Looking for a Deal? Social Visual Attention during Negotiations via Mixed Media Videoconferencing

HANA VRZAKOVA, University of Colorado Boulder, USA
MARY JEAN AMON, University of Central Florida, USA
MCKENZIE REES, Southern Methodist University, USA
MYRTHE FABER, Tilburg University, The Netherlands
SIDNEY K. D'MELLO, University of Colorado Boulder, USA

Whereas social visual attention has been examined in computer-mediated (e.g., shared screen) or video-mediated (e.g., FaceTime) interaction, it has yet to be studied in mixed-media interfaces that combine video of the conversant along with other UI elements. We analyzed eye gaze of 37 dyads (74 participants) who were tasked with negotiating the price of a new car (as a buyer and seller) using mixed-media video conferencing under competitive or cooperative negotiation instructions (experimental manipulation). We used multidimensional recurrence quantification analysis to extract spatio-temporal patterns corresponding to mutual gaze (individuals look at each other), joint attention (individuals focus on the same elements of the interface), and gaze aversion (an individual looks at their partner, who is looking elsewhere). Our results indicated that joint attention predicted the sum of points attained by the buyer and seller (i.e., the joint score). In contrast, gaze aversion was associated with faster time to complete the negotiation, but with a lower joint score. Unexpectedly, mutual gaze was highly infrequent and unrelated to the negotiation outcomes and none of the gaze patterns predicted subjective perceptions of the negotiation. There were also no effects of gender composition or negotiation condition on the gaze patterns or negotiation outcomes. Our results suggest that social visual attention may operate differently in mixed-media collaborative interfaces than in face-to-face interaction. As mixed-media collaborative interfaces gain prominence, our work can be leveraged to inform the design of gaze-sensitive user interfaces that support remote negotiations among other tasks.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**

KEYWORDS

multi-dimensional recurrence quantification analysis; eye tracking; video conferencing; negotiation

ACM Reference format:

1 INTRODUCTION

"This is a reasonable offer for a car in top shape. Don't you agree?" a car salesman stared at a prospective buyer, who averted her gaze from him, looking at the car instead. "Well, I'm not sure about that", she said gazing back with a smirk. As this hypothetical exchange implies, social visual attention plays an important role in human communication. *Mutual gaze* (two individuals looking at each other), *joint attention* (two individuals looking at the same object), and *gaze aversion* (one individual looking at the partner who looks elsewhere) are three patterns of social visual attention that have been studied extensively [6,32,41,56,91,98], and have been linked to various functional roles and interaction outcomes [8,41,99] in *face-to-face interactions.* For example, mutual gaze can signal intimacy and mutual understanding [6], whereas gaze aversion can indicate emotional discomfort [37,45].

However, in the 21st century globalized economy, an increasing number of interactions occur remotely via videoconferencing. Compared to face-to-face interaction, videoconferencing provides different affordances and constraints [77,81], thereby substantially changing the interaction. For example, modern video conferencing offers a range of mixed-media interactions, such as real-time collaboration with multiple participants over a shared content, and various blends of video, voice, text, and screen sharing. Despite technological advances, these systems do not effectively communicate certain social cues, compared to face-to-face interactions [4,96,100,115]. For example, videoconferencing degrades visual (i.e., eye gaze, facial expressions, and hand and body gestures) and discourse cues (i.e., turn taking), which in turn impeded coordination and trust building among between virtual partners [15,118]. When combined with other technical limitations (i.e., low camera resolution, under-sampled and delayed sound transmission), videoconferencing is often cumbersome [57].

Although availability of mixed-media interface and rich-media spaces has been rapidly increasing (e.g., [39,50,62,111]), there is sparsity of research on social visual attention with these interfaces. Prior research on social visual attention during remote interactions has focused on two types of contexts. One line of research [32,40,48] has examined mutual gaze and gaze aversion in video-mediated communication where individuals can view each other on their respective screens without additional interface elements, akin to FaceTime and Google Duo. In another line of research on joint attention and collaborative interaction, individuals communicate without video, but communicate via speech over a shared interface [16,24,26,29,53,88,121].

Despite considerable progress in each of these contexts, research has yet to investigate social visual attention in modern video-conferencing interfaces that afford mixed media including static (e.g., a document), dynamic (e.g., partner's face), and interactive (e.g., note taking) content, with voice and chat. The key point is that it is difficult for a person to accurately infer the locus of visual attention of their partner in such interfaces, thereby degrading a critical communicative and social cue. To illustrate, consider video conferencing with a mixed-media interface, where a webcam is placed on the center-top of a monitor or embedded in a laptop/tablet (as in Figure 1). The position of the camera makes it difficult for a person to ascertain what part of the interface their partner is looking at due to the angle between the web-cam direction and the participant's gaze trajectory [46,80,126]. In general, impaired perception of the partner's eye gaze diminishes the ability to coordinate actions and establish trust and rapport [2,11,104].

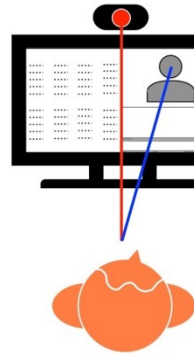


Figure 1 Because of the camera placement and the angle between camera's and user's line of sight, the user's partner cannot tell where the user is looking at.

Another difficulty of remote interaction pertains to referencing linguistically complex objects. Because it is often impossible to physically point at the objects in the remote interface (e.g., when only one can control a mouse cursor), the other partners are required to produce explicit verbal deictic expressions (e.g., "look at that *red horse* in the *top, left corner*" instead of "look there" and pointing to the object) [61]. Explicit referencing together with impoverished non-verbal signals reduce mutual understanding, lowers engagement [96], and elevates workload [76].

Research in the field of computer supportive cooperative work (CSCW) has explored *shared gaze interfaces* to ease demands of explicit referencing in remote interfaces and to facilitate remote collaboration in general [14,16,19,24–26,44,53,63]. In these studies, an individual's eye gaze is visualized on their partner's screen as a gaze cursor, gaze path, highlighted region, or heatmap [16,24,26,53]. The goal is to increase a person's awareness of their partner's locus of visual attention. Despite yielding several insights, for example that shared gaze improves interaction flow and task engagement in some contexts [16,114], it has failed to yield any improvements in others [26,75,123].

Explicit gaze sharing might also not be applicable in many interaction contexts. It has been mainly explored in collaborative interactions (e.g., collaborative visual search or collaborative problem solving) where dyads share a visual display. But what about situations where the interlocutors have different displays or when a person does not choose to share their eye gaze? For example, turning back to negotiation, this is inherently a competitive context where sharing a person's screen or locus of their attention could reveal their goals, strategies, and private information, thereby disadvantaging them. Thus, gaze sharing is not the panacea for addressing the aforementioned challenges of facilitating social visual attention in remote collaborations over mixed-media video conferencing. More basic research is needed on how social visual attention manifests and influences outcomes in this context with an eye for applying insights to the design of more effective CSCW interfaces.

As a step in this direction, we used eye tracking to investigate social visual attention during dyadic collaborations with a mixed-media interface. We chose negotiation as our interaction context because it is a common way in which individuals manage conflict to achieve personally-relevant outcomes [103,106]. Negotiation is also an excellent context to study patterns of social visual attention. To achieve their goals, negotiators need to attend to information provided by their partners by monitoring their responses and understanding their expectations. Eye gaze has been shown to play an important role in facilitating face to face negotiations [38,64,72,125]. In remote contexts, however, negotiations are more challenging when user interfaces fail to transmit key behaviors and features needed for effective communication, coordination, and mutual understanding. For example, with limited communication of nonverbal behaviors, computer-mediated negotiations have been associated with the lack of cooperative behavior and suboptimal outcomes [9,86,102]. Prior research has investigated how various media, such as email, phone call, and video conferencing, affect negotiation outcomes [58,73,107] and contribute to establishing trust among individuals [15,92,124]. In this work, we investigate how social visual attention in remote negotiation with mixed media emerges, and how the patterns of social visual attention are associated with cooperative and competitive negotiation and the outcomes achieved. Because social visual attention is a dynamic process, we adopt and extend a method from dynamical systems theory called multi-dimensional recurrence quantification analysis [117] to study spatio-temporal gaze patterns of mutual gaze, joint attention, and gaze aversion during a negotiation task of "purchasing a car" [74].

2 RELATED WORK

There is a paucity of research examining visual attention during negotiations, so we review the broader literature on social visual attention, starting with face-to-face interactions and then moving to remote interactions. Although there has been considerable research on the design of mixed-media interfaces and social awareness in CSCW [39,62,111], we focus our review on eye-tracking studies that investigate social visual attention in remote, computer-mediated collaboration.

2.1 Social visual attention in face-to-face interaction

Mutual gaze, joint attention, and gaze aversion are central components of social visual attention that have been extensively studied during face-to-face interaction [6,41,47,55,59,99]. For example, mutual gaze, where partners look at each other indexes positive qualities of the interaction, such as engagement [78], intimacy [8,10,82], rapport building [108], and competence [101]. In addition, eye contact (used synonymously for mutual gaze [36,40,51]) between dyads has been shown to be pivotal for information gathering and creating shared understanding [7,59,83,99].

This positive influence of mutual gaze within social interactions extends to negotiation, where mutual gaze is associated with cooperative behaviors [38]. This is consistent with the media richness approach, which posits that "more sight, more sound, and more *synchronicity* are better for achieving high quality [negotiation] outcomes" [27,104]. That said, prolonged mutual gaze has been also associated with power in dominance contests, where the person who averts their gaze loses [21,68,105].

Joint attention, where partners look at the same object, has been associated with effective communication [88] and contributes to overall mutual understanding. Consequently, joint attention has been associated with a variety of positive outcomes, including improved problem solving and learning [85] and contributes to collaborative flow [70]. Nevertheless, joint attention can also signal negative aspects in dyadic interaction, for example when a dominant partner "leads" the attention of their less dominant counterpart [95].

Gaze aversion is another spatial pattern of social visual attention, which occurs when one partner aims to establish mutual gaze and the other partner diverts their gaze. It may correspond with avoiding negative social-emotional experiences and discomfort [37], but can also be the result of increased task difficulty [31]. In negotiation, gaze aversion has been positively associated with competitive behaviors [38]. For example, when a negotiator asks for a larger share of the profit, they avert their gaze to hide their intentions or to avoid negative social-emotional responses.

In summary, research indicates that these three main patterns of social visual attention are instrumental in face-to-face interaction and negotiation. However, does their significance translate to remote interaction? We review pertinent research next.

2.2 Social visual attention and temporal coordination in remote interaction

Much of the research on social visual attention in remote, computer-mediated interaction has focused on temporal coordination or synchrony of gaze patterns [29,53,87–89,95]. This research is grounded in nonlinear dynamical systems theory, where interaction among individuals is modeled as a nonlinear and interlocked system-level process [28,43]. Recurrence quantification analysis (RQA) [119,122] is a related method that explores temporal patterns of such systems. Relevant to social visual attention, cross recurrence quantification analysis (CRQA) – a variant of RQA for dyadic signals – has been used to study joint attention and gaze synchrony in dyads who interact face-to-face or remotely [53,87–89,95].

Initially, the aim of the studies has been to identify when (at what *time lag*) two individuals synchronize their visual attention [88] and how characteristics and beliefs about the shared environment influence this synchrony [87,89]. For example, Dale et al. investigated how joint attention emerges in remote collaborative problem solving [29]. In the tangram task, one participant played a role of a "director" and was proposing next steps, while the other participant played a role of "matcher" who executed the proposed steps and reordered the pieces. At the beginning of the task, the directors' gaze was ahead of the matchers' gaze, but towards the end, the dyads became attuned and their social visual attention more synchronized.

Patterns of gaze synchrony have also been examined with respect to collaborative outcomes. For example, in a study on pair programming, [53] found that programmers' gaze synchrony as measured via CRQA was associated with high quality of collaboration (i.e., coordination of scrolling in the code, answering each other's questions, or complementing each other's understanding of the code), but not with the dyads' ability to comprehend source code. Similarly, Schneider et al., 2016 observed that visual leadership (gaze of one participant ahead of another via CRQA) within +/-2s lag was negatively correlated with dyads' learning gains in collocated collaborative problem solving, suggesting a "free-rider" effect when a dominant student leads the entire problem-solving session.

2.3 Using social visual attention to facilitate computer supported cooperative work

With the increased availability of consumer-grade eye trackers, recent research has investigated leveraging social visual attention to improve awareness in CSCW [50,79,112]. One prominent line of research has focused on the design of shared-gaze interfaces (described above) in a number of domains including remote pair programming [24], collaboratively solving puzzles [24], collaborative learning [94], and various visual search tasks [16,75,114,123]. Most of the work has been done in the context of visual search, therefore we review that here.

