

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters, 71*(3), 397-404. https://doi.org/10.1016/S0165-1765(01)00394-9

Fischbacher, U., Hausfeld, J., & Renerte, B. (2022). Strategic incentives undermine gaze as a signal of prosocial motives. *Games and Economic Behavior*, *136*, 63-91. https://doi.org/10.1016/j.geb.2022.07.006

Foddy, M. (1978). Patterns of Gaze in Cooperative and Competitive Negotiation. *Human Relations*, *31*(11), 925-938. https://doi.org/10.1177/001872677803101101

Frick, M. A., Brocki, K. C., Henriksson, L. H., & Kleberg, J. L. (2023). Disrupted Attention to Other's Eyes is Linked to Symptoms of ADHD in Childhood. *Child Psychiatry & Human Development*, *54*(4), 973-984. https://doi.org/10.1007/s10578-022-01316-9

Frischen, A., Bayliss, A. P., & Tipper, S. P. (2007). Gaze cueing of attention: Visual attention, social cognition, and individual differences. *Psychological Bulletin*, *133*(4), 694-724. https://doi.org/10.1037/0033-2909.133.4.694

Gächter, S., Starmer, C., & Tufano, F. (2015). Measuring the Closeness of Relationships: A Comprehensive Evaluation of the 'Inclusion of the Other in the Self' Scale. *PLoS One*, *10*(6), e0129478. https://doi.org/10.1371/journal.pone.0129478

Gächter, S., Starmer, C., & Tufano, F. (2024). Measuring Group Cohesion to Reveal the Power of Social Relationships in Team Production. *Review of Economics and Statistics*, *107*(2), 1-16. https://doi.org/10.1162/rest_a_01283

Gibbons, R. (1992). *A Primer in Game Theory*. New York: Prentice-Hall.

Gobel, M. S., Kim, H. S., & Richardson, D. C. (2015). The Dual Function of Social Gaze. *Cognition*, *136*, 359-364. https://doi.org/10.1016/j.cognition.2014.11.040

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with ORSEE. *Journal of the Economic Science Association*, *1*(1), 114-125. https://doi.org/10.1007/s40881-015-0004-4

Grossmann, T. (2017). The Eyes as Windows Into Other Minds: An Integrative Perspective. *Perspectives on Psychological Science*, *12*(1), 107-121. https://doi.org/10.1177/1745691616654457

Hagemann, V. (2017). Development of a German-Language Questionnaire to Measure Collective Orientation as an Individual Attitude. *Swiss Journal of Psychology*, *73*, 91-105. https://doi.org/10.1024/1421-0185/a000198

Hagemann, V. (2020). *Deutschsprachiges Instrument zur Erfassung der Kollektiven Orientierung (KO)*. ZIS. https://doi.org/10.6102/zis280

Hagemann, V., Ontrup, G., & Kluge, A. (2021). Collective Orientation and its Implications for Coordination and Team Performance in Interdependent Work Contexts. *Team Performance Management*, *27*(1/2), 30-65. https://doi.org/10.1108/TPM-03-2020-0020

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Haley, K. J., & Fessler, D. M. (2005). Nobody's watching?: Subtle cues affect generosity in an anonymous economic game. *Evolution and Human Behavior*, *26*(3), 245-256. https://doi.org/10.1016/j.evolhumbehav.2005.01.002

Hansson, K., Habibnia, H., Goetze, M., & Fiedler, S. (2024). The beauty of prosocial behavior: The bi-directional link between attractiveness and prosocial behavior. *Journal of Economic Behavior & Organization*, *219*, 305-317. https://doi.org/10.1016/j.jebo.2024.01.013

Hardt, D., Mayer, L., & Rincke, J. (2024). Who Does the Talking Here? The Impact of Gender Composition on Team Interactions. *Management Science: Articles in Advance*, 1-22. https://doi.org/10.1287/mnsc.2023.03411

Hausfeld, J., von Hesler, K., & Goldlücke, S. (2021). Strategic gaze: an interactive eye-tracking study. *Experimental Economics*, *24*, 177-205. https://doi.org/10.1007/s10683-020-09655-x

He, S., Offerman, T., & Van De Ven, J. (2017). The Sources of the Communication Gap. *Management Science*, *63*(9), 2832-2846. https://doi.org/10.1287/mnsc.2016.2518

Heroku (2023, September 12). *Deploy with ease. Manage efficiently. Scale faster*. Salesforce, Inc. https://signup.heroku.com/

Hessels, R. S. (2020). How Does Gaze to Faces Support Face-to-Face Interaction? A Review and Perspective. *Psychonomic Bulletin & Review*, *27*(5), 856-881. https://doi.org/10.3758/s13423-020-01715-w

Hietanen, J. K. (2018). Affective Eye Contact: An Integrative Review. *Frontiers in Psychology*, *9*, e1587. https://doi.org/10.3389/fpsyg.2018.01587

Hietanen, J. K., & Peltola, M. J. (2021). The eye contact smile: The effects of sending and receiving a direct gaze. *Visual Cognition*, *29*(7), 446-462. https://doi.org/10.1080/13506285.2021.1915904

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. Oxford University Press.

Ho, S., Foulsham, T., & Kingstone, A. (2015). Speaking and listening with the eyes: Gaze signaling during dyadic interactions. *PLoS One*, *10*(8), e0136905. https://doi.org/10.1371/journal.pone.0136905

Jarick, M., & Kingstone, A. (2015). The duality of gaze: eyes extract and signal social information during sustained cooperative and competitive dyadic gaze. *Frontiers in Psychology*, *6*, e1423. https://doi.org/10.3389/fpsyg.2015.01423

Jermann, P., & Nüssli, M. A. (2012). Effects of sharing text selections on gaze cross-recurrence and interaction quality in a pair programming task. *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work – CSCW '12*, 1125-1134. https://doi.org/10.1145/2145204.2145371

Jermann, P., & Sharma, K. (2018). Gaze as a Proxy for Cognition and Communication. *Proceedings of the 2018 IEEE 18th International Conference on Advanced Learning Technologies – ICALT '18*, 152-154. https://doi.org/10.1109/ICALT.2018.00043

Jermann, P., Nüssli, M. A., & Li, W. (2010). Using dual eye-tracking to unveil coordination and expertise in collaborative Tetris. *Proceedings of the 24th British Computer Society Conference on Human-Computer Interaction – HCI '10*, 36-44. https://doi.org/10.14236/ewic/HCI2010.7

Jessy, A. (2024, September 16). *Message from CEO Andy Jassy: Strengthening our culture and teams*. Amazon.com, Inc. https://www.aboutamazon.com/news/company-news/ceo-andy-jassy-latest-update-on-amazon-return-to-office-manager-team-ratio?utm_source=chatgpt.com

Jitsi Meet (2024, September 12). *Jitsi Meet Handbook*. 8x8, Inc. https://jitsi.github.io/handbook/

Kahai, S. S., & Cooper, R. B. (2003). Exploring the core concepts of media richness theory: The impact of cue multiplicity and feedback immediacy on decision quality. *Journal of Management Information Systems*, *20*(1), 263-299. https://doi.org/10.1080/07421222.2003.11045754

Kaiser, N., Henry, K., & Eyjólfsdóttir, H. (2022). Eye Contact in Video Communication: Experiences of Co-creating Relationships. *Frontiers in Psychology*, *13*, e852692. https://doi.org/10.3389/fpsyg.2022.852692

Kee, J., Knuth, M., Lahey, J. N., & Palma, M. A. (2021). Does Eye-Tracking Have an Effect on Economic Behavior?. *PLoS One*, *16*(8), e0254867. https://doi.org/10.1371/journal.pone.0254867

Kemper, C. J., Lutz, J., Margraf-Stiksrud, J., Beierlein, C., Kovaleva, A. & Rammstedt, B. (2014). *Attraktivitätsrating (AR1)*. ZIS. https://doi.org/10.6102/zis182

Kitchenham, B., & Charters, S. (2007). *Guidelines for performing Systematic Literature Reviews in Software Engineering*. Technical Report EBSE. https://www.researchgate.net/publication/302924724

Kleinke, C. L. (1986). Gaze and Eye Contact: A Research Review. *Psychological Bulletin*, *100*(1), 78-100. https://doi.org/10.1037/0033-2909.100.1.78

Kollock, P. (1998). Social Dilemmas: The Anatomy of Cooperation. *Annual Review of Sociology*, *24*(1), 183-214. https://doi.org/10.1146/annurev.soc.24.1.183

Koudenburg, N., Postmes, T., & Gordijn, E. H. (2013). Conversational Flow Promotes Solidarity. *PLoS One*, *8*(11), e78363. https://doi.org/10.1371/journal.pone.0078363

Kuhn, G., Teszka, R., Tenaw, N., & Kingstone, A. (2016). Don't be fooled! Attentional responses to social cues in a face-to-face and video magic trick reveals greater top-down control for overt than covert attention. *Cognition*, *146*, 136-142. https://doi.org/10.1016/j.cognition.2015.08.005

Kumar, C., Saini, B. K., & Staab, S. (2024). Enhancing Online Meeting Experience through Shared Gaze-Attention. *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, *128*, 1-6. https://doi.org/10.1145/3613905.3651068

Kuriyama, N., Terai, A., Yasuhara, M., Tokunaga, T., Yamagishi, K., & Kusumi, T. (2011). Gaze matching of referring expressions in collaborative problem solving. *Proceedings of International Workshop on Dual Eye Tracking in CSCW – DUET '11*, 1-8. https://www.cl.c.titech.ac.jp/_media/publication/668.pdf

Kurzban, R. (2001). The Social Psychophysics of Cooperation: Nonverbal Communication in a Public Goods Game. *Journal of Nonverbal Behavior*, *25*, 241-259. https://doi.org/10.1023/A:1012563421824

Lahey, J. N., & Oxley, D. (2016). The Power of Eye Tracking in Economics Experiments. *American Economic Review*, *106*(5), 309-313. https://doi.org/10.1257/aer.p20161009

Laidlaw, K. E., Risko, E. F., & Kingstone, A. (2012). A new look at social attention: Orienting to the eyes is not (entirely) under volitional control. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(5), 1132-1143. https://doi.org/10.1037/a0027075

Langner, M., Toreini, P., & Maedche, A. (2022). EyeMeet: A Joint Attention Support System for Remote Meetings. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems – CHI '22*, 1-7. https://doi.org/10.1145/3491101.3519792

Langton, S. R., Watt, R. J., & Bruce, V. (2000). Do the eyes have it? Cues to the direction of social attention. *Trends in Cognitive Sciences*, *4*(2), 50-59. https://doi.org/10.1016/S1364-6613(99)01436-9

Leiner, D. J. (2023, August 19). *SoSci Survey – the Solution for Professional Online Questionnaires*. SoSci Survey GmbH. https://www.soscisurvey.de/en/index

Madipakkam, A. R., Rothkirch, M., Dziobek, I., & Sterzer, P. (2017). Unconscious avoidance of eye contact in autism spectrum disorder. *Scientific Reports*, *7*, e13378. https://doi.org/10.1038/s41598-017-13945-5

Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review, 107*(12), 3722-3759. https://doi.org/10.1257/aer.20161500

Mason, M. F., Tatkow, E. P., & Macrae, C. N. (2005). The Look of Love: Gaze Shifts and Person Perception. *Psychological Science*, *16*(3), 236-239. https://doi.org/10.1111/j.0956-7976.2005.00809.x

May, D. R., Gilson, R. L., & Harter, L. M. (2004). The psychological conditions of meaningfulness, safety and availability and the engagement of the human spirit at work. *Journal of Occupational and Organizational Psychology*, *77*(1), 11-37. https://doi.org/10.1348/096317904322915892