In a pioneering study, Brennan and colleagues [16] asked 16 dyads seated in separate rooms to collaboratively search for O among Q's while their interaction was enhanced with shared gaze, shared voice, and shared gaze and voice (compared to no communication). Similarly to Brennan's study, Neider and colleagues [75] examined collaboration of 16 dyads during a "sniper" task where one partner had to find and then reach consensus on the location of a red pixel (target) among a simulated background of a cityscape. The shared gaze feedback and experimental conditions were similar to the Brennan et al. study. In both studies, shared gaze (shared gaze only [16] or shared gaze paired with speech [75]) enabled more efficient search. Building of this basic research, researchers have explored alternate designs of shared. For example, Zhang et al. [123] compared four visual shared gaze designs (i.e., cursor, 3s-gaze trajectory, highlight and spotlight). D'Angelo et al. [26] examined three visual shared gaze displays (heatmap, shared-gaze area, and path) and their impact on collaborative problem solving. Wahn et al. [114] investigated also alternative modalities for shared gaze (i.e., auditory and vibrotactile feedback) for visually crowded tasks.

These studies have yielded mixed results on beneficial effects of shared gaze interfaces. Specifically, beneficial effects on search efficiency were only found in specific contexts based on how gaze was presented and on the presence/absence of the search target. The results were more consistent in terms of showing a shared gaze benefit on coordination times, but this is unsurprising as a participant merely needs to fixate on the target to cue his/her partner of its location. Further, as noted above, shared gaze interfaces assume that the task is collaborative with maximal sharing of information. This does not apply to other contexts, such as negotiation, where there is an advantage to keeping information private and there is a competitive element, or when maintaining confidentiality is paramount (e.g., healthcare applications).

3 Current Investigation & Research Questions

Prior research on social visual attention in CSCW has demonstrated that spatial and temporal patterns of social visual attention can be a rich source of understanding group interaction. However, there are some limitations of prior research. Specifically, considerable research has focused on the overall spatial distribution of visual attention (e.g., percent of gaze on a particular area of interest), while ignoring temporal dynamics (e.g., synchronicity) of gaze patterns. Recent research has utilized cross recurrence quantification analysis (CRQA) to investigate the temporal coordination of visual attention [5,42], but this method can only reveal patterns of synchrony (i.e., mutual gaze or joint attention), whereas social visual attention comprises additional patterns, such as gaze aversion and disjoint attention. CRQA is also limited to the pairs of signals (e.g., dyadic gaze) and does not easily scale to multiple signals. For example, an analysis of eye gaze of four participants would entail investigating six dyads via six CRQAs, a proposition, which becomes untenable for larger groups.

To address these limitations, we utilize *multi-dimensional recurrence quantification analysis* (MdRQA) [116] to jointly analyze spatio-temporal patterns of social visual attention in groups of arbitrary size. In principle, MdRQA examines multiple signals as a joint system and quantifies the periods of systematicity when the system exhibit *recurrent* patterns. Contrary to CRQA, these patterns can be synchronous or asynchronous. Thus, MdRQA presents a method to jointly investigate multiple synchronous (mutual gaze and joint attention) and asynchronous (gaze aversion) patterns of social visual attention. And although we use MdRQA to study dyadic negotiation here, our overall approach easily scales to multi-modal and multiparty collaboration (for example, Amon et al. [1] examined three modalities from three participants). Finally, we discuss how our present findings obtained from MdRQA can inform the design of future gaze-sensitive user interfaces.

We conducted a study where we tracked eye gaze of 73 dyads (a total of 37 usable dyads were analyzed here) who engaged in a negotiation task over a mixed-media video conferencing interface. We used MdRQA to investigate the following research questions:

RQ1. What are the spatio-temporal patterns of social visual attention during remote negotiations with mixed media?

Prior research on social visual attention has mainly focused on face-to-face interaction (see review above). Research on social visual attention in remote interaction has predominantly studied two kinds of interfaces: video conferencing without a shared screen [32,40] or interaction over a shared screen without a partner's face video [24,29,53,89]. However, modern remote interaction often occurs via mixed-media interfaces, such as Zoom, Skype, Hangouts, which allow for video conferencing with both video and other windows (e.g., a document, spreadsheet, or web browser) being simultaneously active on the screen or on multiple monitors. Despite the rapid development of mixed-media interfaces, for example [39,50,52,111], we know little about what patterns of social visual attention emerge when participants interact over these interfaces (Figure 1). How attention is allocated and synchronized between distinct areas, such as the dynamic view of their partner and static content (e.g., spreadsheet with task-related information) remains an open question. *We hypothesize that mixed-media interfaces induce similar patterns of mutual gaze and joint attention established in prior work as successful negotiation is likely to rely on both attention to the other partner as well as to task-related information.*

RQ2. How does negotiation orientation influence the spatio-temporal patterns of social visual attention?

It is known that negotiation orientation can impact social visual attention. For example, Foddy [38] observed that being a cooperative or competitive face-to-face negotiator was associated with higher occurrence of mutual gaze and gaze aversion, respectively. Would similar patterns emerge over mixed media interactions? *We hypothesize that mutual gaze and joint attention are instrumental for cooperative negotiation and should also occur with mixed-media videoconferencing. We also expect gaze aversion to emerge more frequently during competitive negotiation since the negotiators focus on their own gain and do not need to be attuned to the other partner.*

RQ3. To what extent do the spatio-temporal patterns of social visual attention predict negotiation outcomes?

We explore the link between social visual attention and negotiation outcomes. We consider multiple outcomes: objective joint score (sum of the score of the two individuals), subjective value inventory (SVI −subjective perceptions of the negotiation processes) [23], and time to initial agreement (time for negotiators to reach an initial agreement). Whereas the joint score represents an objective outcome, SVI pertains to social psychological outcomes and has been linked to social processes such as rapport building [23]. *We hypothesize that mutual gaze and joint attention will reflect negotiators' mutual understanding and, in turn, will be associated with positive negotiation outcomes with respect to higher joint scores and SVI ratings.* We have no specific hypotheses regarding how the gaze patterns will predict time to initial agreement.

4 DATASET: NEW CAR

Data was collected as part of a larger project, in which dyads were tasked with negotiating the purchase of a new car via video conferencing during which their eye movements were recorded with a gaze tracker.

4.1 Participants

A total of 146 students (50% female; average age 21 years) with normal or corrected-to-normal vision from a private, selective, Midwestern US university (School of Psychology and Business School) participated for partial course credit. Sixty-five percent self-identified as Caucasian, 6% African American, 11% Asian, 15% Hispanic, and 3% as another ethnicity. Participants were randomly assigned to dyads; details on gender distributions are discussed below. After applying inclusion criteria (see Section 4.5), 37 dyads (74 participants) were included in the analyses.

4.2 Experimental Task, Manipulation, and Outcome Measures

The task of negotiating the purchase of a new car was adopted from [74]; we used the exact materials except they were delivered electronically. For the task, two participants were randomly assigned roles of buyer and seller. According to the cover story, the buyer represented a manager of a software company who aimed to acquire a new company car for their CEO. The seller represented a local car dealer. The buyer and seller were tasked with negotiating the possible sale of a new luxury model and discussed eight key features of the car: warranty, financing, delivery date, air bags, audio, price, color, and number of car add-ons, each with different assigned points. Although both buyer and seller could see the same description of features, each role had different *potential* scores (or points) associated with various car items For example, buyers received the lowest score (0 points) when they agreed to the basic 6-month car warranty, but sellers received the highest score (1600 points) for this feature. Only two of the features allowed mutual agreement with an equal score for both parties (i.e., a yellow car with the best possible air bags received same points for both the buyer and the seller); the rest of the features had to be negotiated. When the dyad reached agreement on all features, they separately calculated the total points (or their personal score) according to the score table.

We manipulated the negotiation orientation by randomly assigning each dyad to engage in either a cooperative or competitive negotiation, again using the exact same instructions from [74]. Dyads in the *competitive* condition were instructed that the other partner's gain was their loss and that they should try to give in as little as possible and maximize their personal score, even if their partner achieved a lower score. Dyads in the *cooperative* negotiation were instructed that building good relationships with loyal customers were the seller's top priority, that buyer's gain equaled the seller's gain, and they should maximize their personal score by working with their partners.

We calculated dyad's *joint score* as a sum of seller's and buyer's personal score as the main objective outcome of the negotiation; this measure called joint outcome is consistent in the literature [33,110]. A secondary outcome was the *time to initial agreement,* which was the time (in seconds) from the start of the negotiation until the buyer and the seller came to the first agreement. We also used the *Subjective Value Inventory* (SVI) [23], a standardized measure of non-instrumental outcomes in negotiations including feelings about instrumental outcomes, the self, the negotiation process, and the relationship. The SVI predicts a variety of outcomes, particularly individuals' willingness to work with others in future negotiations [22].

4.3 Materials

Each participant was seated at their own computer station, which was equipped with a microphone headset, webcam, and eye tracker. We did not have access to two research-grade eye trackers (which cost upwards of $30,000) and we intended for the results to generalize to real-world settings where consumer-off-the-shelf (COTS) devices are more likely. Accordingly, we used the EyeTribe, a consumer-off-the-shelf remote binocular eye tracker (sampling rate = 50Hz, accuracy = 0.5-1 degree of visual angle) positioned below the computer screen (screen width = 1920px, screen height = 1080px). We used this eye tracker since it was inexpensive (approximately $100) and affords simultaneous collection of data from multiple participants. Participants' eye gaze was recorded using customized software that also controlled the flow of the study (e.g., timing, alerts, etc.). The remote interaction was conducted using Zoom (www.zoom.us), a commercially available video conferencing tool.

4.4 Procedure

The experiment took place in a large room equipped with computer stations. Participants were greeted, consented, randomly assigned to dyads, and seated on their own computer station. Participants first read through instructions for their roles and task condition and familiarized themselves with the collaborative user interface (Figure 2). The interface was comprised of three main areas of interest (AOI): the partner's face view, a static table with eight car characteristics and fixed point values assigned to each (scores were specific to each role), task- and role-specific instructions, space for taking notes, and buttons to report mind wandering[1]. Dyads were connected via Zoom's breakout-room features[2] (simultaneous meetings in separate "virtual rooms"), which allowed us to run multiple dyads at the same time. Video and audio were enabled, but screen sharing was disabled because of role-specific differences in point values, instructions, and the need to keep notes private.

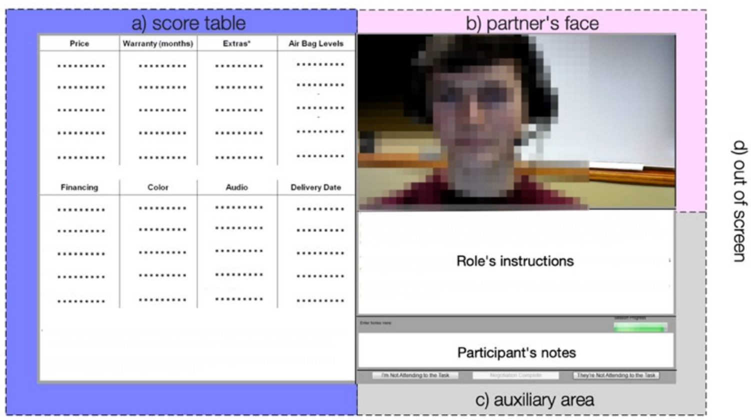


Figure 2. Areas of interest (AOI) of the negotiation interface: score table (purple), partner's view (pink), and auxiliary area (gray). The design of the interface was identical for both partners, however, they could *not* see each other's score table, instructions, or personal notes. Gaze points registered out of the screen bounds were assigned to the general out-of-bounds area. The interface and partner's face are anonymized.

Prior to the negotiation, participants answered a short survey (*instruction check*) to ensure that they thoroughly understood their roles and goals of the negotiation. Participants were asked to select the assigned goal of the negotiation based on four options: (1) to get as many points as possible, even if that means that the other person loses points (correct answer for competitive negotiation); to work together with the other person so that we both get as many points as possible (correct answer for cooperative negotiation); (3) to get the same amount of points as the other person (incorrect answer), or to give the other person as many points as possible, even if that means that the I lose points (incorrect answer). In the case participants answered incorrectly, the user interface highlighted and corrected their erroneous responses. The role-specific instructions were also displayed in the user interface throughout the negotiation period.

After the initial instruction check and calibrating each participants' eye tracker using a nine-point calibration, the 15-minute negotiation task began. If negotiators reached agreement before the 15-minute time limit, the time of their agreement was recorded (time to initial agreement), and they were informed to continue the negotiation and improve their scores until the time limit elapsed. Participants received a notification when the negotiation task

[1] Participants were asked to report whenever they found themselves zoning out during the negotiation and whenever they thought the other person might be zoning out; these data were collected for another purpose and are not reported here.

[2] Zoom documentation: https://support.zoom.us/hc/en-us/articles/206476313-Managing-breakout-rooms

had two minutes left. Thus, all dyads completed 15 minutes of negotiation. Each participant's personal score and the dyad's joint score was recorded. Participants then completed questionnaires assessing their demographics, self-reported individual difference measures (not analyzed here), and the 16-item Subjective Value Inventory [23]. The experiment protocol was approved by the Institutional Review Board, University of Notre Dame (FWA No. 00002462).

4.5 Evaluation of Instruction Check

We observed an association between negotiation condition and the number of correct answers in the instruction check (Chi-squared = 48.586, df = 1, $p < .01$). Whereas most (69 out of 72) participants in the competitive condition answered incorrectly, only 29 out of 72 in the cooperative condition answered correctly. We also evaluated the instruction check at the dyad level based on whether both partners correctly responded. In the full sample, 39 dyads (32 competitive and 7 cooperative) responded correctly whereas 32 dyads (3 competitive and 29 cooperative) responded incorrectly.

Of the 37 dyads who satisfied the inclusion criteria for eye gaze data (see below), 18 competitive and five (out of 19) cooperative dyads successfully answered the instruction check item. Thus, the instruction check was less successful for the cooperative condition, despite us using standard manipulation instructions for this task [74].

We conducted an independent samples t-test to compare personal scores for participants who correctly vs. incorrectly answered the instruction check item for the cooperative condition, but found no significant difference, cooperative buyer: $t(16.51) = 1.08$, $p = 0.297$; cooperative seller: $t(33.12) = -0.68$, $p = 0.498$. There were also no significant differences in joint scores of dyads in the cooperative condition where both participants answered correctly (five dyads) vs. where at least on participant answered incorrectly (14 dyads): $t(15.35) = -1.03$, $p = 0.321$. This lack of a difference might suggest that the corrective instructions that followed the instruction check were effective. Nevertheless, for all subsequent analyses, we analyzed condition as a three factor categorical variable: (1) cooperative who passed the instruction check; (2) cooperative who failed the instruction check; and (3) competitive who passed the instruction check; the one competitive dyad who failed the check was removed.

4.6 Data Preprocessing and Inclusion Criteria

We chose to work with raw gaze data instead of first fixation filtering the data in order to have fixed-internal time bins. First, we manually assessed calibration quality by viewing each participant's gaze plots to examine whether the gaze distribution was approximately aligned with the main areas on the screen (AOIs as defined below). In five cases, where gaze data were miscalibrated, we corrected calibration offset errors by vertically or horizontally shifting participants' entire gaze data and re-examining the corrected gaze plots. Next, each raw gaze point was assigned to one of the three areas of interest (AOIs: score table, partner's face, and auxiliary area). To compensate for potential tracking errors, we enlarged the AOIs with a 100px outer safety margin as recommended by Holmqvist & Andersson (2011). Gaze points outside the screen boundary, they were labeled as "out-of-bounds". Cases where the tracker failed to registered eye gaze were labelled as NA. Finally, the AOI time series were segmented into one-second slices, similar to [30,113]. For each slice, we calculated the proportion of gaze points within each AOI as the *majority AOI* for that slice. Thus, each participants' eye gaze data was represented by a 900-second (for 15-min interaction) sequence of majority AOIs.

Of 73 dyads, one dyad's audio-visual recording failed, and 17 dyads' eye-trackers malfunctioned for one or both participants. For the remaining 55 dyads, we evaluated how many of valid 1-second data segments were in the AOI sequences and only included participants with at least 40% non-missing AOI data (74 participants or 37 dyads). Data loss was expected due to the low-cost sensor with no chin rest, which was important for ecological validity. Across dyads, the rate of valid sequences ranged from 41.67% to 88.11% (M = 65.86%, SD = 14.06). We included the proportion of valid data as a covariate in the statistical models. Proportions of valid data (or data validity) did not predict any of the spatio-temporal gaze patterns nor negotiation outcomes.

Our inclusion criteria did not have a major impact on the distribution of conditions (18 competitive and 19 cooperative dyads), but it changed the distribution of gender composition of dyads and across task conditions. As illustrated in Table 1, the competitive condition remained fairly balanced (10 same-gender dyads and 8 mixed-gender dyads), but the cooperative condition was skewed towards same-gender dyads (13 same-gender dyads and 6 mixed-gender dyads).

Table 1 Gender composition with respect to negotiation condition in the complete and selected dataset.

	Complete dataset				Selected dataset			
Gender composition	**Competitive**	**Competitive**	**Total**	**[%]**	**Cooperative**	**Competitive**	**Total**	**[%]**
Mixed gender	17	20	37	52.11	6	8	14	37.84
Same gender: Female-only	13	10	23	32.39	10	7	17	45.95
Same gender: Male-only	5	6	11	15.50	3	3	6	16.21
Total	**35**	**36**	**71**	**100.00**	**19**	**18**	**37**	**100.00**

5 METHOD: SPATIO-TEMPORAL PATTERNS OF SOCIAL VISUAL ATTENTION USING MDRQA

We investigated spatio-temporal patterns of social visual attention using a relatively new method called multi-dimensional recurrence quantification analysis (MdRQA) [117].

5.1 Principles of MdRQA

Recurrence quantification analysis (RQA) [122] examines temporal coordination of a system by identifying recurrent points (repeated states) across various time delays (lags = 1…n) (for detailed description, refer to [88]). For example, if a time series has the same or similar state at time points 4 and 5, this would constitute a recurrent point. The result of RQA is a recurrence plot (or recurrence matrix), which visualizes recurrent points (marked in black) and absence of recurrence (marked in white) [34,66]. The plot provides a visual description of system dynamics, from which various metrics can be computed (for metric descriptions see [20]). This basic approach can be extended based on the type of signals (continuous or categorical) and dimensionality of the system (number of signals).

Cross-recurrence quantification analysis (CRQA) [20,88], is one type of RQA that identifies the extent to which two time series align across time. CRQA has been used in eye-tracking studies, where eye movements are often investigated with respect to predefined areas of interest (AOI) [88,89]. In these studies, time points when both participants view the same region are counted as recurrent, though these do not need to be simultaneous. For example, Participant A looking at a particular AOI at time t and Participant B looking at the same region at $t + 2$ later would be considered a recurrent point (here B lags A by 2-sec).

Multidimensional quantification analysis (MdRQA)[117] is another type of RQA that accommodates multiple signals, (e.g., from multiple participants [113] and/or from multiple modalities (gaze, speech, activity on the screen) [1,30,35]. Notably, MdRQA contrasts CRQA by measuring the extent to which the multidimensional system visits repeated (recurrent) states, irrespective of whether or not the individual signals are in alignment. For example, Participant A viewing AOI 1 while Participant B viewing AOI 2 would constitute a repeated pattern despite each viewing different areas.

In our case, we compute MdRQA for two categorical time series of gaze AOIs (see above), but note the method can be extended to multiple time series [1,116]. The time series in question consists of pairs of gaze AOIs, for example: $\langle Face_1^B, Face_1^S\rangle, \langle Face_2^B, Score_2^S\rangle, \langle Score_3^B, Score_3^S\rangle, \langle Face_4^B, Score_4^S\rangle, \langle Face_5^B, Face_5^S\rangle$ where B and S refer to the buyer and seller respectively, and the subscript is the time point. We first compute a binary recurrence matrix representing time points where the system is in the same state, irrespective of whether the underlying signals are synchronous (time points 1 and 5 in example above) or not (time points 2 and 4).

Figure 3 (left) illustrates two AOI time series (buyer's and seller's AOI sequences) with the colors corresponding to each AOI: the score table, the partner's face, auxiliary area, and out of the screen. The corresponding MdRQA plot is shown in Figure 3 (middle) where black points indicating recurrent patterns. The main diagonal represents the line of identity, where the patterns are by definition recurrent (i.e., the signal is compared to itself at lag 0). Parallel diagonal lines further from the line of identity represent dynamic patterns at greater lags between time points. Figure 3(right) illustrates how the recurrence plot can be decomposed further as depicted next.

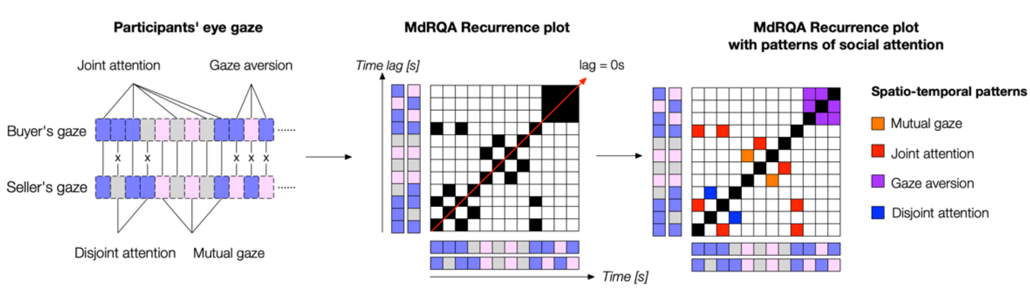


Figure 3 Data processing of time series (left) to the overall recurrence plot (middle) to the recurrence plot with extracted spatio-temporal patterns of social visual attention (right). Participants' eye gaze is first assigned to areas of interest (AOI) of the negotiation interface: score table (purple), partner's view (pink), and auxiliary area (gray). *Mutual gaze* (MG) is established when both partners look at each other $(PS_{PB's\,face} \wedge PB_{PS'face} \rightarrow MG)$. *Joint attention* (JA) is established when both partners look at same regions of the screen other than the face $(PS_{PB's\,screen} \wedge PB_{PS's\,screen} \rightarrow JA)$. *Gaze aversion* (GA), as in this figure, occurs when one of the partners look at their counterpart , who the looks elsewhere $((PS_{PB's\,face} \wedge PB_{PS's\,screen}) \vee (PS_{PB's\,screen} \wedge PB_{PS's\,screen})) \rightarrow GA)$. Recurrence of these patterns is depicted in the recurrence plot (right).

5.2 Decomposing MdRQA Plot into Spatio-temporal Patterns of Social Visual Attention

A key advantage of MdRQA is that it can identify patterns beyond basic alignment as in CRQA. In this case, each recurrent point presents a unique combination of AOIs. Considering our four AOIs, each recurrent point can represent one of 16 (4x4) possible combinations. Because MdRQA captures the recurrence of all possible recurrent AOI patterns, specific patterns can be filtered within the recurrence matrix. Here, we focus on recurrent points corresponding to three types of social visual attention: mutual gaze, gaze aversion, and joint attention, as well as disjoint attention, which was not analyzed further[3]. Figure 3(right) and Figure 4 illustrate how we decompose the recurrence plot into these patterns.

We operationalized *mutual gaze* as recurrent points when both partners simultaneously viewed their partners' face on the screen. This operationalization is in line with prior research on social visual attention [45,54,71]. However, studies on child development adopt slightly different operationalizations, such that mutual gaze is established when one partner looks at the other one and he/she reciprocates. Similarly, gaze aversion occurs when both partners demonstrate mutual gaze and then one of them looks elsewhere. In these cases, mutual gaze is a prerequisite to gaze aversion and vice versa [60,67].

We consider *gaze aversion* to occur when one of the participant's views their partner's face, but the partner's gaze was on another AOI (e.g., score table, auxiliary area, or out of the screen). This opalization accommodates both intentional (e.g., "looking away" or gaze avoidance) and involuntary components of gaze aversion and is in line with other studies (e.g., [31,32,45,71]).

Our operationalization of *joint attention* considers gaze alignment on AOIs related to the task (score table and auxiliary area). Joint attention could also be examined at a finer level, for example, looking at each *individual score category* (e.g., looking at the column "car price") or even *item* (e.g., the price "$6500") compared to the level of *activity* (e.g., viewing the entire score table) analyzed here. However, we chose to examine joint attention at a higher level of granularity because we were primarily interested in the interplay between conceptually different activities (e.g., looking up scores in the score table vs. note taking).

[3] For completeness, the fourth pattern of disjoint attention represents points where gaze was misaligned on all AOIs (e.g., the buyer viewed the score table, while the seller viewed the auxiliary area) except the face AOI (since this constitutes gaze-aversion). Since disjoint attention is not theoretically interesting in this context, we omit this pattern from further analysis.