Molinari, G. (2017). From learners' concept maps of their similar or complementary prior knowledge to collaborative concept map: Dual eye-tracking and concept map analyses. *Psychologie Française*, *62*(3), 293-311. https://doi.org/10.1016/j.psfr.2015.11.001

Molinari, G., Sangin, M., Nüssli, M. A., & Dillenbourg, P. (2008). Effects of Knowledge Interdependence with the Partner on Visual and Action Transactivity in Collaborative Concept Mapping. *Proceedings of the 8th International Conference of the Learning Sciences – ICLS '08*, 91-98. https://repository.isls.org//handle/1/3203

Naef, M., & Schupp, J. (2009). Measuring trust: Experiments and surveys in contrast and combination. *SOEP Paper No. 167*. http://dx.doi.org/10.2139/ssrn.1367375

Nalbantian, H. R., & Schotter, A. (1997). Productivity under Group Incentives: An Experimental Study. *The American Economic Review*, *87*(3), 314-341. https://www.jstor.org/stable/2951348

Nosenzo, D., Quercia, S., & Sefton, M. (2015). Cooperation in Small Groups: The Effect of Group Size. *Experimental Economics*, *18*, 4-14. https://doi.org/10.1007/s10683-013-9382-8

Olsen, J. K., Ringenberg, M., Aleven, V., & Rummel, N. (2015). Dual Eye Tracking as a Tool to Assess Collaboration. *Proceedings of the 4th Workshop on Intelligent Support for Learning in Groups – ISLG '15*, 25-30. http://ceur-ws.org/Vol-1432/islg_proc.pdf#page=29

Olsen, J., Sharma, K., Aleven, V., & Rummel, N. (2018). Combining Gaze, Dialogue, and Action from a Collaborative Intelligent Tutoring System to Inform Student Learning Processes. *Proceedings of the 13th International Conference of the Learning Sciences – ICLS '18*, 689-696. https://repository.isls.org//handle/1/484

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22-27. https://doi.org/10.1016/j.jbef.2017.12.004

Pfeiffer, U. J., Vogeley, K., & Schilbach, L. (2013). From gaze cueing to dual eye-tracking: Novel approaches to investigate the neural correlates of gaze in social interaction. *Neuroscience & Biobehavioral Reviews*, *37*(10), 2516-2528. https://doi.org/10.1016/j.neubiorev.2013.07.017

Pletzer, J. L., Balliet, D., Joireman, J., Kuhlman, D. M., Voelpel, S. C., & Van Lange, P. A. (2018). Social value orientation, expectations, and cooperation in social dilemmas: A meta–analysis. *European Journal of Personality*, *32*(1), 62-83. https://doi.org/10.1002/per.2139

Pupil Labs (2023, February 18). *Pupil Invisible*. Pupil Labs GmbH. https://docs.pupil-labs.com/invisible

PyGaze (2025, January 16). PyGaze Analyser. PyGaze.org. https://www.pygaze.org/2015/06/pygaze-analyser/

R Core Team (2023, August 19). *R: A Language and Environment for Statistical Computing*. The R Foundation. https://www.r-project.org

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, *41*(1), 203-212. https://doi.org/10.1016/j.jrp.2006.02.001

Rammstedt, B., Kemper, C. J., Klein, M. C., Beierlein, C., & Kovaleva, A. (2014). *Big Five Inventory (BFI-10)*. ZIS. https://doi.org/10.6102/zis76

Reuscher, T. F., Seitz, J., Greif-Winzrieth, A., Langner, M., Soballa, K., Maedche, A., & Nieken, P. (2024). Designing gaze-adaptive visualizations of mutual gaze for video meetings. *Proceedings of the NeuroIS Retreat 2024*, 228-235. https://publikationen.bibliothek.kit.edu/1000172247

Reuscher, T. F., Toreini, P., & Maedche, A. (2023). The State of the Art of Diagnostic Multiparty Eye Tracking in Synchronous Computer-Mediated Collaboration. *Journal of Eye Movement Research*, *16*(2). https://doi.org/10.16910/jemr.16.2.4

Richardson, D. C., & Dale, R. (2005). Looking to Understand: The Coupling between Speakers' and Listeners' Eye Movements and its Relationship to Discourse Comprehension. *Cognitive Science*, *29*(6), 1045-1060. https://doi.org/10.1207/s15516709cog0000_29

Riedl, A., Rohde, I. M., & Strobel, M. (2016). Efficient Coordination in Weakest-Link Games. *The Review of Economic Studies*, *83*(2), 737-767. https://doi.org/10.1093/restud/rdv040

Ristic, J., & Capozzi, F. (2022). Mechanisms for individual, group-based and crowd-based attention to social information. *Nature Reviews Psychology*, *1*, 721-732. https://doi.org/10.1038/s44159-022-00118-z

Rockmann, K. W., & Northcraft, G. B. (2008). To be or not to be trusted: The influence of media richness on defection and deception. *Organizational Behavior and Human Decision Processes*, *107*(2), 106-122. https://doi.org/10.1016/j.obhdp.2008.02.002

Rogers, S. L., Speelman, C. P., Guidetti, O., & Longmuir, M. (2018). Using dual eye tracking to uncover personal gaze patterns during social interaction. *Scientific Reports*, *8*, e4271. https://doi.org/10.1038/s41598-018-22726-7

Sajons, G. B. (2020). Estimating the causal effect of measured endogenous variables: A tutorial on experimentally randomized instrumental variables. *The Leadership Quarterly*, *31*(5), e101348. https://doi.org/10.1016/j.leaqua.2019.101348

Salas, E., Grossman, R., Hughes, A. M., & Coultas, C. W. (2015). Measuring Team Cohesion: Observations from the Science. *Human Factors*, *57*(3), 365-374. https://doi.org/10.1177/0018720815578267

Sally, D. (1995). Conversation and Cooperation in Social Dilemmas: A Meta-Analysis of Experiments from 1958 to 1992. *Rationality and Society*, *7*(1), 58-92. https://doi.org/10.1177/104346319500700100 4

Scharlemann, J. P., Eckel, C. C., Kacelnik, A., & Wilson, R. K. (2001). The Value of a Smile: Game Theory with a Human Face. *Journal of Economic Psychology*, *22*(5), 617-640. https://doi.org/10.1016/S0167-4870(01)00059-9

Schuessler, M., Hormann, L., Dachselt, R., Blake, A., & Rother, C. (2024). Gazing Heads: Investigating Gaze Perception in Video-Mediated Communication. *ACM Transactions on Computer-Human Interaction*, *31*(3), 1-31. https://doi.org/10.1145/3660343

Senju, A., & Johnson, M. H. (2009). Atypical eye contact in autism: Models, mechanisms and development. *Neuroscience & Biobehavioral Reviews*, *33*(8), 1204-1214. https://doi.org/10.1016/j.neubiorev.2009.06.001

Sharma, K., Caballero, D., Verma, H., Jermann, P., & Dillenbourg, P. (2015). Looking AT versus looking THROUGH: A Dual Eye-Tracking Study in MOOC Context. *Proceedings of the 11th International Conference on Computer Supported Collaborative Learning – CSCL '15*, 260-267. https://repository.isls.org//handle/1/416

Sharma, K., Jermann, P., Nüssli, M. A., & Dillenbourg, P. (2012). Gaze Evidence for Different Activities in Program Understanding. *Proceedings of the 24th Annual Conference of Psychology of Programming Interest Group – PPIG '12*, 1-12. https://infoscience.epfl.ch/record/184006

Sharma, K., Jermann, P., Nüssli, M. A., & Dillenbourg, P. (2013). Understanding Collaborative Program Comprehension: Interlacing Gaze and Dialogues. *Proceedings of the 10th International Conference on Computer Supported Collaborative Learning – CSCL '13*, 430-437. https://repository.isls.org/handle/1/1944

Sharma, K., Olsen, J. K., Aleven, V., & Rummel, N. (2021a). Measuring causality between collaborative and individual gaze metrics for collaborative problem-solving with intelligent tutoring systems. *Journal of Computer Assisted Learning*, *37*(1), 51-68. https://doi.org/10.1111/jcal.12467

Sharma, K., Olsen, J. K., Verma, H., Caballero, D., & Jermann, P. (2021b). Challenging Joint Visual Attention as a Proxy for Collaborative Performance. *Proceedings of the 14th International Conference on Computer-Supported Collaborative Learning – CSCL '21*, 91-98. https://repository.isls.org//handle/1/7364

Shen, L. (2023). Does working from home work? A natural experiment from lockdowns. *European Economic Review*, *151*, e104323. https://doi.org/10.1016/j.euroecorev.2022.104323

Simpson, B. (2006). Social Identity and Cooperation in Social Dilemmas. *Rationality and Society*, *18*(4), 443-470. https://doi.org/10.1177/1043463106066381

Standaert, W., Muylle, S., & Basu, A. (2021). How shall we meet? Understanding the importance of meeting mode capabilities for different meeting objectives. *Information & Management*, *58*(1), e103393. https://doi.org/10.1016/j.im.2020.103393

StataCorp. (2023). *Stata Statistical Software*. StataCorp LLC. https://www.stata.com/

Tchanou, A. Q., Léger, P. M., Boasen, J., Senecal, S., Taher, J. A., & Fredette, M. (2020). Collaborative Use of a Shared System Interface: The Role of User Gaze—Gaze Convergence Index Based on Synchronous Dual-Eyetracking. *Applied Sciences*, *10*(13), e4508. https://doi.org/10.3390/app10134508

Thielmann, I., Spadaro, G., & Balliet, D. (2020). Personality and Prosocial Behavior: A Theoretical Framework and Meta-Analysis. *Psychological Bulletin*, *146*(1), 30-90. https://doi.org/10.1037/bul0000217

Tobii (2024, September 12). *Specifications for the Tobii Eye Tracker 4C*. Tobii AB. https://help.tobii.com/hc/en-us/articles/213414285-Specifications-for-the-Tobii-Eye-Tracker-4C

Tomasello, M., Hare, B., Lehmann, H., & Call, J. (2007). Reliance on head versus eyes in the gaze following of great apes and human infants: the cooperative eye hypothesis. *Journal of Human Evolution*, *52*(3), 314-320. https://doi.org/10.1016/j.jhevol.2006.10.001

Uono, S., & Hietanen, J. K. (2015). Eye Contact Perception in the West and East: A Cross-Cultural Study. *PLoS One*, *10*(2), e0118094. https://doi.org/10.1371/journal.pone.0118094

Valtakari, N. V., Hooge, I. T., Viktorsson, C., Nyström, P., Falck-Ytter, T., & Hessels, R. S. (2021). Eye tracking in human interaction: Possibilities and limitations. *Behavior Research Methods*, *53*(4), 1592-1608. https://doi.org/10.3758/s13428-020-01517-x

Van Lange, P. A., Joireman, J., Parks, C. D., & Van Dijk, E. (2013). The Psychology of Social Dilemmas: A Review. *Organizational Behavior and Human Decision Processes*, *120*(2), 125-141. https://doi.org/10.1016/j.obhdp.2012.11.003

Villamor, M., & Rodrigo, M. M. (2017). Characterizing Collaboration Based on Prior Knowledge in a Pair Programming and Debugging Eye-Tracking Experiment. *Proceedings of the 15th National Conference on Information Technology Education – NCITE '17*, 1-8. https://www.researchgate.net/publication/320893405

Villamor, M., & Rodrigo, M. M. (2018). Impact of Pair Programming Dynamics and Profiles to Pair Success. *Proceedings of the 26th International Conference on Computers in Education – ICCE '18*, 123-132. https://www.researchgate.net/publication/329390104