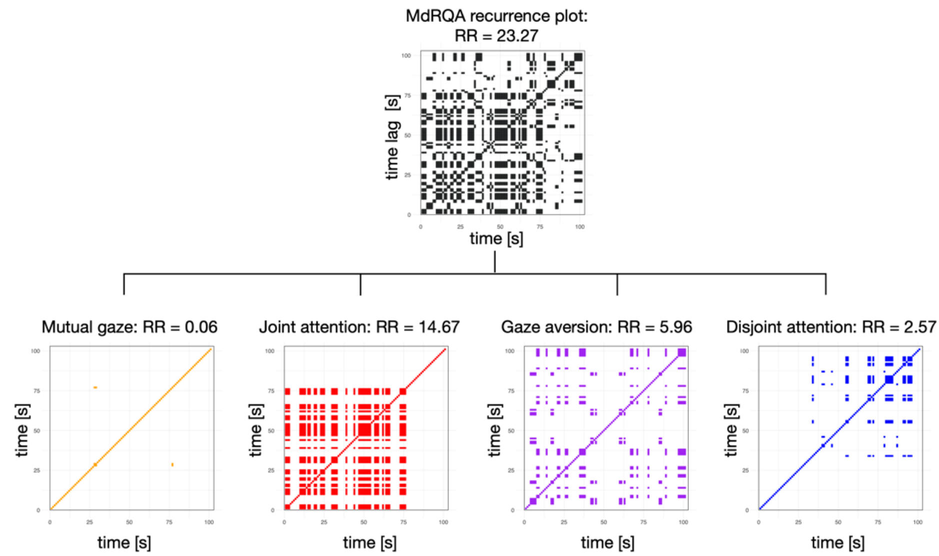


Figure 4 MdRQA decomposition. Overall MdRQA recurrence plot is split into recurrence plots for mutual gaze (orange), joint (red) and disjoint (blue) attention, and gaze aversion (purple). The recurrence rates (RR) sum up to the recurrence rate of the original recurrence plot.

A variety of measures can be used to quantify patterns in a recurrence matrix [88,116]. Here we focus on the most basic measure of *recurrence rate*, or the percentage of recurrent points in the decomposed recurrence matrices [90,109] because it was most germane to our research questions and hypotheses. The other measures are usually highly correlated with recurrence rate [3,30], as it was in our case.

5.3 Technical Details of Computing MdRQA

The RQA plot and measures were computed using the R package *mdrqa* [116] with default parameters for categorical input [20,116]: delay = 1, radius= 0.0001, embedding dimension = 1, rescaling norm = 0 (Euclidean distance). Data preprocessing (described in Section 4.4) was performed in Python using Pandas [69]. Further analyses were conducted using R [84] with the *lme4* [12] package for model fitting and *ggplot2* [120] for visualizations.

6 RESULTS

We begin with an exploratory analysis of the patterns of social visual attention before delving into our three research questions. Figure 5 illustrates proportional distributions of *individual* participants' eye gaze on the three areas of interest (AOI): score table, partner's face, and auxiliary area. We found that a majority of the eye gaze was devoted to the score table (M = 0.436, SD = 0.138) compared to the partner's face (M = 0.168, SD = 0.104) and auxiliary area (M = 0.129, SD = 0.079). We regressed these proportions on negotiation condition (coded as competitive who passed the instruction check, cooperative who passed the instruction check, vs. cooperative who failed in the instruction check) and role (buyer vs. seller) with the participant's gender (male, female) and data validity as covariates (see Table 2). There were no main effects of condition, role, and gender composition on gaze proportions on the various AOIs, suggesting that these factors did not influence overall gaze allocation.

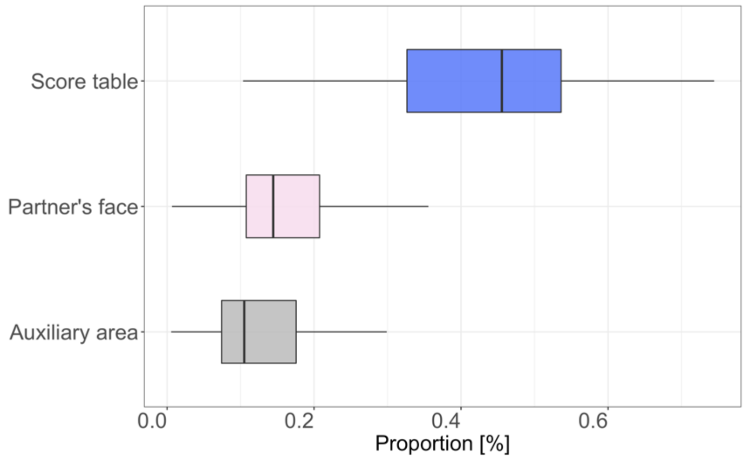


Figure 5 Subject-level proportions of eye gaze towards three areas of interest in the user interface: score table (blue), partner's face (pink), and auxiliary area (grey). The proportions for the "Out of bounds" area and missing data are not shown so the proportions do not sum to 1.

Table 2 Participant-level linear regression of negotiation condition (competitive passed, cooperative passed vs. cooperative failed) with respect to participants' role (buyer vs. seller) and data validity.

	Eye gaze at Score Table		**Eye gaze at Face**		**Eye gaze at Auxiliary area**	
Predictors	*β*	*p*	*β*	*p*	*β*	*p*
Role: Buyer	0.05	0.565	-0.09	0.44	-0.16	0.134
Condition: Cooperative_failed	-0.11	0.257	0.16	0.21	0.17	0.134
Condition: Cooperative_passed	-0.12	0.219	0.06	0.641	0.18	0.106
Gender: Male	-0.1	0.257	0.18	0.135	-0.01	0.941
Proportion of Valid Data	0.71	**<0.001**	0.13	0.285	0.41	**<0.001**
Observations	74		74		74	
R^2 / adjusted R^2	0.487 / 0.449		0.080 / 0.012		0.266 / 0.212	

6.1 RQ1: Frequencies and systematicies of systematic spatio-temporal patterns of social visual attention

For our first research question, we investigated the frequencies and systematicities of mutual gaze, joint attention, gaze aversion obtained from the decomposed MdRQA recurrence plot. Overall, about a fifth (*mean RR* = 18.686%, *SD* = 5.370) of the patterns were recurrent, suggesting considerable structure in the plots.

As Figure 7, illustrates that the most frequent spatio-temporal pattern was joint attention (*mean RR* = 10.342%, *SD* = 6.272), followed by gaze aversion (*mean RR* = 4.409%, *SD* = 3. 479). In contrast to these two patterns, mutual gaze was highly infrequent (*mean RR* = 0.637%, *SD* = 1.461).

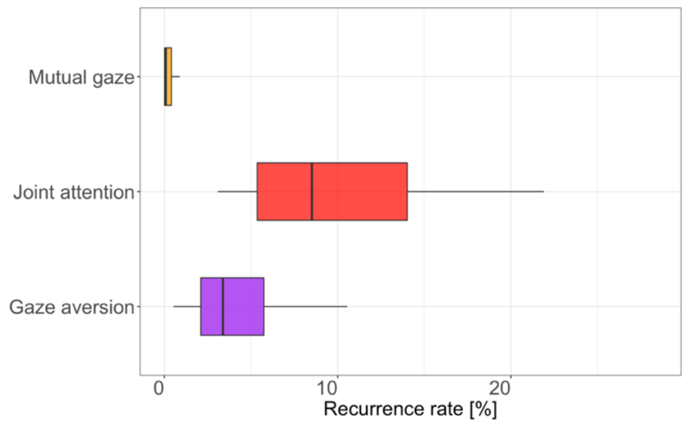


Figure 6 Dyads' recurrence rates of mutual gaze (orange), joint attention (red) and gaze aversion (purple).

Next, we assessed whether these patterns were significantly different from chance by comparing their occurrence to *shuffled baselines* [29]. We adopted the shuffling method from [29], which takes two original time series of dyad's eye gaze, preserves the concurrent values of buyer and seller AOIs, and shuffles their temporal order. Thus, the alignment between components of the time series (e.g., AOIs of each partner at a given time) remains intact at the current time, but other temporal dependencies are broken. For example, $\langle Face_1^B, Face_1^S\rangle, \langle Face_4^B, Score_4^S\rangle, \langle Face_2^B, Score_2^S\rangle, \langle Score_3^B, Score_3^S\rangle, \langle Face_5^B, Face_5^S\rangle$ would represent one shuffling of the above example time series.

Since the shuffling preserved alignment between partner's eye gaze, the observed and shuffled *global* recurrence rates, computed over the entire recurrence plot, will be identical (since the time series are compared at every combination of time points). However, the differences between the observed and shuffled plots should be revealed in *local* systematic patterns, which should be present in the observed, but not the shuffled plots, where the recurrence points should be uniformly distributed over the entire plot (see Figure 7).

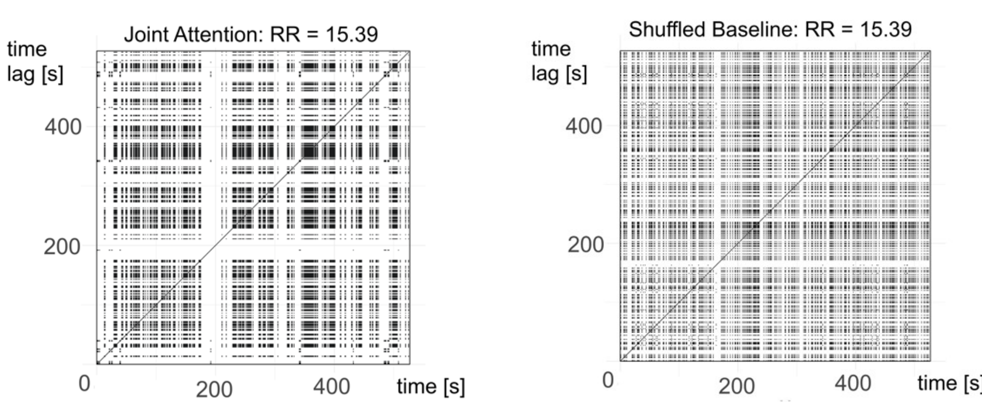
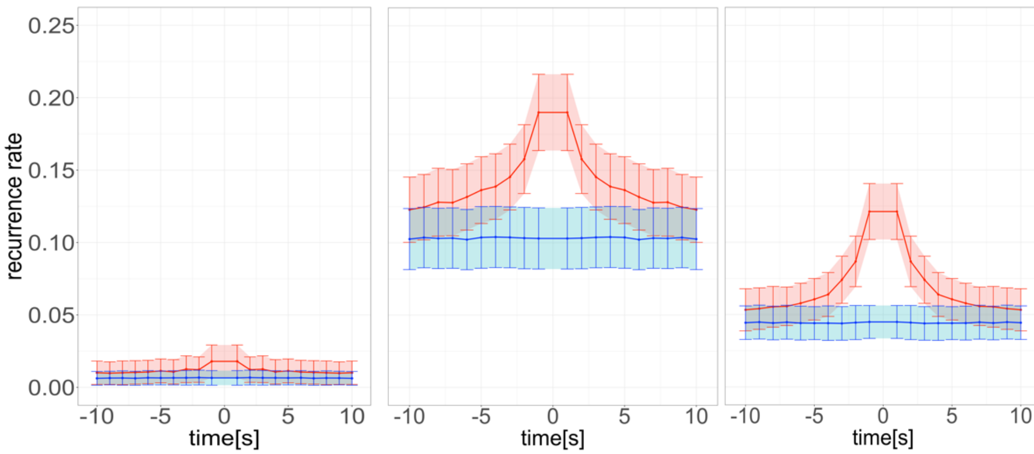


Figure 7 Recurrence plot of joint attention of one team using observed time series (left) and its corresponding plot created by shuffling the time series (right). The observed recurrence plot reveals local patterns of joint attention that are easy to spot. The shuffled version of that plot breaks the local patterns and spreads the recurrence points almost uniformly. Both plots have an equal recurrence rate (RR = 15.39%).



(a) mutual gaze (b) joint attention (c) gaze aversion

Figure 8 Comparison of recurrence rates from actual time series (red) and shuffled baselines (blue). Whereas joint attention and gaze aversion significantly differed from the shuffled baseline at all lags, mutual gaze significantly differed from the shuffled baseline at only a 1s lag. The error bars illustrate 95% confidence intervals.

We computed recurrence rates corresponding to 1-10 seconds around the line of identity as a measure of local systematic patterns. We conducted paired-samples *t*-tests comparing observed vs. baseline recurrence rates at each lag after applying a Bonferroni correction for multiple comparisons (*p* of .05/10 [lags]). Whereas recurrence rates for joint attention and gaze aversion significantly differed for all lags ($p < 0.005$), mutual gaze was only significantly higher than the shuffled baseline for the 1 second lag (observed $M = 0.017$, $SD = 0.034$; baseline $M = 0.006$, $SD = 0.014$; $t(36) = 3.60$, $p = 0.010$), indicating very fine-grained temporal alignment. Overall, the results support the presence of systematic patterns in dyadic gaze in the remote negotiations.

6.2 RQ2: Influence of Negotiation Condition on Spatio-temporal Patterns of Social Visual Attention

For our second research question, we examined whether engaging in different negotiation conditions (competitive or cooperative) influenced gaze behavior as observed in prior research on face-to-face negotiation [38]. Accordingly, we regressed recurrence rate on negotiation condition using mixed effects regression models [12] due to the inherent nesting in our data where participants are nested within dyads. These models include dyad as a random intercept, condition as a three-factor categorical fixed effect (see above), and dyad's gender composition (mixed gender, male-only, and female-only) and data validity as covariates. Negotiation condition was not significantly associated with any of the spatio-temporal patterns nor was dyad's gender composition or data validity (Table 3).

Table 3 Dyad-level linear regression of spatio-temporal patterns and negotiation condition (cooperative vs. competitive).

	Mutual gaze		Joint attention		Gaze aversion	
Predictors	β	p	β	p	β	p
Condition: Cooperative failed	0.17	0.362	-0.1	0.58	0.01	0.94
Condition: Cooperative passed	-0.13	0.513	-0.17	0.381	-0.12	0.528
Dyad: Male-only	0.25	0.195	-0.17	0.385	0.28	0.152
Dyad: Mixed Gender	-0.06	0.762	0.02	0.908	0.17	0.369
Data Validity	0.01	0.97	0.25	0.172	-0.09	0.605
Observations	37		37		37	
R^2 / adjusted R^2	0.099 / -0.046		0.107 / -0.037		0.086 / -0.061	

6.3 RQ3: Spatio-temporal Patterns with Respect to Dyad's Outcomes

Lastly, we tested the extent to which the patterns of social visual attention predict subjective and objective outcomes of the negotiation by regressing the joint score, time to initial agreement, and SVI (averaged per dyad; distributions are illustrated in Figure 9) on the three as individual predictors. We used negative binomial mixed effects regressions for time to initial agreement since it represents non-normal count data; standard linear mixed effects models were used for the joint score and SVI. We also included comparison models with proportion of gaze on each AOI as independent variables. We adopted this individual model approach in lieu of simultaneously entering them in the same model due to a concern that the sample size would result in unstable models. We included negotiation condition, dyads' gender composition, and data validity as control variables.

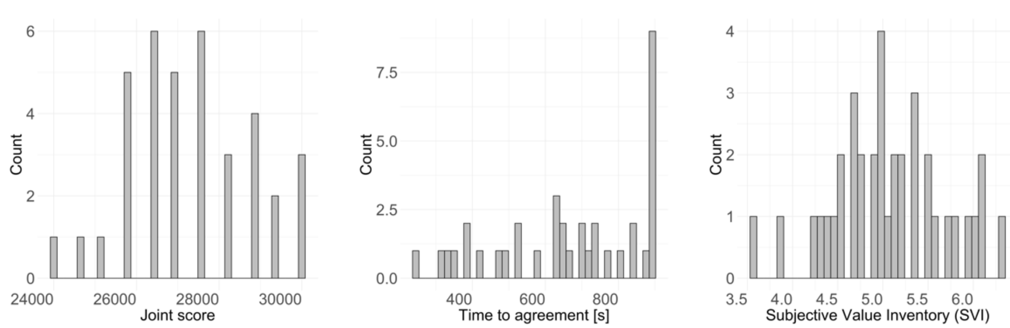


Figure 9 Distribution of outcome measures in 37 teams. Given the non-normal distribution of time to initial agreement, we reported a negative binomial regression model in Table 7.

The results are shown in Tables 5-9 in the Appendix and summarized in Table 4. We found that joint attention significantly predicted the *joint score* (β = 0.42, p = 0.013) whereas gaze aversion negatively predicted it (β = -0.54, p = 0.001). Mutual gaze was not a significant predictor (β = -0.01, p = 0.966) of joint score. Importantly, gaze proportions on the various AOIs were not predictive of joint score, suggesting that spatio-temporal dynamics of attention mattered more than the spatial distribution alone.

Table 4 Model estimates for the patterns of social visual attention and gaze proportions with respect to joint score, time to initial agreement, and Subjective Value Inventory (SVI). The complete models are reported in the Appendix.

	Joint score	Time to Initial Agreement	SVI
Predictor	*β (p-value)*	*Incidence Rate Ratios (p-value)*	*β (p-value)*
Social attention			
Mutual gaze	-0.01 (p = 0.966)	1.03 (p = 0.450)	-0.02 (p = 0.921)
Joint attention	**0.42 (p = 0.013)**	0.99 (p = 0.092)	0.10 (p = 0.600)
Gaze aversion	**-0.54 (p = 0.001)**	**1.03 (p = 0.035)**	-0.31 (p = 0.095)
Gaze proporions			
Score table	0.40 (p = 0.053)	0.58 (p = 0.442)	0.06 (p = 0.799)
Partner's face	-0.34 (p = 0.052)	**3.63 (p = 0.039)**	-0.23 (p = 0.237)
Auxiliary area	-0.02 (p = 0.898)	**0.16 (p = 0.037)**	0.03 (p = 0.891)

We found that gaze aversion was associated with taking longer to reach initial agreement (*Incidence Rate Ratio* = 1.03, p = 0.035; an IRR > 1 indicates a positive effect) whereas joint attention was a marginal negative predictor (*Incidence Rate Ratio* = .99, p = 0.09). In this case, gaze allocation on partners' face AOI (*Incidence Rate Ratio* = 3.36, p = 0.039) and the auxiliary area (*Incidence Rate Ratio* = 0.16, p = 0.037) were also positive predictors. Notably, dyads who were slower at reaching initial agreement had lower joint scores (Spearman's *rho* = -0.45, p = 0.005) and were less satisfied with the negotiation (Spearman's *rho* = -0.44, p = 0.006).

We were also interested in how the patterns of social visual attention predict *SVI,* which was positively correlated with the joint score (Spearman's *rho* = 0.51, p = 0.001). Surprisingly, none of the spatio-temporal patterns nor proportions on the various AOIs predicted SVI. One trend emerged in that gaze aversion negatively predicted SVI, but this was not statistically significant (β = -0.31, p =0.095), so should be considered as tentative, though in the expected direction. Finally, negotiation condition and dyad gender composition were generally not predictive of any of the outcomes.

6.4 Follow-up analysis on mutual gaze

We were surprised by the low overall occurrence of mutual gaze (*mean RR* = 0.637%; *SD* = 1.461). Mutual gaze also did not predict any of the outcome variables. Further, we also found that recurrence rate for mutual gaze were only significantly different from the shuffled baseline at a 1-s lag (Section 6.2), suggesting that it might be a highly localized pattern. Thus, it might be the case that computing mutual gaze over the entire recurrence plot might suppress this pattern. We addressed this concern in two ways. First, we computed mutual gaze at a 1-sec lag, but this did not yield any significant effects in terms of predicting the outcome variables. Second, we eliminated the recurrence analysis entirely and simply computed *simultaneous* mutual gaze as the proportion of time points where both partners viewed the face AOI, which occurred5% of the time (M = 0.052, SD= 0.062). However, this variable also did not predict any of the negotiation outcomes. Thus, neither global nor local patterns in mutual gaze were associated with any of the negotiation outcomes in our study.

7 DISCUSSION

Remote negotiation using mixed-media interfaces such as Zoom or Skype is becoming normative to our daily social interactions, but faces several limitations as discussed in the Introduction. Although prior research on face-to-face interaction has investigated social visual attention as a prevalent and critical communicative signal, equivalent research during remote interaction with mixed media is sparse. Thus, there is a need to advance basic research on negotiations (and other interactions) in this context so as to generate insights for the design of next-generation collaborative interfaces to facilitate such interactions. As a step in this direction, we report on empirical investigation of patterns of social visual attention that emerged during remote negotiation. Specifically, we employed MdRQA and decomposed the resultant recurrence plot to quantify three spatio-temporal patterns of social visual attention, mutual gaze, joint attention, and gaze aversion. We examined the incidence and systematicity of these patterns and whether they were influenced by negotiation orientation (collaborative or cooperative) and dyad gender composition. Finally, we evaluated how these patterns were associated with subjective and objective negotiation outcomes. We review our main findings below.

7.1 Main Findings

For our first research question, we hypothesized that patterns of social visual attention observed in face-to-face interaction would be sustained in remote interactions with mixed media. Our results partially confirmed this hypothesis. Specifically, we found that joint attention was the most prominent pattern (M = 10.34%, SD = 6.27) followed by gaze aversion (M = 4.41%, SD = 3.48) and systematicies were detected for both these patterns. However, even though participants attended to their partner's face (M = 16.80%, SD = 10.30) mutual gaze was very sporadic (M = 0.64%, SD = 1.46) and only exhibit systematicies within a 1-sec window.

We did not assume that mutual gaze would be more frequently than other patterns, but expected that it would occur with similar frequencies as in face-to-face negotiation (e.g., proportion of mutual gaze: 35-57% [38], 60% [17], 0–45% [93]). Although the high proportions of joint attention were expected due to information processing characteristics of the task (i.e., participants had to frequently scan and compare information in the score table to reach an agreement), the very low proportions of mutual gaze were unexpected. Furthermore, we presumed that joint attention would be prominent because the task-related areas covered 75% of the screen compared to the area with the partner's face (25% of the screen or a 1:3 ratio), however, mutual gaze occurred as a 1:16-ratio compared to joint attention.

There are several reasons why mutual gaze was low in this task. First, participants were engaged in a complex negotiation with eight car features, which may have required them to pay closer attention to the point values in the score table and, in turn, less attention to their partner. Second, the layout of the user interface paired with the size of the screen meant that it may not have been obvious to the negotiators when their partner was looking at them. Thus, mutual gaze might not have facilitated rapport building and other subjective aspects of social interaction as in face-to-face interaction. This finding is informative for the design of collaborative interfaces because it suggests that even a large region for a face display (in this case 25% of the screen) does not ensure mutual gaze between remote partners.

For our second research question, we examined how negotiation orientation (i.e., cooperative vs. competitive negotiation) influenced patterns of social visual attention. Prior research on face-to-face negotiation linked gaze aversion with competitive negotiation and mutual gaze with cooperative negotiation [38]. However, we did not observe this association in our study and there were a general lack of effects pertaining to negotiation orientation. Of course, our conclusions on this respect are tentative due to concerns about whether the cooperative manipulation itself was successful.

To address the third research question, we investigated how the patterns of social visual attention predicted subjective and objective negotiation outcomes. Joint attention was positively associated with overall joint score, which is consistent with prior research. For example, Jermann and Nüssli [53] reported that joint attention mediated establishing common ground in pair programming and resulted in improved task performance. Joint attention was also found to be instrumental in detection of misunderstandings in collaborative work [19]. Our findings are also consistent with previous research on gaze sharing, where establishing joint attention in the virtual environment has been associated with mutual understanding between participants [14,24].

Whereas our findings on joint attention during mixed-media interaction are consistent with previous work in computer-mediated contexts, the results for mutual gaze and gaze aversion provide new insights. For one, gaze aversion was positively associated with time to initial agreement, but negatively associated with joint score and (marginally) with subjective perceptions of the negotiation. Dyads who were quicker at reaching an initial agreement also had higher joint scores and more positive subjective ratings. One interpretation of these results is that gaze aversion reflects social-emotional difficulty, awkwardness, or general discomfort in the dyad, resulting in longer times to reach initial agreement and overall lower joint scores. It might also reflect the use of hardball negotiation tactics on the part of one or both of the partners, which may result in averted gaze [38], and as a result, overall lower joint score and dissatisfaction with the negotiation. Further research is needed to adjudicate among these possibilities.

Second, mutual gaze was not associated with any of our negotiation outcomes. We expected it to be predictive of SVI scores since mutual gaze has been linked to constructs such as rapport building in face-to-face interaction [8,10,78,82,108], but this was not observed in our data. As noted above, one reason could be that characteristics of the negotiation task was not conducive to the type of relationship or rapport building that would be reflected in mutual gaze. An alternate possibility, however, is that current mixed-media videoconferencing technologies do not support establishing mutual gaze to the same extent as face-to-face interactions. This possibility has profound design implications, which we discussed next.

7.2 Design Implications

How can the present findings inform the development of CSCW interfaces that support negotiations and similar tasks? As discussed earlier, much of the work on eye-gaze interfaces has focused on gaze sharing as a form of feedback (e.g., [26,63]), which may not be suitable in the context of negotiation and other tasks that are competitive in nature. Negotiation encompasses both collaborative and competitive goals and strategies as opposed to traditional collaborative tasks, such as collaborative visual search or collaborative problem solving, in which transparency and maximizing shared knowledge are important goals. Therefore, sharing screen content or revealing the locus of users' attention is unlikely to help a person's negotiation goals and outcomes. Other tasks also fall into this category, e.g., remote interviewing, business meetings with multiple remote partners, financial or law consultations, and telemedicine appointments.