Voit, M., Weiß, M., & Hewig, J. (2023). The benefits of beauty–Individual differences in the pro-attractiveness bias in social decision making. *Current Psychology*, *42*(14), 11388-11402. https://doi.org/10.1007/s12144-021-02366-3

Vrzakova, H., Amon, M. J., Rees, M., Faber, M., & D'Mello, S. (2021). Looking for a Deal? Visual Social Attention during Negotiations via Mixed Media Videoconferencing. *Proceedings of the ACM on Human-Computer Interaction*, *4,* 1-35. https://doi.org/10.1145/3434169

Vrzakova, H., Amon, M. J., Stewart, A. E., & D’Mello, S. K. (2019). Dynamics of Visual Attention in Multiparty Collaborative Problem Solving using Multidimensional Recurrence Quantification Analysis. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems – CHI '19*, 1-14. https://doi.org/10.1145/3290605.3300572

Wallot, S., & Leonardi, G. (2018). Analyzing Multivariate Dynamics Using Cross-Recurrence Quantification Analysis (CRQA), Diagonal-Cross-Recurrence Profiles (DCRP), and Multidimensional Recurrence Quantification Analysis (MdRQA) – A Tutorial in R. *Frontiers in Psychology*, *9*, e2232. https://doi.org/10.3389/fpsyg.2018.02232

Wallot, S., Roepstorff, A., & Mønster, D. (2016). Multidimensional Recurrence Quantification Analysis (MdRQA) for the Analysis of Multidimensional Time-Series: A Software Implementation in MATLAB and Its Application to Group-Level Data in Joint Action. *Frontiers in Psychology*, *7*, e1835. https://doi.org/10.3389/fpsyg.2016.01835

Wang, J. T. Y., Spezio, M., & Camerer, C. F. (2010). Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games. *American Economic Review*, *100*(3), 984-1007. https://doi.org/10.1257/aer.100.3.984

Wilson, R. K., & Eckel, C. C. (2006). Judging a Book by its Cover: Beauty and Expectations in the Trust Game. *Political Research Quarterly*, *59*(2), 189-202. https://doi.org/10.1177/106591290605900202

Wongpakaran, T., Wongpakaran, N., Intachote-Sakamoto, R., & Boripuntakul, T. (2013). The Group Cohesiveness Scale (GCS) for Psychiatric Inpatients. *Perspectives in Psychiatric Care*, *49*(1), 58-64. https://doi.org/10.1111/j.1744-6163.2012.00342.x

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT press, London.

Wyman, E., Rakoczy, H., & Tomasello, M. (2013). Non-verbal communication enables children's coordination in a "Stag Hunt" game. *European Journal of Developmental Psychology*, *10*(5), 597-610. https://doi.org/10.1080/17405629.2012.726469

Yang, L., Holtz, D., Jaffe, S., Suri, S., Sinha, S., Weston, J., Joyce, C., Shah, N., Sherman, K., Hecht, B., & Teevan, J. (2022). The effects of remote work on collaboration among information workers. *Nature Human Behaviour*, *6*(1), 43-54. https://doi.org/10.1038/s41562-021-01196-4

APPENDIX A

Additional Material for Chapter 2

	(1) Task & Context									(2) Remote Interaction							(3) Data Collection					(4) Data Processing									(5) Group-Level Metrics					
	Context		Type							Group Size		Input		Medium			Devices		Multimodality			Features		AOIs		Computation Methods					Eye-Based Constructs				Dependent Variables	
Authors	CSCW	CSCL	Artificial	Programming	Decision-Making	Math Problems	Concept Mapping	Visual Search	Tangram Puzzle	Dyads	Triads	Balanced	Operator/Helper	Chat	Audioconference	Videoconference	Screen-Based	Standalone	Eye Tracking **only**	Audio Logs	Audio & Video Logs	Fixations **only**	Fixation- & Pupil-Based	Two-Dimensional Grid	Interface Components	Aggregation **only**	Cross RQA	Multidimensional RQA	Proportionality Vectors	Other	Joint Attention	Joint Mental Effort	Mutual Gaze	Gaze Aversion	Task Performance	Learning Gains
Abdullah et al., 2021	x				x						x	x				x		x			x	x			x	x									x	
Bednarik & Kauppinen, 2013		x				x				x		x			x		x		x			x			x	x										x
Belenky et al., 2014; Olsen et al., 2015		x				x				x			x		x		x			x		x		x			x				x					x
Çakır & Uzunosmanoğlu, 2014		x				x				x		x		x			x		x			x		x			x								x	
Cherubini et al., 2008	x				x					x		x		x			x		x			x		x						x	x				x	
Cherubini et al., 2010	x				x					x		x		x			x		x			x		x			x				x				x	
Dale et al., 2011			x						x	x			x		x			x	x			x		x			x				x				x	
Fındık-Coşkunçay & Çakır, 2022	x				x					x		x		x				x	x			x		x			x				x				x	
Jermann & Nüssli, 2012; Jermann & Sharma, 2018	x			x						x		x			x		x			x		x			x		x				x				x	
Kuriyama et al., 2011			x						x	x			x		x		x			x		x		x			x				x				x	
Molinari et al., 2008; Molinari, 2017		x					x			x		x			x		x		x			x			x	x										x
Olsen et al., 2018		x				x				x			x		x		x			x		x		x					x		x				x	
Sharma et al., 2012	x			x						x		x			x		x			x		x			x					x					x	
Sharma et al., 2013	x			x						x		x			x		x			x		x			x				x		x				x	
Sharma et al., 2015	x				x					x		x			x		x		x			x			x				x		x					x
Sharma et al., 2021a		x				x				x			x		x		x			x		x		x					x		x				x	
Sharma et al., 2021b		x					x			x		x			x		x			x			x		x		x				x	x			x	
Tchanou et al., 2020			x					x		x		x			x			x			x		x							x	x	x			x	
Villamor & Rodrigo, 2017; 2018	x			x						x		x		x				x	x			x			x		x				x				x	
Vrzakova et al., 2019	x			x							x		x			x		x			x	x			x		x	x			x				x	
Vrzakova et al., 2021	x				x					x			x			x		x			x	x			x			x			x		x	x	x	

Table A.1: Extracted data tabulated by identified relevant aspects.

APPENDIX B

Additional Material for Chapter 3

B.1 Instructions: Experiment 1

Welcome,

before we start, we would like to give you some essential information about our study.

In the context of the study, we use the currency “ECU”. This will be converted into Euros for your compensation at the end of the study. Thereby, 1.00 € equals 9.60 ECU.

At the beginning of the study, you will receive an endowment of 72 ECU. The amount of your payoff depends on your decision as well as the decisions of your team members in the experimental team task. After the study, you will receive a minimum payoff of 48 ECU for your participation.

The study consists of a main part (about 30 minutes) and two short surveys (5 minutes each) at the beginning and at the end. Please take your time when answering the questions.

Please click on the continue button to start. There is no possibility to return to a previous page. Therefore, please answer all questions in the given order.

Thank you for completing the pre-survey,

before we continue, we would like to describe the procedure of the main part of this study.

In the main part, you will work with two other participants to solve a team task. The goal of the team task is to create a unique shape based on geometric pieces. To do this, you will receive a tangram puzzle, which we will describe in more detail below.

The main part is divided into two phases.

1) Practice phase (15 minutes): First, we want to make sure that you gain a basic understanding of how to work on the team task. For this purpose, you will receive a detailed

explanation about the objective and the rules of the team task. We will also describe in detail what will affect the amount of your payoff.

2) Team task (10 minutes): After the practice phase, you will be equipped with eye-tracking glasses and guided to the room where the team task will be performed. After completing the team task with your team members, you will be guided back to the individual cubicle you are currently in.

Tangram puzzle

The team task is based on a tangram puzzle. A tangram is a set of building blocks in geometric shapes. These building blocks can be used to create various shapes reminiscent of animals or objects.

The tangram puzzle has no particular rules. For example, the building blocks do not necessarily have to touch each other. Thus, figures can also include distinct components.

Instructions

Below you will receive detailed information about the team task as well as the payoff principle. Please take your time to understand the objective and the rules of the game.

<u>Team task</u>

Once the team task begins, you will be equipped with eye-tracking glasses and led to a group room. In this room, you will be asked to take a seat at a round table, which is divided by partitions. The partitions contain rectangular cut outs so that you can see and communicate with your team members despite being spatially separated.

You will have 10 minutes to complete the team task. At the end of the 10 minutes, you will be guided back to your individual cubicle.

The team task is based on the tangram puzzle, which was introduced on the previous page. In the team task, you will be given your own set of 12 tangram building blocks. Together with your team members, you will have a total of 36 building blocks to complete the task.

The objective of the team task is to work together with your team members to create a shape from the available building blocks. You can talk with your team members during the 10 minutes and place as many building blocks as you like on the table. You can also take your own blocks off the table at any time. To make it easier to assign the building blocks to the individual team members, they have different colors.

Within the 10 minutes, you and your team members need to agree on a figure as well as the building blocks required for it.

Afterwards, you will be escorted back to your individual cubicle to make a final decision about how many of your 12 building blocks you would like to contribute to the team task.

Your individual decision and the decisions of your two team members will determine the amount of your payoff.

Payoff

To complete the team task, each team member receives a set of 12 tangram blocks. Thus, a total of 36 blocks will be available to create a shape. Each team member decides individually on the number of pieces they want to contribute to the team task.

The amount of your payoff depends on two factors.

1) Individual revenue: First, the sum of the building blocks contributed by all three team members is calculated. This sum can be between 0 and 36, since all three participants can contribute between 0 and 12 building blocks. The sum of the building blocks is then multiplied by 12 to determine the team's overall revenue. In the second step, the team revenue is divided equally between the team members, so that each participant receives one third as individual revenue.

The following table shows your individual revenue based on the sum of contributed building blocks.

Building Blocks	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Individual Revenue	0	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	104	108	112	116	120	124	128	132	136	140	144

2) Individual costs: Each building block you contribute to the team task incurs a cost to yourself. These individual costs increase with each block you have already contributed and are deducted from your individual revenue.

Building Blocks	0	1	2	3	4	5	6	7	8	9	10	11	12
Individual Costs	0	0,5	2	4,5	8	12,5	18	24,5	32	40,5	50	60,5	72

Consequently:

Payoff = 72 + (R - C)

72:	Endowment	<u>**Example**</u>**:**	**R (10)** = 40; **C (6)** = 18
R:	Individual Revenue		**Payoff** = 72 + (40 - 18)
C:	Individual Costs		**Payoff** = 94 ECU

Comprehension tasks

Before we continue with the practice phase, we would like to ask you to complete the following comprehension tasks. For this purpose, please use the auxiliary materials provided at your workplace.

1) Please indicate the maximum number of building blocks you can personally contribute to the team task.

[Select option between 0 and 12] building blocks

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> To complete the team task, each participant receives a set of 12 tangram building blocks.

2) Please indicate the maximum number of building blocks that your entire team can contribute to the team task.

[Select option between 0 and 12] building blocks

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> To complete the team task, each participant receives a set of 12 tangram building blocks. Thus, each team receives a total of 36 building blocks to complete the task.

3) Please select all decisions that influence your individual revenue.

[] Your individual decision

[] Decisions of the other two participants

> *[If wrong]* Unfortunately, your answer to the question was not correct.

Both your individual decision and the decisions of the other two participants influence your individual revenue, since it is based on the total number of building blocks contributed (0 to 36).

4) Please select all decisions that influence your individual costs.