This raises the question of whether there is any use of social visual attention in remote negotiation? We argue that understanding the dynamics of social visual attention can be informative for the design of gaze-sensitive interfaces that aim to maximize the outcome for both partners. For example, we found that joint attention was a positive indicator of joint negotiation outcomes, while gaze aversion was a negative indicator, ostensibly. Although this correlational link does not imply a causal relationship, there might nevertheless be benefits to increasing joint attention and reducing gaze aversion. One way to accomplish this is with subtle visual feedback that is sufficiently coarse grained so as to conceal the precise locations of the partner's gaze. For example, in Figure 10, the visual feedback (bottom) does not reveal where specifically the users are looking compared to gaze sharing (top). Further, the gradual changes in color intensity of visual feedback [13] could reflect different degrees of joint attention in a unit time. Of course, the feedback itself should not be distracting or increase perceptual load.

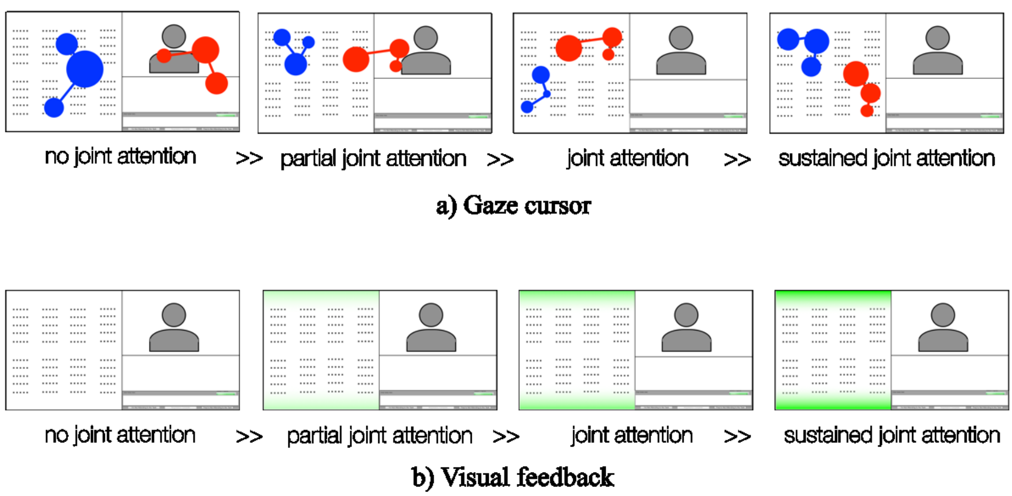


Figure 10 Comparisons between a) a gaze cursor (or direct gaze sharing) and b) the proposed indirect visual feedback. The gaze cursor comprises scan paths of both partners (blue and red) displayed at the exact location of the screen, which is unsuitable in the negotiation context since it might reveal the intentions of the partner. On the other hand, the proposed visual feedback (green) is activated based on the degree of joint attention on the score table and thus, does not reveal potentially sensitive information about partners' goals. The color intensity changes according to the degree of joint attention.

A further design implication of our work is related to the lack of mutual gaze in remote negotiation. Mutual gaze is a vital part of face-to-face negotiation [38], however, in our study we observed low levels of mutual gaze. This is possibly because of the large viewing angle between the webcam (placed in the middle of the monitor) and the partner's face, (on the right side of the screen) as illustrated in Figure 11a. The result is that it is difficult for a user to ascertain what part of the interface their partner is looking at. For example, when two partners look at each other, perhaps in an attempt to establish mutual gaze, it can appear that the other is looking to the right. This gives an inaccurate representation of mutual gaze. To improve the current state, we propose a wizard for positioning the camera. For example, prior to the interaction, the wizard would suggest the participant move the camera horizontally or vertically along the monitor to minimize the angle between the camera and the partner's face. The minimal angle would ensure more realistic mutual gaze (Figure 11b and 11c). If the camera cannot be moved, then the wizard would suggest repositioning the window displaying the partner's face so as to minimize the angle. Future research could evaluate whether and how such interventions increase mutual gaze and improve partners' subjective perceptions of the negotiation, due to an increase in rapport, for example.

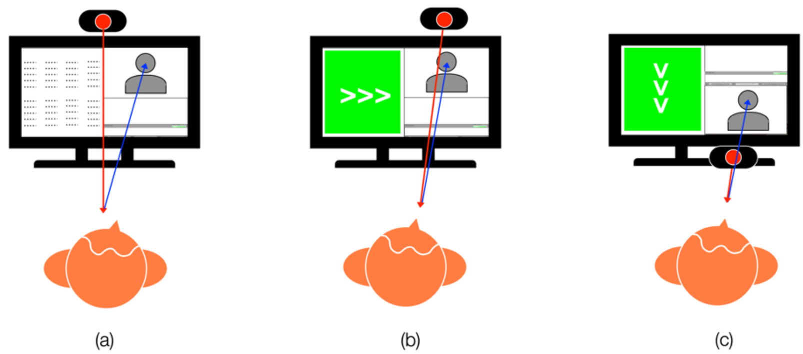


Figure 11 Wizard for positioning the webcam. In the default settings at Panel (a), there is a significant angle between the webcam (red) and the user's eye gaze towards their partner's face (blue). Prior to negotiation, the wizard (green) would suggest moving the webcam closer to the partner's face to establish better representation of mutual gaze. In Panels (b) and (c), the wizard suggests moving the camera right or down respectively to minimize the angle between the webcam and the partner's face.

7.3 Limitations and Future Work

Like all studies, ours has limitations. Although we used standard instructions and thoroughly and repeatedly instructed participants about their roles and the negotiation instructions, a large number of participants in the cooperative condition incorrectly responded to the instruction check item. We note that the interface provided corrective feedback for those participants who incorrectly responded to the instructional check item. When we separated the cooperative condition based on whether participants (and the dyad as a whole) responded correctly and incorrectly, we found no differences in how the two groups performed on the task, suggesting that the correction was successful. Although, we cannot rule out a somewhat unsuccessful manipulation for the lack of effects with respect to negotiation orientation, thereby rendering RQ2 inconclusive, this does not affect RQ1 and RQ3, which did not involve the manipulation.

A second limitation is that our study was conducted in a lab setting, which might also explain why the manipulation did not yield any effects. For example, our study was time-limited, and negotiators did not have strong emotional investment with the outcomes. This does not reflect the complexity of real-world situations when negotiators may have significant performance incentives (e.g., negotiating a salary raise), may be familiar with each other prior to the negotiation (e.g., long-term business partners), or time restrictions differ (e.g., "I have only five minutes for you"). In these cases, we expect that negotiations in-situ may yield different patterns of results. Thus, future research will need to examine the replicability of this work under more realistic conditions (e.g., compensating participants based on the outcomes).

Third, we did not directly compare face-to-face with remote negotiations. Given the small number of studies on social visual attention during negotiation, it would be worth investigating how patterns of social visual attention emerge in face-to-face and remote interaction with the same task. Another comparison worth exploring would comprise negotiation over videoconferencing *without* mixed media, for example, by providing the score table, instructions, and notes on paper. It would be interesting to investigate the role of mutual gaze when there are no competing items on the screen. We did not pursue this here because our primary goal was to understand the affordances of mixed-media tools.

Another limitation is related to the eye trackers we used. The choice of low-cost, portable eye trackers was appropriate given that these devices are more likely to be integrated in real-world videoconferencing. However, the affordable eye trackers often could not accommodate the unrestricted range of participants' body and head movements and provided a lower sampling rate. Consequently, we observed elevated rates of miscalibrated or dropped eye-tracking data. We corrected cases of miscalibrated data by applying a linear transformation, filtering out the missing data chunks, and enlarging the examined areas of interest with a safety margin. Despite these steps, the dataset was inevitably reduced by about 50%, thereby reducing statistical power. The reduced data set also altered the gender distribution to be female-dominated and presumably reduced statistical power to detect any effects pertaining to gender (male-only, female-only, vs. mixed gender teams). Thus, to assess whether negotiation in virtual environments reduce gender-related differences, as reviewed in [103], awaits repeating the experiment with a larger and more balanced sample, higher quality eye tracking, and perhaps a face-to-face condition.

Finally, we focused on a single modality (eye gaze), but additional modalities such as facial expressions and speech likely also contribute valuable information. In particular, we expect that social visual attention in our task is coordinated by speech, and, thus, incorporating time series of speech information (e.g., pitch, speech rate, linguistic content) and eye gaze in a multimodal MdRQA will shed additional light on social visual attention during remote dyadic negotiation. In addition, it will be interesting to analyze the underlying discourse patterns, for example, by investigating how patterns of social visual attention change in response to high-level negotiation behaviors.

In our preliminary work in this direction, we qualitatively examined dialogues from selected dyads (a total of eight dyads from high vs. low-scoring competitive and cooperative negotiations) in conjunction with the patterns of social visual attention. We isolated the dialogues that were accompanied by a single attentional pattern, and transcribed the objectives of negotiators' discourse. Our goal was to investigate whether any discourse patterns clearly accompanied various gaze patterns. For example, prior research has showed that negotiators intensify staring at their partner during the deception [18,65,97]. However, this was not the case, and we observed instead that the patterns of social visual attention were associated with a variety of negotiation behaviors. For example, joint attention was associated with both deceptive behaviors (e.g., a seller pretending that they did not have the desired car color or a seller making excuses as to why a green car is more expensive) as well as compromising behaviors (e.g., a buyer proposing a compromise and a seller agreeing to the proposal). Similarly, sequences of gaze aversion were linked to various behaviors, such as a buyer disagreeing or agreeing with a proposed car option, a seller accepting a proposed car option or rejecting and proposing alternative options. Mutual gaze occurred only sporadically and usually was part of longer sequences of joint attention and gaze aversion. In several occasions, in which mutual gaze was established for longer (2-3 second) periods, a seller was persuading the buyer to change their mind, such as "That's a phenomenal car! Have you seen it in green?" or "you don't need that [four extras]! That's the same as you don't need additional four windows in the car!". However, these findings were often mixed and contradictory; therefore, suggesting that a more complete analysis is warranted and an important item for future work.

8 CONCLUSIONS

Collaborative mixed-media interfaces (e.g., Skype and Zoom) are ubiquitous in our daily lives, allowing us to instantly communicate and collaborate. Despite the technological advances, these interfaces are still imperfect and narrow the communicative bandwidth compared to face-to-face interactions and research on non-verbal communication with these interfaces is sparse. Here, we focused on social visual attention because of its instrumental role in effective collaboration by aiding coordination, communication, and signaling socio-emotional states. Since traditional measures (such as summary statistics) cannot capture temporal dynamics, of social visual attention, we utilized and enhanced a technique called multidimensional recurrent quantification analysis (MdRQA) to explore spatio-temporal dynamics of social visual attention. We found that social visual attention in remote interaction partly resembles characteristics of face-to-face interaction. Whereas joint attention and gaze aversion were two prominent patterns, mutual gaze was largely diminished. Contrary to some findings from face-to-face interaction, social visual attention in our study was not associated with factors, such as gender composition and negotiation orientation. However, social visual attention was a powerful predictor of objective negotiation outcomes. These findings broaden our understanding of social visual attention in remote interaction with modern mixed-media interfaces and provide guidance for the design of next-generation collaborative interfaces.

ACKNOWLEDGEMENTS

This research was supported by the National Science Foundation (NSF DUE 1745442, SES 1928612) and the Institute of Educational Sciences (IES R305A170432). Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding agencies.

REFERENCES

[1] Mary Jean Amon, Hana Vrzakova, and Sidney K D'Mello. 2019. Beyond Dyadic Coordination: Multimodal Behavioral Irregularity in Triads Predicts Facets of Collaborative Problem Solving. *Cogn. Sci.* 43, 10 (2019).

[2] Peter A. Andersen. 2008. *Nonverbal communication: forms and functions*. Waveland Press Inc.

[3] Nicola C. Anderson, Walter F. Bischof, Kaitlin E.W. W Laidlaw, Evan F. Risko, and Alan Kingstone. 2013. Recurrence quantification analysis of eye movements. *Behav. Res. Methods* 45, 3 (2013), 842–856. DOI:https://doi.org/10.3758/s13428-012-0299-5

[4] Hayward P. Andres. 2002. A comparison of face-to-face and virtual software development teams. *Team Perform. Manag. An Int. J.* 8, 1 (2002), 39–48. DOI:https://doi.org/10.1108/13527590210425077

[5] Sean Andrist, A. R. Ruis, and David Williamson Shaffer. 2018. A network analytic approach to gaze coordination during a collaborative task. *Comput. Human Behav.* 89, July (2018), 339–348. DOI:https://doi.org/10.1016/j.chb.2018.07.017

[6] Michael Argyle and Mark Cook. 1976. Gaze and mutual gaze. (1976).

[7] Michael Argyle and Janet Dean. 1965. Eye-contact, distance and affiliation. *Sociometry* (1965), 289–304.

[8] Michael Argyle and Roger Ingham. 1972. Gaze, mutual gaze, and proximity. *Semiotica* 6, 1 (1972), 32–49.