[] Your individual decision

[] Decisions of the other two participants

[If wrong] Unfortunately, your answer to the question was not correct.

Only your individual decision influences your individual costs, as it is based on your individual contribution (0 to 12).

5) Please select the option that correctly reflects the payoff principle of the team task.

[] Payoff = Individual Costs - Individual Revenue + 72

[] Payoff = (Individual Costs - 72) + Individual Costs

[] Payoff = (Individual Revenue + 72) + Individual Costs

[] Payoff = 72 + (Individual Revenue - Individual Costs)

[If wrong] Unfortunately, your answer to the question was not correct.

The payoff principle is: Payoff = 72 + (Individual Revenue - Individual Costs)

Practice phase

Please take 5 minutes to get familiar with the team task.

You will find a box with 12 tangram blocks in front of you. Please take out all the building blocks and try to create different shapes on the table in front of you.

The number of building blocks used is neither observed nor recorded during the practice phase and thus has no influence on the payoff.

To continue, please click on the button at the bottom right corner of the screen as soon as the timer has expired.

Thank you for completing the practice phase,

you have successfully completed the first part of the study. Next, the team task begins.

<u>Reminder</u>

The team task is divided into two phases.

1) During the 10 minutes, you and your team members need to agree on a shape to build as well as the building blocks required to achieve it. You can talk with each other during the 10 minutes and place as many building blocks as you like on the table. You can also remove your own building blocks from the table at any time.

2) After the 10 minutes, you will be guided back to your individual cubicle. Next, you need to indicate how many of your 12 building blocks you would like to contribute to the team task.

The goal in the first stage is to agree on a solution to the team task. In the second stage, you decide on how many building blocks you want to contribute to the agreed upon solution. This individual decision is not disclosed to the other participants.

Your individual decision and the decisions of your two team members in the second stage determine your payoff.

Please remain seated until you will be guided to the group room to complete the team task.

Decision stage

Please indicate how many of your building blocks you would like to contribute to the agreed upon solution.

<u>Payoff principle:</u> **Payoff = 72 + (R - C)**

72: Endowment

R: Individual Revenue

C: Individual Costs

[Select option between 0 and 12] building blocks

Thank you for completing the team task,

now please take your time to answer the questions included in the post-survey.

Please click on the continue button to start. There is no possibility to return to a previous page. Therefore, please answer the questions in the given order.

B.2 Instructions: Experiment 2

Welcome,

before we start, we would like to give you some essential information about our study.

In the context of the study, we use the currency “ECU”. This will be converted into Euros for your compensation at the end of the study. Thereby, 1.00 € equals 10 ECU.

At the beginning of the study, you will receive an endowment of 72 ECU. The amount of your payoff depends on your decision as well as the decisions of your team members in the experimental team task. You will be informed of the exact amount of your payoff in two weeks.

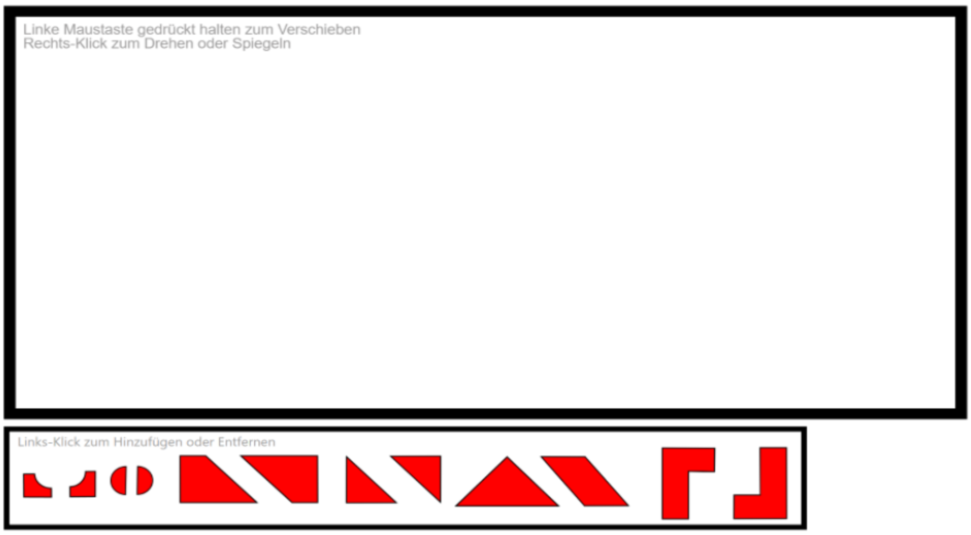
Participation in the study takes about 45 minutes. Please take your time when answering the questions.

Please click on the continue button to start. There is no possibility to return to a previous page. Therefore, please answer all questions in the given order.

Thank you for completing the pre-survey,

before we continue, we would like to describe the procedure of the main part of this study.

In the main part, you will work with two other participants to solve a team task. The goal of the team task is to create a unique shape based on geometric pieces. To do this, you will be given access to an individual computer where you can work together with your team members in a virtual workspace.



The main part is divided into two phases.

1) Practice phase: First, we want to make sure that you gain a basic understanding of how to work on the team task. For this purpose, you will receive a detailed explanation about the objective and the rules of the team task. We will also describe in detail what will affect the amount of your payoff.

2) Team task: After the practice phase, you will be equipped with eye-tracking glasses and guided to the room where the team task will be performed. After completing the team task with your team members, you will be guided back to the individual cubicle you are currently in.

Tangram puzzle

The team task is based on a tangram puzzle. A tangram is a set of building blocks in geometric shapes. These building blocks can be used to create various shapes reminiscent of animals or objects.

The tangram puzzle has no particular rules. For example, the building blocks do not necessarily have to touch each other. Thus, figures can also include distinct components.

Instructions

Below you will receive detailed information about the team task as well as the payoff principle. Please take your time to understand the objective and the rules of the game.

Team task

Once the team task begins, you will be equipped with eye-tracking glasses and led to another room.

[If treatment = face-to-face] In this room, you will be asked to take a seat at a table with a computer. The table is separated from those of your team members by partitions. However, the partitions contain rectangular cut outs so that you can see and communicate with your team members despite being spatially separated.

[If treatment = video meeting] In this room, you will be asked to take a seat at a table with a computer and three monitors. While performing the team task on the central monitor, your team members will be displayed on the left and right monitor via video meetings so that you can see and communicate with your team members despite being spatially separated.

You will have 5 minutes to complete the team task. At the end of the 5 minutes, you will be guided back to your individual cubicle.

The team task is based on the tangram puzzle, which was introduced on the previous page. In the team task, you will be given access to 12 tangram building blocks within a virtual workspace. Together with your team members, you will have a total of 36 building blocks to complete the task.

The objective of the team task is to work together with your team members to create a shape from the available building blocks. You can talk with your team members during the 5 minutes and add as many blocks as you like into the shared area for creating the tangram. You can also remove your own blocks from the interactive workspace at any time. The blocks have different colors to make it easier to distinguish between team members.

Thus, the team task is divided into two phases:

1) Team phase: Within the 5 minutes, you and your team members need to agree on a tangram shape as well as the building blocks required for it.

2) Decision phase: After completing the team phase, you will be escorted back to your individual cubicle to make a final decision about how many of your 12 building blocks you would like to contribute to the team task.

Your individual decision will not be disclosed to the other participants and will therefore be anonymous. Likewise, you will not be informed of the individual decisions of your team members.

Your individual decision and the decisions of your two team members will determine the amount of your payoff.

<u>Payoff</u>

To complete the team task, each team member receives a set of 12 tangram blocks. Thus, a total of 36 blocks will be available to create a shape. Each team member decides individually on the number of pieces they want to contribute to the team task.

The amount of your payoff depends on two factors.

1) Individual revenue: First, the sum of the building blocks contributed by all three team members is calculated. This sum can be between 0 and 36, since all three participants can contribute between 0 and 12 building blocks. The sum of the building blocks is then multiplied by 18 to determine the team's overall revenue. In the second step, the team revenue is divided equally between the team members, so that each participant receives one third as individual revenue.

$$= \frac{18 * (x_1 + x_2 + x_3)}{3} = 6 * (x_1 + x_2 + x_3)$$

2) Individual costs: Each building block you contribute to the team task incurs a cost to yourself. These individual costs increase with each block you have already contributed and are deducted from your individual revenue.

$$= x_i^2$$

In combination with your endowment of 72 ECU, your individual payoff is calculated as follows:

$$= 72 + 6 * (x_1 + x_2 + x_3) - x_i^2$$

Comprehension tasks

Before we continue with the practice phase, we would like to ask you to complete the following comprehension tasks. For this purpose, please use the auxiliary materials provided at your workplace.

1) Please indicate the maximum number of building blocks you can personally contribute to the team task.

[Select option between 0 and 12] building blocks

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> To complete the team task, each participant receives a set of 12 tangram building blocks.

2) Please indicate the maximum number of building blocks that your entire team can contribute to the team task.

[Select option between 0 and 12] building blocks

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> To complete the team task, each participant receives a set of 12 tangram building blocks. Thus, each team receives a total of 36 building blocks to complete the task.

3) Please select all decisions that influence your individual revenue.

[] Your individual decision

[] Decisions of the other two participants

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> Both your individual decision and the decisions of the other two participants influence your individual revenue, since it is based on the total number of building blocks contributed (0 to 36).

4) Please select all decisions that influence your individual costs.

[] Your individual decision

[] Decisions of the other two participants

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> Only your individual decision influences your individual costs, as it is based on your individual contribution (0 to 12).

5) Please select the option that correctly reflects the payoff principle of the team task.

[] Payoff = Individual Costs - Individual Revenue + 72

[] Payoff = (Individual Costs - 72) + Individual Costs

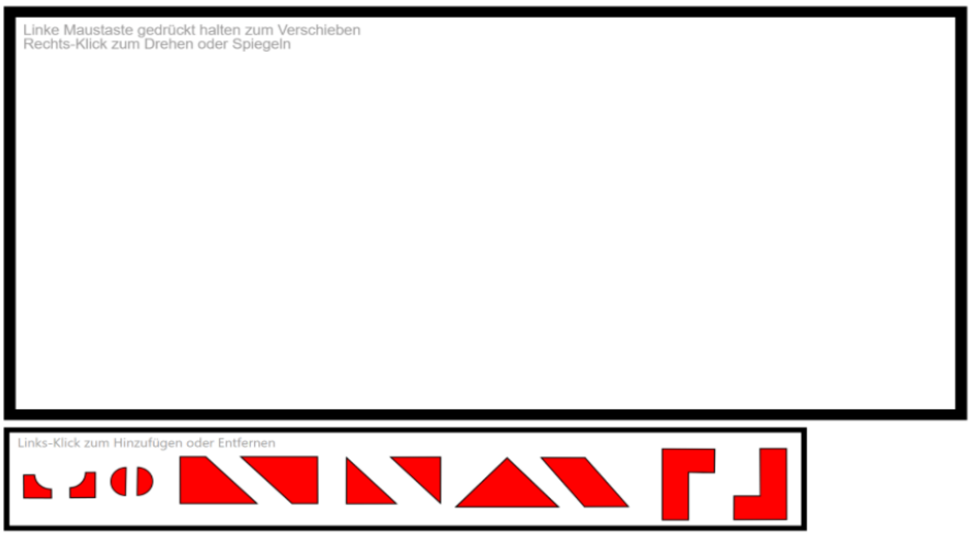
[] Payoff = (Individual Revenue + 72) + Individual Costs

[] Payoff = 72 + (Individual Revenue - Individual Costs)

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> The payoff principle is: Payoff = 72 + (Individual Revenue - Individual Costs)

Practice phase

On the following page, you will have the opportunity to get familiar with the operation of the virtual workspace for working together on the team task. In the virtual workspace, which is not shared with your team members during the practice phase, you have access to 12 Tangram blocks.