[9] Vairam Arunachalam and William N Dilla. 1995. Judgment accuracy and outcomes in negotiation: A causal modeling analysis of decision-aiding effects. *Organ. Behav. Hum. Decis. Process.* 61, 3 (1995), 289–304.

[10] Jeremy N Bailenson, Jim Blascovich, Andrew C Beall, and Jack M Loomis. 2001. Equilibrium theory revisited: Mutual gaze and personal space in virtual environments Jeremy. *Thesis* (2001).

[11] Boris B. Baltes, Marcus W. Dickson, Michael P. Sherman, Cara C. Bauer, and Jacqueline S. LaGanke.

2002. Computer-mediated communication and group decision making: A meta-analysis. *Organ. Behav. Hum. Decis. Process.* (2002). DOI:https://doi.org/10.1006/obhd.2001.2961

[12] Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. Fitting Linear Mixed-Effects Models Using {lme4}. *J. Stat. Softw.* 67, 1 (2015), 1–48. DOI:https://doi.org/10.18637/jss.v067.i01

[13] Roman Bednarik, Tersia Gowases, and Markku Tukiainen. 2009. interaction enhances problem solving: Effects of dwell-time based, gaze-augmented, and mouse interaction on problem-solving strategies and user experience. *J. Eye Mov. ...* 3, 1 (2009), 1–10. Retrieved April 26, 2014 from http://www.cs.joensuu.fi/pages/int/pub/bednarik09a.pdf

[14] Roman Bednarik, Andrey Shipilov, and Sami Pietinen. 2011. Bidirectional gaze in remote computer mediated collaboration: Setup and initial results from pair-programming. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, 597–600.

[15] Nathan Bos, Judy Olson, Darren Gergle, Gary Olson, and Zach Wright. 2002. Effects of four computer-mediated communications channels on trust development. *Conf. Hum. Factors Comput. Syst. - Proc.* 4, 1 (2002), 135–140. DOI:https://doi.org/10.1145/503399.503401

[16] Susan E. Brennan, Xin Chen, Christopher A. Dickinson, Mark B. Neider, and Gregory J. Zelinsky. 2008. Coordinating cognition: The costs and benefits of shared gaze during collaborative search. *Cognition* (2008). DOI:https://doi.org/10.1016/j.cognition.2007.05.012

[17] Frank Broz, Hagen Lehmann, Chrystopher L Nehaniv, and Kerstin Dautenhahn. 2012. Mutual gaze, personality, and familiarity: Dual eye-tracking during conversation. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*, 858–864.

[18] David B Buller and Judee K Burgoon. 1996. Interpersonal deception theory. *Commun. theory* 6, 3 (1996), 203–242.

[19] Mauro Cherubini, Marc-Antoine Nüssli, and Pierre Dillenbourg. 2008. Deixis and gaze in collaborative work at a distance (over a shared map): a computational model to detect misunderstandings. In *Proceedings of the 2008 symposium on Eye tracking research & applications*, 173–180.

[20] Moreno I. Coco and Rick Dale. 2014. Cross-recurrence quantification analysis of categorical and continuous time series: An R package. *Front. Psychol.* 5, JUN (2014), 1–14. DOI:https://doi.org/10.3389/fpsyg.2014.00510

[21] Mark Cook. 1977. Gaze and Mutual Gaze in Social Encounters: How long—and when—we look others" in the eye" is one of the main signals in nonverbal communication. *Am. Sci.* 65, 3 (1977), 328–333.

[22] Jared R Curhan, Hillary Anger Elfenbein, and Noah Eisenkraft. 2010. The objective value of subjective value: A multi-round negotiation study. *J. Appl. Soc. Psychol.* 40, 3 (2010), 690–709.

[23] Jared R Curhan, Hillary Anger Elfenbein, and Heng Xu. 2006. What do people value when they negotiate? Mapping the domain of subjective value in negotiation. *J. Pers. Soc. Psychol.* 91, 3 (2006), 493.

[24] Sarah D'Angelo and Andrew Begel. 2017. Improving Communication Between Pair Programmers Using Shared Gaze Awareness. *Proc. 2017 CHI Conf. Hum. Factors Comput. Syst. - CHI '17* (2017), 6245–6290. DOI:https://doi.org/10.1145/3025453.3025573

[25] Sarah D'Angelo and Darren Gergle. 2016. Gazed and confused: Understanding and designing shared gaze for remote collaboration. *Conf. Hum. Factors Comput. Syst. - Proc.* (2016), 2492–2496. DOI:https://doi.org/10.1145/2858036.2858499

[26] Sarah D'Angelo and Darren Gergle. 2018. An eye for design: Gaze visualizations for remote collaborative work. *Conf. Hum. Factors Comput. Syst. - Proc.* 2018-April, (2018). DOI:https://doi.org/10.1145/3173574.3173923

[27] Richard L Daft and Robert H Lengel. 1986. Organizational information requirements, media richness and structural design. *Manage. Sci.* 32, 5 (1986), 554–571.

[28] Rick Dale, Riccardo Fusaroli, Nicholas D Duran, and Daniel C Richardson. 2013. The self-organization of human interaction. In *Psychology of learning and motivation*. Elsevier, 43–95.

[29] Rick Dale, Natasha Z. Kirkham, and Daniel C. Richardson. 2011. The dynamics of reference and shared visual attention. *Front. Psychol.* 2, NOV (2011), 1–11. DOI:https://doi.org/10.3389/fpsyg.2011.00355

[30] Muhterem Dindar, Iman Alikhani, Jonna Malmberg, Sanna Järvelä, and Tapio Seppänen. 2019. Examining shared monitoring in collaborative learning: A case of a recurrence quantification analysis approach. *Comput. Human Behav.* April 2018 (2019).

[31] Gwyneth Doherty-Sneddon, Vicki Bruce, Lesley Bonner, Sarah Longbotham, and Caroline Doyle. 2002. Development of gaze aversion as disengagement from visual information. *Dev. Psychol.* 38, 3

(2002), 438.

[32] Gwyneth Doherty-Sneddon and Fiona G Phelps. 2005. Gaze aversion: A response to cognitive or social difficulty? *Mem. Cogn.* 33, 4 (2005), 727–733. DOI:https://doi.org/10.3758/BF03195338

[33] Carsten K W De Dreu, Bianca Beersma, Wolfgang Steinel, and Gerben A Van Kleef. 2007. The psychology of negotiation: Principles and basic processes. (2007).

[34] J P Eckmann, S Oliffson Kamphorst, D Ruelle, and others. 1995. Recurrence plots of dynamical systems. *World Sci. Ser. Nonlinear Sci. Ser. A* 16, (1995), 441–446.

[35] Lucca Eloy, Angela E.B. Stewart, Mary Jean Amon, Caroline Reinhardt, Amanda Michaels, Chen Sun, Valerie Shute, Nicholas D Duran, and Sidney D'Mello. 2019. Modeling Team-level Multimodal Dynamics During Multiparty Collaboration. In *2019 International Conference on Multimodal Interaction* (ICMI '19), 244–258. Retrieved from http://doi.acm.org/10.1145/3340555.3353748

[36] N. J. Emery. 2000. The eyes have it: The neuroethology, function and evolution of social gaze. Neuroscience and Biobehavioral Reviews. *Neurosci. Biobehav. Rev.* 24, (2000), 581–604. Retrieved from https://www.sciencedirect.com/science/article/pii/S0149763400000257

[37] Ralph V Exline. 1963. Explorations in the process of person perception: visual interaction in relation to competition, sex, and need for affiliation 1. *J. Pers.* 31, 1 (1963), 1–20.

[38] Margaret Foddy. 1978. Patterns of gaze in cooperative and competitive negotiation. *Hum. relations* 31, 11 (1978), 925–938.

[39] Azadeh Forghani, Gina Venolia, and Kori Inkpen. 2014. Media2gether: Sharing media during a call. In *Proceedings of the 18th International Conference on Supporting Group Work*, 142–151.

[40] Megan Freeth, Tom Foulsham, and Alan Kingstone. 2013. What Affects Social Attention? Social Presence, Eye Contact and Autistic Traits. *PLoS One* 8, 1 (2013). DOI:https://doi.org/10.1371/journal.pone.0053286

[41] Alexandra Frischen, Andrew P Bayliss, and Steven P Tipper. 2007. Gaze cueing of attention: visual attention, social cognition, and individual differences. *Psychol. Bull.* 133, 4 (2007), 694.

[42] Riccardo Fusaroli, Ivana Konvalinka, and Sebastian Wallot. 2014. Analyzing social interactions: the promises and challenges of using cross recurrence quantification analysis. In *Translational recurrences*. Springer, 137–155.

[43] Riccardo Fusaroli, Joanna Raczaszek-Leonardi, and Kristian Tylén. 2014. Dialog as interpersonal synergy. *New Ideas Psychol.* 32, (2014), 147–157.

[44] Darren Gergle and Alan T Clark. 2011. See What I ' m Saying ? Using Dyadic Mobile Eye Tracking to Study Collaborative Reference. *Electr. Eng.* (2011), 435–444.

[45] Arthur M Glenberg, Jennifer L Schroeder, and David A Robertson. 1998. Averting the gaze disengages the environment and facilitates remembering. *Mem. Cognit.* 26, 4 (1998), 651–658.

[46] David M. Grayson and Andrew F. Monk. 2003. Are you looking at me? Eye contact and desktop video conferencing. *ACM Trans. Comput. Interact.* 10, 3 (2003), 221–243. DOI:https://doi.org/10.1145/937549.937552

[47] Roy S. Hessels. 2019. How does gaze to faces support face-to-face interaction? A review and perspective. *Psychon. Bull. Rev.* 31, 1 (2019), 63–68.

[48] Roy S. Hessels, Gijs A. Holleman, Alan Kingstone, Ignace T.C. Hooge, and Chantal Kemner. 2019. Gaze allocation in face-to-face communication is affected primarily by task structure and social context, not stimulus-driven factors. *Cognition* 184, June 2018 (2019), 28–43. DOI:https://doi.org/10.1016/j.cognition.2018.12.005

[49] Kenneth Holmqvist and R Andersson. 2011. *Eye tracking: a comprehensive guide to methods and measures*. Retrieved June 16, 2012 from http://dspace.learningnetworks.org/handle/1820/3441

[50] Hiroshi Ishii, Minoru Kobayashi, and Jonathan Grudin. 1993. Integration of Interpersonal Space and Shared Workspace: ClearBoard Design and Experiments. *ACM Trans. Inf. Syst.* 11, 4 (1993), 349–375. DOI:https://doi.org/10.1145/159764.159762

[51] Ryo Ishii, Shiro Kumano, and Kazuhiro Otsuka. 2017. Analyzing Gaze Behavior during Turn-Taking for Estimating Empathy Skill Level. 9 (2017), 365–373. DOI:https://doi.org/10.1145/3136755.3136786

[52] Alejandro Jaimes and Jun Miyazaki. 2005. Building a smart meeting room: From infrastructure to the video gap (research and open issues). In *Proceedings - International Workshop on Biomedical Data Engineering, BMDE2005*. DOI:https://doi.org/10.1109/ICDE.2005.202

[53] Patrick Jermann and Marc-Antoine Nüssli. 2012. Effects of sharing text selections on gaze cross-recurrence and interaction quality in a pair programming task. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*, 1125–1134.

[54] Kristiina Jokinen. 2013. Eye-trackers and Multimodal Communication Studies. (2013), 29–39.

[55] Chiara Jongerius, Roy S. Hessels, Johannes A. Romijn, Ellen M. A. Smets, and Marij A. Hillen. 2020. The Measurement of Eye Contact in Human Interactions: A Scoping Review. *J. Nonverbal Behav.* (2020). DOI:https://doi.org/10.1007/s10919-020-00333-3

[56] Adam Kendon and Mark Cook. 1969. The consistency of gaze patterns in social interaction. *Br. J. Psychol.* 60, 4 (1969), 481–494.

[57] Norbert L Kerr and R Scott Tindale. 2004. Group performance and decision making. *Annu. Rev. Psychol.* 55, (2004), 623–655.

[58] Gregory E. Kersten and Hsiangchu Lai. 2007. Negotiation support and e-negotiation systems: An overview. *Gr. Decis. Negot.* 16, 6 (2007), 553–586. DOI:https://doi.org/10.1007/s10726-007-9095-5

[59] Chris L Kleinke. 1986. Gaze and eye contact: a research review. *Psychol. Bull.* 100, 1 (1986), 78.

[60] Dorit Kliemann, Isabel Dziobek, Alexander Hatri, Rosa Steimke, and Hauke R. Heekeren. 2010. Atypical reflexive gaze patterns on emotional faces in autism spectrum disorders. *J. Neurosci.* 30, 37 (2010), 12281–12287. DOI:https://doi.org/10.1523/JNEUROSCI.0688-10.2010

[61] Robert E. Kraut, Darren Gergle, and Susan R. Fussell. 2002. The use of visual information in shared visual spaces: Informing the development of virtual co-presence. *Proc. ACM Conf. Comput. Support. Coop. Work* (2002), 31–40.