1) Left-click to add or remove: By clicking with the left mouse button (left-click), the blocks can be added to the larger area for creating and editing the tangram. You can also remove a block from the editing area by clicking on it again in the lower bar.

2) Hold down the left mouse button to move blocks: In the editing area, you can move the blocks by holding down the left mouse button (continued left-click).

3) Right-click to rotate or mirror: Furthermore, you can edit the alignment of the blocks in the editing area by clicking on them with the right mouse button (right-click). As soon as you have clicked on a block, you can rotate and mirror it around its own axis. Right-click on the block again to finish editing the alignment.

The number of building blocks used is neither observed nor recorded during the practice phase and thus has no influence on the payoff.

To continue, please click on the button at the bottom right corner of the screen as soon as the time on it has expired.

Thank you for completing the practice phase,

you have successfully completed the first part of the study. Next, the team task begins.

<u>Reminder</u>

The team task is divided into two phases.

1) During the 5 minutes, you and your team members need to agree on a shape to build as well as the building blocks required to achieve it. You can talk with your team members during the 5 minutes and add as many blocks as you like into the shared area for creating the tangram. You can also remove your own blocks from the interactive workspace at any time.

2) After the 5 minutes, you will be guided back to your individual cubicle. Next, you need to indicate how many of your 12 building blocks you would like to contribute to the team task.

Your individual decision and the decisions of your two team members in the second stage determine your payoff.

Please remain seated until you will be guided to the group room to complete the team task.

Decision stage

Please make a final decision on the number of building blocks you would like to contribute to the team task.

[Select option between 0 and 12] building blocks

<u>Reminder</u>

The amount of your payoff depends on two factors.

1) Individual revenue: First, the sum of the building blocks contributed by all three team members is calculated. This sum can be between 0 and 36, since all three participants can contribute between 0 and 12 building blocks. The sum of the building blocks is then multiplied by 18 to determine the team's overall revenue. In the second step, the team revenue is divided equally between the team members, so that each participant receives one third as individual revenue.

$$= \frac{18 * (x_1 + x_2 + x_3)}{3} = 6 * (x_1 + x_2 + x_3)$$

2) Individual costs: Each building block you contribute to the team task incurs a cost to yourself. These individual costs increase with each block you have already contributed and are deducted from your individual revenue.

$$= x_i^2$$

In combination with your endowment of 72 ECU, your individual payoff is calculated as follows:

$$= 72 + 6 * (x_1 + x_2 + x_3) - x_i^2$$

Thank you for completing the team task,

now please take your time to answer the questions included in the post-survey.

Please click on the continue button to start. There is no possibility to return to a previous page. Therefore, please answer the questions in the given order.

B.3 Additional Figures and Tables

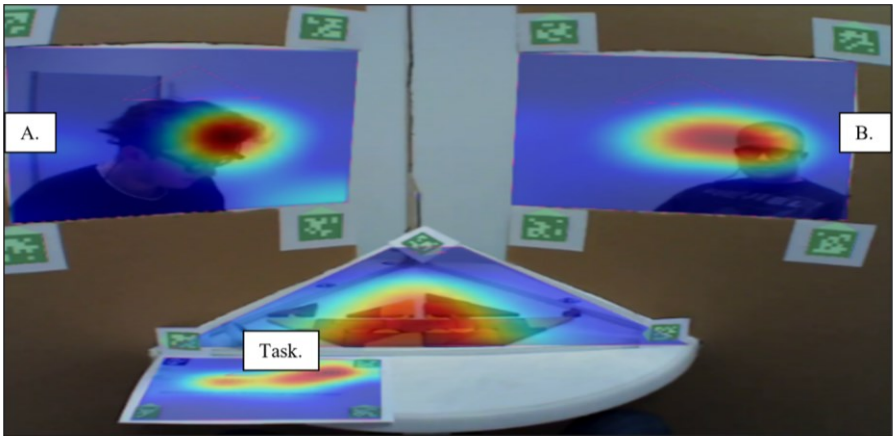


Figure B.1: Areas of interest A, B, and Task in the first experiment, as seen from the visual perspective of team member C with heatmaps depicting the foci of visual attention.

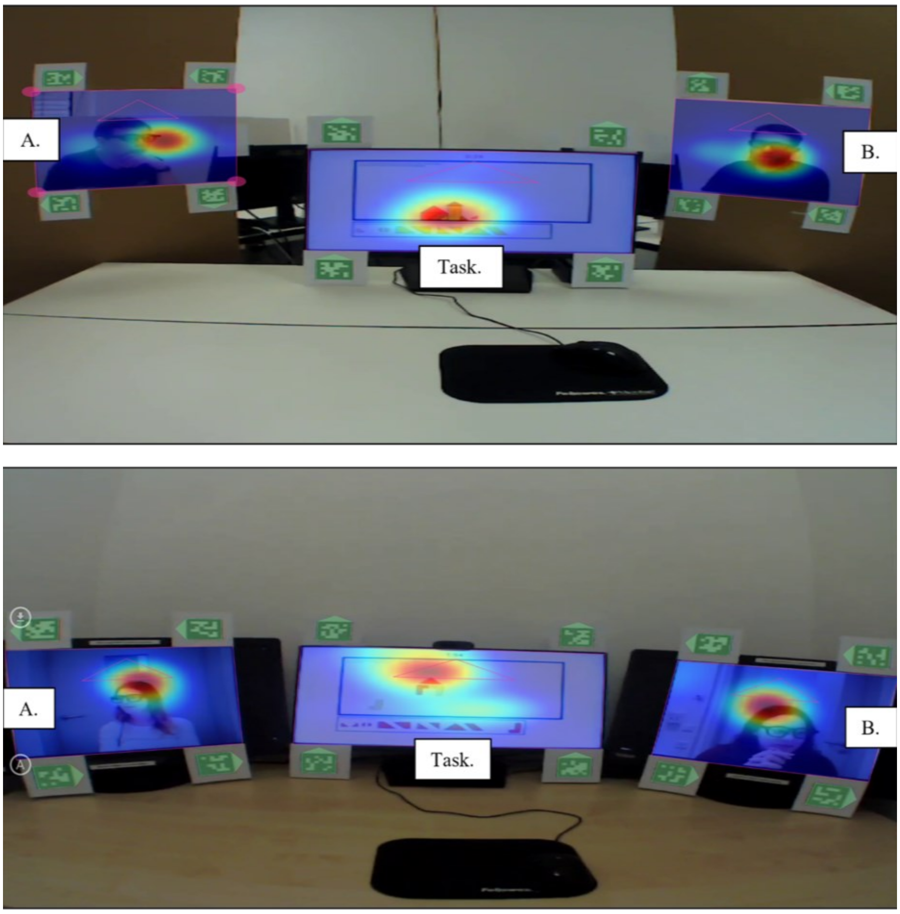


Figure B.2: Areas of interest A, B, and Task in the second experiment, as seen from the visual perspective of team member C with heatmaps depicting the foci of visual attention.

Variable	***M***	***SD***	**Min**	**Max**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
(1) Female	0.50	0.51	0.00	1.00													
(2) Age	24.27	2.21	21.00	29.00	-0.12												
(3) Individual Contribution	11.20	1.54	8.00	12.00	0.18	-0.16											
(4) Team Cohesion	0.00	0.83	-2.05	1.01	0.21	-0.12	0.36*										
(5) Belongingness	5.50	1.43	2.00	7.00	0.21	-0.09	0.13	0.81***									
(6) Social Cohesion	4.32	0.59	3.00	5.00	0.20	0.05	0.40**	0.91***	0.68***								
(7) Task Cohesion	4.72	0.33	4.00	5.00	0.10	-0.26	0.36**	0.78***	0.35*	0.58***							
(8) Collective Orientation	2.99	0.33	2.25	3.69	-0.25	0.28	0.12	0.07	-0.06	0.15	0.08						
(9) Interpersonal Trust	3.83	0.43	3.00	4.67	-0.08	0.11	0.21	-0.15	-0.29	0.03	-0.12	0.36*					
(10) Extraversion	3.17	0.80	2.00	5.00	0.17	-0.19	0.42**	0.12	-0.02	0.07	0.25	-0.02	-0.10				
(11) Agreeableness	3.30	0.68	2.00	4.50	0.10	-0.14	0.24	0.08	0.00	0.06	0.16	0.24	0.14	0.35*			
(12) Conscientiousness	3.65	0.88	2.00	5.00	0.13	0.32*	-0.32*	-0.22	-0.13	-0.19	-0.23	-0.12	-0.22	0.10	0.07		
(13) Neuroticism	2.78	0.99	1.00	5.00	0.36*	0.00	-0.03	0.13	0.23	0.18	-0.09	-0.26	0.06	-0.45**	-0.14	-0.09	
(14) Openness	3.37	1.04	1.50	5.00	0.07	0.09	0.38**	0.17	-0.01	0.18	0.24	-0.05	-0.01	0.07	-0.37**	-0.11	0.24

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$, $n = 30$

Table B.1: Summary statistics and pairwise correlations at the individual level (n = 30) in experiment 1.

Variable	*M*	*SD*	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)
(1) Female	0.50	0.53	0.00	1.00						
(2) Age	24.27	1.45	21.67	27.00	-0.19					
(3) Team Output	33.60	4.30	24.00	36.00	0.20	-0.08				
(4) Team Cohesion	0.00	1.62	-2.37	2.01	0.33	0.26	0.36			
(5) Mutual Gaze	8.52	6.39	2.66	24.79	0.43	-0.35	0.25	0.37		
(6) Gaze Aversion	21.96	7.08	13.48	34.28	0.13	0.46	-0.26	0.37	0.47	
(7) Joint Attention	46.12	13.17	23.63	60.57	0.04	-0.37	0.04	-0.52	-0.58*	-0.88***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $n = 10$

Table B.2: Summary statistics and pairwise correlations at the team level (n = 10) in experiment 1.

Variable	(1) Team Output	(2) Team Output
Mutual Gaze	0.323	0.430**
	(0.193)	(0.162)
Gaze Aversion	-0.293	-0.394
	(0.297)	(0.229)
Collective Orientation		7.410
		(4.919)
Constant	37.290***	16.421
	(4.519)	(15.106)
Pseudo R^2	0.050	0.083
Observations	10	10

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Tobit regressions with *team output* as the dependent variable.

Variable	(1) Contribution	(2) Contribution	(3) Contribution
Mutual Gaze	0.082	0.098	0.016
	(0.073)	(0.070)	(0.073)
Gaze Aversion	-0.182	-0.182	-0.251***
	(0.128)	(0.118)	(0.088)
Joint Attention	-0.059	-0.048	-0.106*
	(0.049)	(0.057)	(0.055)
Collective Orientation		1.014	1.093
		(0.866)	(0.876)
Interpersonal Trust		0.172	0.422
		(0.257)	(0.347)
Female			1.195
			(0.830)
Age			-0.041
			(0.090)
Constant	17.218***	12.899*	16.979***
	(4.163)	(6.462)	(5.610)
Pseudo R^2	0.077	0.096	0.126
Observations	30	30	30

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Tobit regressions with *individual contribution* as the dependent variable.

Variable	*M*	*SD*	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Face-to-Face	0.50	0.50	0.00	1.00														
(2) Female	0.53	0.50	0.00	1.00	-0.06													
(3) Age	24.40	4.85	18.00	54.00	0.06	-0.06												
(4) Individual Contribution	5.95	2.80	0.00	12.00	0.10	-0.09	0.10											
(5) Team Cohesion	5.47	1.04	2.06	7.00	-0.07	0.19***	-0.03	0.21***										
(6) Belongingness	4.74	1.60	1.00	7.00	-0.05	0.10	0.02	0.25***	0.86***									
(7) Social Cohesion	5.65	1.10	1.50	7.00	-0.11	0.24***	-0.07	0.10	0.86***	0.55***								
(8) Task Cohesion	6.02	0.99	2.00	7.00	-0.01	0.15**	-0.04	0.15**	0.81***	0.48***	0.69***							
(9) Collective Orientation	2.94	0.32	1.88	3.88	0.00	0.00	0.06	0.14**	0.08	0.15**	0.02	0.00						
(10) Interpersonal Trust	3.12	0.45	1.67	4.33	-0.01	-0.01	0.00	0.03	0.15**	0.08	0.17**	0.18**	0.03					
(11) Extraversion	3.26	0.96	1.00	5.00	-0.04	0.04	0.03	-0.11	0.04	0.02	0.01	0.08	-0.23***	0.03				
(12) Agreeableness	3.33	0.83	1.00	5.00	-0.04	0.18**	-0.05	0.14*	0.17**	0.10	0.21***	0.14*	0.19***	0.27***	0.02			
(13) Conscientiousness	3.58	0.83	1.50	5.00	0.02	0.04	0.03	0.02	0.13*	0.11	0.14*	0.09	-0.05	0.02	0.10	0.00		
(14) Neuroticism	3.00	1.01	1.00	5.00	-0.04	0.38***	-0.01	0.05	0.07	0.08	0.03	0.06	0.12*	0.08	-0.17**	0.02	0.02	
(15) Openness	3.51	1.08	1.00	5.00	0.05	0.23***	0.17**	-0.03	0.00	-0.02	0.06	-0.03	-0.04	-0.08	0.15**	-0.12*	0.05	0.20***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $n = 204$

Table B.5: Summary statistics and pairwise correlations at the individual level ($n = 204$) in experiment 2.

Variable	*M*	*SD*	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Face-to-Face	0.50	0.50	0.00	1.00								
(2) Female	0.53	0.50	0.00	1.00	-0.06							
(3) Age	24.40	2.76	20.67	34.33	0.10	-0.10						
(4) Team Output	17.84	6.90	3.00	36.00	0.12	-0.11	0.14					
(5) Team Cohesion	16.41	2.21	8.94	19.61	-0.10	0.26**	-0.12	0.13				
(6) Attentional Reciprocity	18.94	13.87	0.00	51.51	0.54***	-0.05	0.00	0.11	0.14			
(7) Mutual Gaze	8.03	7.98	0.00	33.49	0.41***	-0.04	-0.17	0.01	0.16	0.91***		
(8) Gaze Aversion	26.77	12.67	2.76	56.03	-0.16	0.04	-0.30**	-0.36***	0.05	0.26**	0.47***	
(9) Joint Attention	58.10	20.03	14.66	96.10	0.03	0.01	0.28**	0.29**	0.01	-0.47***	-0.65***	-0.91***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $n = 68$

Table B.6: Summary statistics and pairwise correlations at the team level (n = 68) in experiment 2.

	Video Meeting	Face-to-Face			
Variable	***M* (*SD*)**	***M* (*SD*)**	***t*(202)**	***p***	**Cohen's *d***
Co Presence	6.00 (0.90)	6.05 (0.77)	0.39	.697	0.05
Attention Allocation	5.17 (1.18)	5.22 (1.07)	0.27	.787	0.04
Message Understanding	5.57 (1.10)	5.69 (1.08)	0.78	.435	0.11
Affective Understanding	4.17 (1.30)	4.35 (1.20)	1.03	.303	0.14
Emotional Interdependence	4.18 (1.22)	4.34 (1.16)	0.98	.323	0.14
Behavioral Interdependence	5.04 (0.86)	5.13 (0.91)	0.73	.468	0.10

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Semi-parametric treatment comparisons (two-sided t-tests) of *social presence* according to Biocca et al. (2003) by *FT* and *VT*.

B.4 Two-Stage Least Squares (2SLS)

Definition. Two-stage least squares (2SLS) estimation extends ordinary least squares (OLS) to address cases where the assumptions of OLS are violated. In particular, OLS assumes that all factors influencing y are captured by the variation in x and that x is exogenous, meaning it is uncorrelated with the error term ε (Wooldridge, 2010). When these assumptions hold, OLS provides unbiased and consistent estimates. However, when x is endogenous, meaning it is correlated with the error term, OLS estimates become biased. The 2SLS method modifies the OLS approach by introducing instrumental variables to isolate the exogenous variation in x, thereby addressing endogeneity (Sajons, 2020).

The general form of the OLS regression is shown in Equation 1, where y is the dependent variable, x is the independent variable, β_0 is the intercept, β_1 is the coefficient of x, and ε is the error term, representing all unobserved factors affecting y (Bastardoz et al., 2023). For OLS to produce reliable estimates of β_1, x must be exogenous. If x is endogenous, the estimates will be biased and unsuitable for causal interpretation.

$$y = \beta_0 + \beta_1 x + \varepsilon \quad \text{(Eq. 1)}$$

Endogeneity, defined as the correlation between the explanatory variable and the error term, is a common issue in regression models (Bound et al., 1995; Wooldridge, 2010). It can arise due to omitted variables, sample selection bias, measurement error, or simultaneity/reverse causality.

Procedure. 2SLS estimation mitigates endogeneity through a two-stage process. In the first stage, the endogenous variable x is regressed on an instrumental variable z that is uncorrelated with the error term (Equation 2). This produces an estimated predictor $\hat{x}$, which captures only the exogenous variation in x.

$$x = \delta_0 + \delta_1 z + u \quad \text{(Eq. 2)}$$

In the second stage, $\hat{x}$ replaces x in the original model, and y is regressed on $\hat{x}$, as shown in Equation 3.

$$y = \alpha_0 + \alpha_1 \hat{x} + w \quad \text{(Eq. 3)}$$

APPENDIX C

Additional Material for Chapter 4

C.1 Additional Figures and Tables

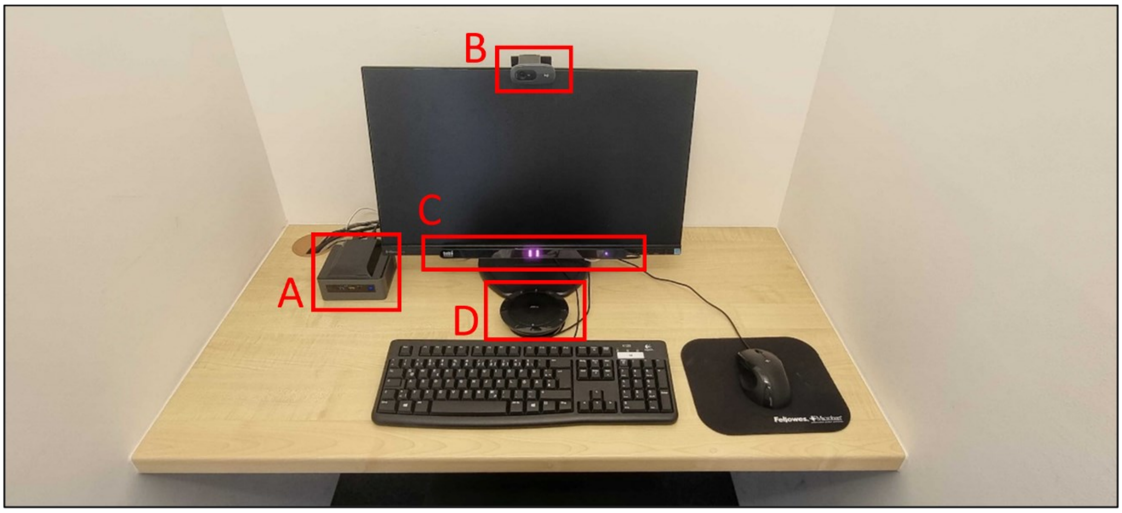
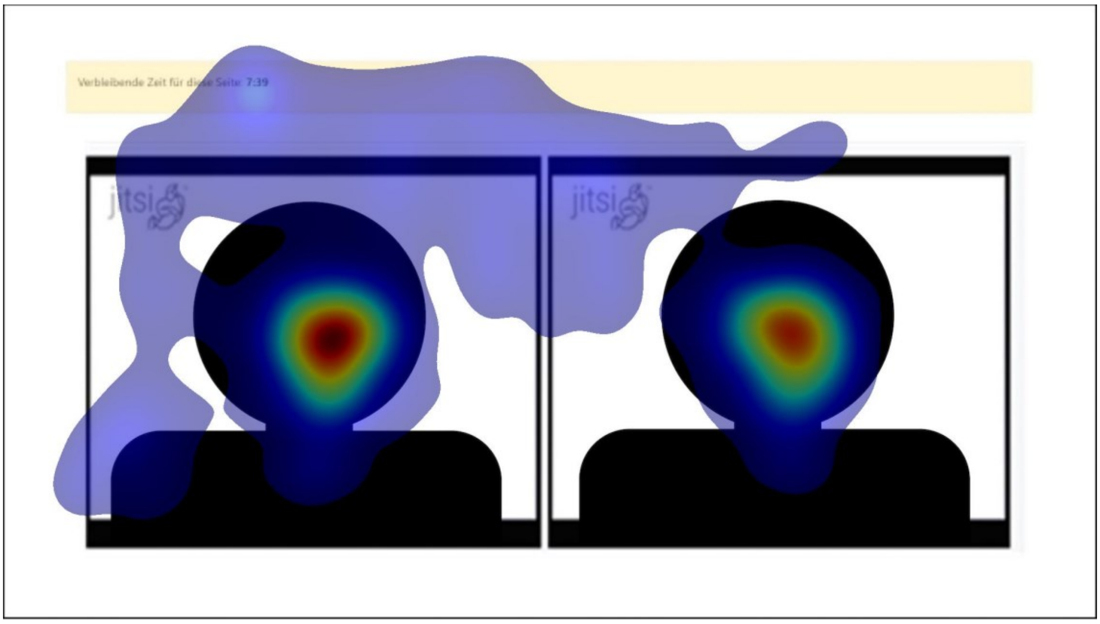


Figure C.1: Experimental setup including a monitor (Philipps Brilliance 241), computer (Intel NUC8; A), webcam (Logitech V-U0018; B), desktop-mounted eye-tracking device (Tobii 4C; C), and speakerphone (Jabra Speak 510; D).



Note. We used PyGaze Analyser to create the heatmap (PyGaze, 2025). First, each participant's time series of eye movement data was trimmed to the eight-minute duration of the video meeting. Next, we calculated fixations within the interface following established guidelines (Dalmaijer et al., 2013). Finally, we aggregated these fixations across all participants (n = 156) to plot the heatmap onto an anonymized screenshot of the video meeting page.

Figure C.2: Heatmap showing that participants primarily directed their gaze at their team members' faces within the video feeds.

		Transformation	
Variable	**Elicitation**	**Dichotomized Control Variable**	**Homophily Subindex**
Gender	Nominal variable with 1 (female), 2 (male), 3 (diverse)	Dummy variable with 0 (female), 1 (male)	No transformation
Age	Interval variable ranging from 18 to 100 (years)	No transformation	1 (under 21), 2 (21 to 24), 3 (25 to 29), 4 (over 29)
Ethnicity	Nominal variable with 1 (Asian/Pacific Islander), 2 (Black/Afro-American), 3 (Hispanic/Latin-American), 4 (White/Caucasian)	Dummy variable with 0 (Asian/Pacific Islander, Black/Afro American, Hispanic/Latin-American), 1 (White/Caucasian)	No transformation
Attractiveness	Interval variable ranging from -5 to 5 (deviation from average attractiveness)	No transformation	1 (under 2; average attractiveness), 2 (2 to 5; exceptional attractiveness)
Field of Studies	Free text	Dummy variable with 0 (Not economics-related), 1 (Economics-related)	1 (engineering), 2 (mathematics/physics/informatics), 3 (natural sciences), 4 (arts/education)
Previous Participation in Experimental Study	Nominal variable with 1 (yes), 2 (no)	Dummy variable with 0 (no), 1 (yes)	Not included
Familiarity	Ordinal variable with 1 (No, never met before), 2 (Yes, briefly met before), 3 (Yes, we are familiar)	Dummy variable with 0 (no familiarity), 1 (familiarity)	Not included

Table C.1: Overview of variable transformations, highlighting the initial elicitation, dichotomization for inclusion in the analysis, and categorization for the computation of homophily subindices.

Variable	Baseline (n = 26)	Gaze Contact (n = 26)	Two-sided Mann-Whitney U		Two-sided t-test	
	M (SD)	M (SD)	z	p	t(50)	p
Male-dominant Ratio	0.69 (0.47)	0.58 (0.50)	0.86	.392	0.85	.398
Average Age	23.54 (2.59)	24.10 (2.31)	1.04	.300	0.83	.411
Team Cohesion	3.66 (1.24)	3.83 (1.31)	0.40	.687	0.47	.639
Homophily	0.70 (0.06)	0.71 (0.08)	0.31	.758	0.13	.893

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: Non-parametric and semi-parametric treatment comparisons of the team-level control variables by *Baseline* and *Gaze Contact*.

Variable	Baseline (n = 78)	Gaze Contact (n = 78)	Two-sided Mann-Whitney U		Two-sided t-test	
	M (SD)	M (SD)	z	p	t(154)	p
Male	0.56 (0.50)	0.53 (0.50)	0.48	.631	0.48	.632
Age	23.54 (3.87)	24.10 (4.10)	1.00	.316	0.88	.378
White/Caucasian	0.83 (0.38)	0.83 (0.38)	0.00	1.00	0.00	1.00
Attractiveness	0.94 (1.82)	1.21 (1.48)	0.70	.485	1.01	.312
Econ-related Field of Study	0.49 (0.50)	0.50 (0.50)	0.16	.873	0.16	.874
Prev. Part. in Exp. Study	0.69 (0.46)	0.76 (0.43)	0.89	.372	0.89	.374
Familiarity	0.05 (0.22)	0.05 (0.22)	0.00	1.00	0.00	1.00
Oneness	3.66 (1.65)	3.83 (1.55)	0.63	.526	0.65	.517

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Non-parametric and semi-parametric treatment comparisons of the individual-level control variables by *Baseline* and *Gaze Contact*.

Variable	*M*	*SD*	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Gaze Contact	0.50	0.50	0.00	1.00							
(2) Minimum Effort	10.69	9.36	0.00	37.00	0.17						
(3) Average Effort	15.17	8.88	2.33	37.67	0.19	0.98***					
(4) Wasted Effort	13.44	6.00	2.00	28.00	0.04	-0.34**	-0.13				
(5) Team Cohesion	3.74	1.26	1.50	6.50	0.07	0.79***	0.75***	-0.36***			
(6) Homophily	0.70	0.07	0.53	0.87	0.02	-0.07	-0.08	-0.05	-0.14		
(7) Male-dominant Ratio	0.63	0.49	0.00	1.00	-0.12	0.28**	0.29**	0.01	0.22	0.06	
(8) Average Age	23.82	2.45	19.67	30.00	0.12	-0.08	-0.12	-0.17	-0.09	0.15	-0.18

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $n = 52$

Table C.4: Summary statistics and pairwise correlations at the team level ($n = 52$).

Variable	M	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Gaze Contact	0.50	0.50	0.00	1.00															
(2) Individual Effort	15.17	9.28	0.00	40.00	0.18**														
(3) Oneness	3.74	1.60	1.00	7.00	0.05	0.52***													
(4) Male	0.54	0.50	0.00	1.00	-0.04	0.12	-0.03												
(5) Age	23.82	3.99	18.00	42.00	0.07	-0.09	0.00	-0.17**											
(6) White/Caucasian	0.83	0.37	0.00	1.00	0.00	0.11	0.17**	0.11	-0.07										
(7) Attractiveness	1.07	1.66	-3.00	5.00	0.08	0.01	0.10	-0.10	-0.17**	-0.18**									
(8) Econ-related F.o.S.	0.49	0.50	0.00	1.00	0.01	-0.03	-0.03	0.08	-0.14*	0.06	0.18**								
(9) Prev. Part. in Exp. S.	0.72	0.45	0.00	1.00	0.07	-0.04	-0.08	-0.13	0.22***	-0.08	0.13	-0.02							
(10) Familiarity	0.05	0.22	0.00	1.00	0.00	-0.15*	-0.14*	0.04	-0.08	0.03	-0.05	0.18**	-0.12						
(11) Gaze Anxiety	0.75	0.37	0.00	1.88	-0.20**	-0.09	-0.14*	-0.20**	0.00	-0.17**	-0.16*	-0.25***	0.09	0.04					
(12) Risk Taking	5.42	2.22	1.00	10.00	0.10	0.09	0.07	0.31***	-0.11	0.04	0.16*	0.09	-0.02	-0.06	-0.20**				
(13) Altruism	0.00	0.80	-2.32	2.61	-0.11	0.03	0.10	-0.21***	0.05	0.13	0.08	0.04	-0.04	-0.09	-0.13	0.07			
(14) Positive Reciprocity	0.00	0.74	-2.35	1.20	-0.04	0.14*	0.13	0.16**	-0.10	0.14*	-0.08	-0.06	-0.16**	-0.07	-0.07	0.07	0.24***		
(15) Negative Reciprocity	0.00	0.76	-1.64	2.19	0.17**	-0.02	-0.14*	0.11	0.11	-0.14*	-0.11	0.16**	-0.01	0.03	-0.11	0.17**	-0.06	0.07	
(16) Interpersonal Trust	0.00	0.80	-2.70	1.40	0.21***	0.32***	0.25***	-0.04	0.02	0.13*	0.07	-0.01	-0.12	-0.12	-0.22***	-0.06	0.05	0.16**	-0.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, $n = 156$

Table C.5: Summary statistics and pairwise correlations at the individual level ($n = 156$).

Dep. Var.: Wasted Effort	**(1) All Rounds**	**(2) All Rounds**	**(3) All Rounds**	**(4) All Rounds**
Gaze Contact	0.500	0.726	1.204	1.233
	(1.678)	(1.596)	(1.437)	(1.426)
Male-dominant Ratio		-0.183	0.920	1.065
		(1.647)	(1.367)	(1.375)
Average Age		-0.438	-0.499	-0.463
		(0.327)	(0.310)	(0.328)
Team Cohesion			-1.902 ***	-1.970***
			(0.593)	(0.613)
Homophily				-8.029
				(10.354)
Constant	28.981***	39.411**	47.044***	51.995***
	(2.321)	(7.964)	(8.030)	(8.579)
R^2	0.265	0.271	0.299	0.301
χ^2-statistic	124.37	122.93	153.34	153.75
p-value	<.001	<.001	<.001	<.001
Observations	520	520	520	520

Cluster-robust standard errors in parentheses; round dummies (relative to 1) always included
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: OLS panel regressions (random effects) with *wasted effort* across all rounds as the dependent variable.

Dep. Var.: **Individual Effort**	**(1)** **First Round**	**(2)** **First Round**	**(3)** **First Round**	**(4)** **First Round**	**(5)** **First Round**
Gaze Contact	0.274*	0.268*	0.293*	0.315*	0.195
	(0.166)	(0.162)	(0.159)	(0.163)	(0.166)
Oneness		0.047	0.053	0.055	0.024
		(0.055)	(0.058)	(0.057)	(0.055)
Male			0.246	0.269	0.342*
			(0.188)	(0.194)	(0.208)
Age			-0.045**	-0.043*	-0.050**
			(0.022)	(0.022)	(0.024)
White/Caucasian			0.032	0.057	0.006
			(0.254)	(0.267)	(0.275)
Attractiveness			-0.027	-0.021	-0.024
			(0.054)	(0.056)	(0.059)
Econ-related Studies			0.073	0.097	0.095
			(0.193)	(0.194)	(0.209)
Prev. Part. Econ-Study			0.364*	0.351*	0.474**
			(0.210)	(0.212)	(0.221)
Familiarity			-0.478	-0.499	-0.382
			(0.325)	(0.340)	(0.281)
Gaze Anxiety				0.152	0.301
				(0.277)	(0.262)
Risk Taking					-0.012
					(0.044)
Altruism					0.009
					(0.116)
Positive Reciprocity					-0.057
					(0.128)
Negative Reciprocity					0.074
					(0.136)
Interpersonal Trust					0.450***
					(0.118)
Log-pseudolikelihood	-230.235	-229.841	-224.820	-224.646	-217.332
Pseudo R^2	0.006	0.007	0.029	0.030	0.061
Observations	156	156	156	156	156

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.7: Ordered probit regressions with *individual effort* in the first round as the dependent variable.

Dep. Var.: Individual Effort	**(1) All Rounds**	**(2) All Rounds**	**(3) All Rounds**	**(4) All Rounds**	**(5) All Rounds**
Gaze Contact	0.588	0.498*	0.552**	0.587**	0.481*
	(0.399)	(0.286)	(0.275)	(0.281)	(0.276)
Oneness		0.485***	0.488***	0.492***	0.455***
		(0.080)	(0.080)	(0.081)	(0.072)
Male			0.440***	0.476***	0.507**
			(0.156)	(0.174)	(0.229)
Age			-0.043	-0.041	-0.043
			(0.032)	(0.032)	(0.033)
White/Caucasian			-0.089	-0.053	-0.136
			(0.246)	(0.263)	(0.270)
Attractiveness			-0.059	-0.050	-0.062
			(0.069)	(0.068)	(0.066)
Econ-related Studies			-0.071	-0.033	-0.019
			(0.192)	(0.200)	(0.210)
Prev. Part. Econ-Study			0.056	0.034	0.143
			(0.246)	(0.243)	(0.230)
Familiarity			-0.538*	-0.569*	-0.407
			(0.320)	(0.339)	(0.290)
Gaze Anxiety				0.239	0.384
				(0.353)	(0.340)
Risk Taking					0.014
					(0.048)
Altruism					0.045
					(0.119)
Positive Reciprocity					0.028
					(0.147)
Negative Reciprocity					0.021
					(0.145)
Interpersonal Trust					0.399***
					(0.129)
Log-pseudolikelihood	-1726.571	-1703.246	-1698.427	-1698.120	-1693.715
Pseudo R^2	0.000	0.014	0.016	0.016	0.019
Observations	1560	1560	1560	1560	1560

Cluster-robust standard errors in parentheses; round dummies (relative to 1) always included
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.8: Ordered probit panel regressions (random effects) with *individual effort* across all rounds as the dependent variable.

Dep. Var.: **Beliefs**	**(1)** **First Round**	**(2)** **First Round**	**(3)** **First Round**	**(4)** **First Round**	**(5)** **First Round**
Gaze Contact	0.355**	0.349**	0.372**	0.356**	0.230
	(0.176)	(0.173)	(0.172)	(0.172)	(0.180)
Oneness		0.044	0.065	0.063	0.043
		(0.057)	(0.059)	(0.058)	(0.056)
Male			0.464**	0.448**	0.510**
			(0.200)	(0.203)	(0.229)
Age			-0.027	-0.029	-0.036
			(0.022)	(0.022)	(0.023)
White/Caucasian			-0.210	-0.228	-0.256
			(0.261)	(0.267)	(0.277)
Attractiveness			-0.021	-0.025	-0.026
			(0.057)	(0.059)	(0.063)
Econ-related Studies			0.261	0.243	0.223
			(0.202)	(0.206)	(0.226)
Prev. Part. Econ-Study			0.407*	0.419**	0.520**
			(0.212)	(0.210)	(0.222)
Familiarity			-0.418	-0.403	-0.312
			(0.447)	(0.445)	(0.384)
Gaze Anxiety				-0.116	-0.019
				(0.250)	(0.238)
Risk Taking					-0.012
					(0.040)
Altruism					-0.024
					(0.118)
Positive Reciprocity					-0.095
					(0.125)
Negative Reciprocity					0.111
					(0.146)
Interpersonal Trust					0.391***
					(0.124)
Log-pseudolikelihood	-225.347	-225.004	-217.424	-217.322	-211.479
Pseudo R^2	0.010	0.011	0.044	0.045	0.071
Observations	156	156	156	156	156

Cluster-robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.9: Ordered probit regressions with *beliefs* about the minimum effort level in the first round as the dependent variable.

Dep. Var.: Interpersonal Trust	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Gaze Contact	0.328***	0.308***	0.313***	0.272***	0.286**
	(0.117)	(0.104)	(0.117)	(0.104)	(0.117)
Oneness		0.121***	0.094**	0.089**	0.086**
		(0.037)	(0.039)	(0.038)	(0.037)
Constant	-0.164**	-0.608***	-0.688	-0.286	-0.073
	(0.078)	(0.162)	(0.424)	(0.516)	(0.543)
Demographics	✗	✗	✓	✓	✓
Gaze Anxiety	✗	✗	✗	✓	✓
Global Preferences	✗	✗	✗	✗	✓
R^2	0.043	0.102	0.142	0.157	0.187
F-statistic	7.93	9.23	3.79	3.62	2.99
p-value	.006	<.001	<.001	<.001	<.001
Observations	156	156	156	156	156

Cluster-robust standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table C.10: First-stage 2SLS regressions with *interpersonal trust* as the dependent variable.

C.2 Instructions

Welcome,

In this study, we investigate how people make decisions in different situations. The study consists of two parts and a questionnaire and takes about 45 minutes. For the first and second part, you form a team with two other participants. Your team will remain the same throughout the study. This means that your team will always consist of the same members.

In Part 1, you will get to know your team members in a video meeting. You have 8 minutes to get to know each other and exchange ideas. In Part 2, you will receive detailed information about the nature of the task and the payoff from this part. As part of this task, you will form a virtual team again with your team members from Part 1.

We will then ask you to complete an individual questionnaire.

Payoff

In this study, we use the currency "ECU". This is converted into euros for your compensation at the end of the study. Here, 10 ECU = 0.30 €.

You will receive a fixed payoff of 200 ECU for your participation in the study. You may also receive an additional payoff from Part 2. You will receive further information on the additional payoff before the start of Part 2.

You will also receive a further 100 ECU if you complete the final questionnaire carefully. We check this by means of control questions in which you are given a specific answer option. If you answer more than one control question incorrectly, you will not receive any additional compensation.

Please note: The payoff is anonymous, i.e. none of the participants will know how much another participant has received.

Part 1

In the first part of the study, you get to know your two team members in a video meeting.

Your webcam is located centrally above the screen. There is a speakerphone under the monitor so that you can hear each other and talk to each other.

Please watch the following video to familiarize yourself with the user interface of the video meeting.

[*If treatment* = *Baseline*: tutorial demonstrating the video meeting system’s interface]

[*If treatment* = *Gaze Contact*: tutorial demonstrating the video meeting system's interface and capability to visualize bidirectional gaze contact]

Part 1

Before the video meeting begins, please indicate your preferences regarding different types of vacation so that you can discuss them with your team members. In the video meeting, you have a total of 8 minutes to discuss the vacation types. The video meeting then ends automatically.

Please indicate how much you would enjoy the following types of vacation.

[7-point Likert scale for each vacation type: "Sun, sea and beach vacation", "Party vacation", "Winter sports vacation", "City trip", "Educational trip", "Camping vacation", and "Cruise"]

Once you have made your selection, please click the "Next" button to start the video meeting.

Video Meeting

Remaining time for this page: *min:sec*

[*If treatment* = *Baseline*: conventional video meeting system]

[*If treatment* = *Gaze Contact*: gaze-adaptive video meeting system]

Part 2: Instructions

The second part of the study consists of 10 identical, consecutive rounds.

Imagine that you and your two team members are part of a virtual team at a company. You can think of a round as a working week. In each working week, each member of the virtual team works 40 hours for the company. In each working week, you have to decide how to divide your time between two projects, project A and project B.

Project A. Project A is a team project. The success of the project depends on all members of your virtual team. Specifically, success is determined by the team member who contributes the least.

Project B. Consider project B as your individual project. This project was assigned to you by the company and you are solely responsible for its success.

Decision. Please indicate in each round how many hours you would like to work on project A. You can work 0 hours, 10 hours, 20 hours, 30 hours or 40 hours on project A. You will work the remaining hours on your individual project B.

You should consider the following when making your decision: Working on project A causes you more effort than working on your individual project B. Specifically, every hour that you work on project A instead of project B incurs additional costs of 5 ECU. These costs are deducted from your individual payoff in the respective round. Please also note that the other two members of your virtual team also decide how many hours they work on project A.

Please click the "Continue" button to receive detailed information on your individual payoff.

Part 2: Payoff

In each of the 10 rounds, you will receive an individual payoff consisting of a fixed salary, a bonus and your individual costs for the hours worked on Project A.

Fixed salary. In each round you will receive a fixed salary of 200 ECU.

Bonus. The bonus increases your fixed salary and depends on the success of project A. Success is based on the least number of hours that someone in your team works on project A (h_{min}). This means that the success of project A is determined by the team member who spends the least amount of time on project A. To calculate the bonus, the least number of hours someone in your team works on project A is multiplied by 6 ECU: Bonus = 6 ECU * h_{min}.

Individual costs. Every hour that you work on project A (h_A) incurs costs of 5 ECU: Individual costs = 5 ECU * h_A.

>> Payoff: 200 ECU + (6 ECU * h_{min}) - (5 ECU * h_A) <<

Your individual payoff in each round therefore consists of your fixed salary plus bonus minus the individual costs for working on project A. You do not need to memorize this formula. We will show you the following table at each point in time when you decide on your hourly distribution:

Vergütungstabelle		Geringste Stundenzahl, die Ihre Teammitglieder an Projekt A arbeiten (h_{min})				
Ihre Stundenzahl, die Sie an Projekt A arbeiten (h_A)		**0**	**10**	**20**	**30**	**40**
	0	200	200	200	200	200
	10	150	210	210	210	210
	20	100	160	220	220	220
	30	50	110	170	230	230
	40	0	60	120	180	240

Playing a Round

In each of the 10 rounds, you decide how many hours you will work on project A. The other two team members make the same decision. Please note that the calculation of the individual payoff is the same for everyone. However, depending on the decisions made in a round, the individual payoff may vary for the individual team members. When making your decision, also bear in mind that you do not know how your team members will decide in a round.

We will not disclose the number of hours contributed to project A by individual team members. At the end of each round, we will inform you of your compensation and the lowest number of hours contributed to project A within your team.

Payoff. After the 10 rounds, the computer will randomly select a round. The result of the randomly selected round determines your payoff from this second part of the study.

Comprehension tasks

Before starting the task, please answer the following comprehension questions.

1) What would your payoff be if you worked 0 hours on project A and the least contribution of another team member to project A was 10 hours?

[Free text]

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> The correct answer is 200.

2) What would your payoff be if you worked 20 hours on project A and the least contribution of another team member to project A was 10 hours?

[Free Text]

> *[If wrong]* Unfortunately, your answer to the question was not correct.
>
> The correct answer is 160.

3) What would your payoff be if you worked 40 hours on project A and the least contribution of another team member to project A was 30 hours?

[Free Text]

[If wrong] Unfortunately, your answer to the question was not correct.

The correct answer is 180.

4) What does your payoff depend on? Please select all correct options.

[] Number of hours you are working on project A

[] Sum of all hours worked on project A in the team

[] Lowest number of hours someone in your team works on project A

[If wrong] Unfortunately, your answer to the question was not correct.

Your payoff depends on the number of hours you work on project A and the lowest number of hours a member of your team works on project A.

Thank you for processing the instructions and comprehension questions,

Please click the "Next button" to start the task. The first round starts automatically as soon as all team members are ready.

Decision: Round 1

Please decide how many hours you would like to work on project A. The remaining hours will be allocated to your individual project B.

[Payoff table; drop-down list with default "Please select" and response options "0", "10", "20", "30", and "40"; choosing an option highlights the associated row in the payoff table; response confirmation by pressing the next button]

Belief: Round 1

Please give us an estimate of the least number of hours that someone in your team will work on Project A in this round.

[Payoff table; drop-down list with default "Please select" and response options "0", "10", "20", "30", and "40"; choosing an option highlights the associated row in the payoff table; response confirmation by pressing the next button]

Result: Round 1

In this round, the least number of hours worked on project A within your team was X hours.

You have decided to work X hours on project A. Your payoff in this round therefore amounts to X ECU.

Decision: Round [2, ..., 9]

Please decide how many hours you would like to work on project A. The remaining hours will be allocated to your individual project B.

[Payoff table; drop-down list with default "Please select” and response options “0”, “10”, “20”, “30”, and “40”; choosing an option highlights the associated row in the payoff table; response confirmation by pressing the next button]

Result: Round [2, ..., 9]

In this round, the least number of hours worked on project A within your team was X hours.

You have decided to work X hours on project A. Your payoff in this round therefore amounts to X ECU.

Decision: Round 10

Please decide how many hours you would like to work on project A. The remaining hours will be allocated to your individual project B.

[Payoff table; drop-down list with default "Please select” and response options “0”, “10”, “20”, “30”, and “40”; choosing an option highlights the associated row in the payoff table; response confirmation by pressing the next button]

Belief: Round 10

Please give us an estimate of the least number of hours that someone in your team will work on Project A in this round.

[Payoff table; drop-down list with default "Please select” and response options “0”, “10”, “20”, “30”, and “40”; choosing an option highlights the associated row in the payoff table; response confirmation by pressing the next button]

Result: Round 10

In this round, the least number of hours worked on project A within your team was X hours.

You have decided to work X hours on project A. Your payoff in this round therefore amounts to X ECU.

Part 3

Finally, we ask you to complete the individual questionnaire. Please read the questions carefully and thoroughly before selecting an answer option.

Reminder for payoff: You will receive a further 100 ECU if you complete the questionnaire carefully. We will check this by means of control questions in which you are given a specific answer option. If you answer more than one control question incorrectly, you will not receive the additional 100 ECU.

Eidesstattliche Versicherung

gemäß § 13 Abs. 2 Ziff. 3 der Promotionsordnung des Karlsruher

Instituts für Technologie für die KIT-Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema „Social Gaze in Team Collaboration: Multiparty Eye-Tracking and Gaze-Adaptive Video Meeting Systems" handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich bislang nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt.

Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, den 20.01.2025

Tom Frank Reuscher (M.Sc.)