[62] Hideaki Kuzuoka, Jun Yamashita, Keiichi Yamazaki, and Akiko Yammmld. 1999. Agora: A remote collaboration system that enables mutual monitoring. In *Conference on Human Factors in Computing Systems - Proceedings*. DOI:https://doi.org/10.1145/632716.632836

[63] Jerry Li, Mia Manavalan, Sarah D'Angelo, and Darren Gergle. 2016. Designing Shared Gaze Awareness for Remote Collaboration. In *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion* (CSCW '16 Companion), 325–328. DOI:https://doi.org/10.1145/2818052.2869097

[64] M. G. Lincoln. 2005. Negotiation: The Opposing Sides of Verbal and Nonverbal Communication. *J. Collect. Negot. (formerly J. Collect. Negot. Public Sect.* 29, 4 (2005), 297–306. DOI:https://doi.org/10.2190/l278-etet-3blg-e9qp

[65] Samantha Mann, Aldert Vrij, Sharon Leal, Pär Anders Granhag, Lara Warmelink, and Dave Forrester. 2012. Windows to the soul? Deliberate eye contact as a cue to deceit. *J. Nonverbal Behav.* 36, 3 (2012), 205–215.

[66] Norbert Marwan, M Carmen Romano, Marco Thiel, and Jürgen Kurths. 2007. Recurrence plots for the analysis of complex systems. *Phys. Rep.* 438, 5–6 (2007), 237–329.

[67] Daphne Maurer and Philip Salapatek. 2018. Developmental Changes in the Scanning of Faces by Young Infants Author (s): Daphne Maurer and Philip Salapatek Published by : Wiley on behalf of the Society for Research in Child Development Stable URL : http://www.jstor.org/stable/1128813 Developmental. 47, 2 (2018), 523–527.

[68] Allan Mazur, Eugene Rosa, Mark Faupel, Joshua Heller, Russell Leen, and Blake Thurman. 1980. Physiological aspects of communication via mutual gaze. *Am. J. Sociol.* 86, 1 (1980), 50–74.

[69] Wes McKinney and others. 2010. Data structures for statistical computing in python. In *Proceedings of the 9th Python in Science Conference*, 51–56.

[70] Anne Meier, Hans Spada, and Nikol Rummel. 2007. A rating scheme for assessing the quality of computer-supported collaboration processes. *Int. J. Comput. Collab. Learn.* 2, 1 (2007), 63–86.

[71] Louis Philippe Morency and Trevor Darrell. 2008. Conditional sequence model for context-based recognition of gaze aversion. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* 4892 LNCS, (2008), 11–23. DOI:https://doi.org/10.1007/978-3-540-78155-4_2

[72] Janice Nadler. 2003. Rapport in negotiation and conflict resolution. *Marquette Law Rev.* 285, 1990 (2003), 875–882. Retrieved from http://heinonlinebackup.com/hol-cgi-bin/get_pdf.cgi?handle=hein.journals/marqlr87&section=52

[73] Janice Nadler and Donna Shestowsky. 2006. Negotiation, information technology, and the problem of the faceless other. *Negot. theory Res.* (2006), 145–172.

[74] Janice Nadler and Leigh Thompson. 2008. New car. Teaching materials for negotiations and decision making, Northwestern University. *Disput. Resolut. Res. Center, Evanst.* (2008).

[75] Mark B. Neider, Xin Chen, Christopher A. Dickinson, Susan E. Brennan, and Gre Gory J. Zelinsky. 2010. Coordinating spatial referencing using shared gaze. *Psychon. Bull. Rev.* 17, 5 (2010), 718–724. DOI:https://doi.org/10.3758/PBR.17.5.718

[76] Catherine Neubauer, Joshua Woolley, Peter Khooshabeh, and Stefan Scherer. 2016. Getting to know you: a multimodal investigation of team behavior and resilience to stress. *Proc. 18th ACM Int. Conf.*

Multimodal Interact. - ICMI 2016 (2016), 193–200. DOI:https://doi.org/10.1145/2993148.2993195
[77] Donald A Norman. 1999. Affordance, conventions, and design. *interactions* 6, 3 (1999), 38–43.
[78] David G Novick, Brian Hansen, and Karen Ward. 1996. Coordinating turn-taking with gaze. In *Proceeding of Fourth International Conference on Spoken Language Processing. ICSLP'96*, 1888–1891.
[79] Ken Ichi Okada, Fumihiko Maeda, Yusuke Ichikawaa, and Yutaku Matsushita. 1994. Multiparty videocormferencing at virtual social distance: MAJIC design. *Proc. 1994 ACM Conf. Comput. Support. Coop. Work. CSCW 1994* (1994), 385–393. DOI:https://doi.org/10.1145/192844.193054
[80] Mai Otsuki, Taiki Kawano, Keita Maruyama, Hideaki Kuzuoka, and Yusuke Suzuki. 2017. ThirdEye: Simple add-on display to represent remote participant's gaze direction in video communication. *Conf. Hum. Factors Comput. Syst. - Proc.* 2017-May, (2017), 5307–5312. DOI:https://doi.org/10.1145/3025453.3025681
[81] Gale Parchoma. 2014. The contested ontology of affordances: Implications for researching technological affordances for collaborative knowledge production. *Comput. Human Behav.* 37, (2014), 360–368.
[82] Miles L Patterson. 1976. An arousal model of interpersonal intimacy. *Psychol. Rev.* 83, 3 (1976), 235.
[83] Miles L Patterson. 1982. A sequential functional model of nonverbal exchange. *Psychol. Rev.* 89, 3 (1982), 231.
[84] R Core Team, R Core Team, and others. 2013. R: A Language and Environment for Statistical Computing. (2013). Retrieved from https://www.r-project.org/
[85] Tehran J Davis Michael A Riley Kevin Shockley Ramenzoni Veronica C., Aimee A Baker, V C Ramenzoni, T Davis, M A Riley, K Shockley, and Aimee A Baker. 2011. Joint action in a cooperative precision task: Nested processes of intrapersonal and interpersonal coordination. *Exp. Brain Res.* 211, (2011), 447–457.
[86] Arvind Rangaswamy and G Richard Shell. 1997. Using computers to realize joint gains in negotiations: toward an "electronic bargaining table." *Manage. Sci.* 43, 8 (1997), 1147–1163.
[87] Daniel C. Richardson, Rick Dale, and John M. Tomlinson. 2009. Conversation, Gaze coordination, and beliefs about visual context. *Cogn. Sci.* 33, 8 (2009), 1468–1482. DOI:https://doi.org/10.1111/j.1551-6709.2009.01057.x
[88] Daniel C Richardson and Rick Dale. 2005. Looking to understand: The coupling between speakers' and listeners' eye movements and its relationship to discourse comprehension. *Cogn. Sci.* 29, 6 (2005), 1045–1060.
[89] Daniel C Richardson, Rick Dale, and Natasha Z Kirkham. 2007. The Art of Conversation Is Coordination. *Psychol. Sci.* 18, 5 (2007), 407–413. DOI:https://doi.org/10.1111/j.1467-9280.2007.01914.x
[90] Michael A Riley, Michael Richardson, Kevin Shockley, and Verónica C Ramenzoni. 2011. Interpersonal synergies. *Front. Psychol.* 2, (2011), 38.
[91] Evan F. Risko, Kaitlin E.W. Laidlaw, Megan Freeth, Tom Foulsham, and Alan Kingstone. 2012. Social attention with real versus reel stimuli: Toward an empirical approach to concerns about ecological validity. *Front. Hum. Neurosci.* 6, MAY 2012 (2012), 1–11. DOI:https://doi.org/10.3389/fnhum.2012.00143
[92] Elena Rocco. 1998. Trust breaks down in electronic contexts but can be repaired by some initial face-to-face contact. *Conf. Hum. Factors Comput. Syst. - Proc.* 496 (1998), 496–502. DOI:https://doi.org/10.1145/274644.274711
[93] Shane L. Rogers, Craig P. Speelman, Oliver Guidetti, and Melissa Longmuir. 2018. Using dual eye tracking to uncover personal gaze patterns during social interaction. *Sci. Rep.* 8, 1 (2018), 1–9. DOI:https://doi.org/10.1038/s41598-018-22726-7
[94] Bertrand Schneider and Roy Pea. 2013. Real-time mutual gaze perception enhances collaborative learning and collaboration quality. *Int. J. Comput. Collab. Learn.* 8, 4 (2013), 375–397. DOI:https://doi.org/10.1007/s11412-013-9181-4
[95] Bertrand Schneider, Kshitij Sharma, Sebastien Cuendet, Guillaume Zufferey, Pierre Dillenbourg, and Roy Pea. 2016. Detecting collaborative dynamics using mobile eye-trackers. . Singapore: International Society of the Learning Sciences.
[96] Julian Schulze and Stefan Krumm. 2017. The "virtual team player": A review and initial model of knowledge, skills, abilities, and other characteristics for virtual collaboration. *Organ. Psychol. Rev.* 7, 1 (2017), 66–95. DOI:https://doi.org/10.1177/2041386616675522
[97] Maurice E Schweitzer, Susan E Brodt, and Rachel T A Croson. 2002. Seeing and believing: Visual access and the strategic use of deception. *Int. J. Confl. Manag.* 13, 3 (2002).

[98] Stephen V. Shepherd. 2010. Following gaze: Gaze-following behavior as a window into social cognition. *Front. Integr. Neurosci.* 4, MARCH 2010 (2010), 1–13. DOI:https://doi.org/10.3389/fnint.2010.00005

[99] Kevin Shockley, Daniel C Richardson, and Rick Dale. 2009. Conversation and coordinative structures. *Top. Cogn. Sci.* 1, 2 (2009), 305–319.

[100] John Short, Ederyn Williams, and Bruce Christie. 1976. The social psychology of telecommunications. (1976).

[101] Charles L Sodikoff, Ira J Firestone, and Kalman J Kaplan. 1974. Distance matching and distance equilibrium in the interview dyad. *Proc. Div. Personal. Soc. Psychol.* 1, 1 (1974), 243–245.

[102] Katrin Starke and Arvind Rangaswamy. 1999. Computer-mediated negotiations: Review and research opportunities. *Encycl. Microcomput.* 26, (1999), 47–72. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.334.3400&rep=rep1&type=pdf

[103] Alice F. Stuhlmacher, Maryalice Citera, and Toni Willis. 2007. Gender differences in virtual negotiation: Theory and research. *Sex Roles* 57, 5–6 (2007), 329–339. DOI:https://doi.org/10.1007/s11199-007-9252-y

[104] Roderick I Swaab, Adam D Galinsky, Victoria Medvec, and Daniel A Diermeier. 2012. The communication orientation model: Explaining the diverse effects of sight, sound, and synchronicity on negotiation and group decision-making outcomes. *Personal. Soc. Psychol. Rev.* 16, 1 (2012), 25–53.

[105] David Tang and Brandon J Schmeichel. 2015. Look me in the eye: Manipulated eye gaze affects dominance mindsets. *J. Nonverbal Behav.* 39, 2 (2015), 181–194.

[106] Leigh L Thompson, Jiunwen Wang, and Brian C Gunia. 2010. Negotiation. *Annu. Rev. Psychol.* 61, 1 (2010), 491–515.

[107] Leigh Thompson and Janice Nadler. 2002. Negotiating via information technology: Theory and application. *J. Soc. Issues* 58, 1 (2002), 109–124.

[108] Linda Tickle-Degnen and Robert Rosenthal. 1990. The nature of rapport and its nonverbal correlates. *Psychol. Inq.* 1, 4 (1990), 285–293.

[109] M T Tolston, K Shockley, M A Riley, and M J Richardson. 2014. Movement constraints on interpersonal coordination and communication. *J. Exp. Psychol. Hum. Percept. Perform.* 40, (2014), 1891–1902.

[110] Thomas M Tripp and Harris Sondak. 1992. An evaluation of dependent variables in experimental negotiation studies: Impasse rates and Pareto efficiency. *Organ. Behav. Hum. Decis. Process.* 51, 2 (1992), 273–295.

[111] Baris Unver, Jasmine Jones, Alexander Thayer, and Svetlana Yarosh. 2019. Heterogeneous Device Arrangements Affect Both Partners' Experiences in Collaborative Media Spaces. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. DOI:https://doi.org/10.1007/978-3-030-22643-5_7

[112] Roel Vertegaal. 1999. The GAZE groupware system: mediating joint attention in multiparty communication and collaboration. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, 294–301.

[113] Hana Vrzakova, Mary Jean Amon, Angela E B Stewart, and Sidney K D'Mello. 2019. Dynamics of Visual Attention in Multiparty Collaborative Problem Solving Using Multidimensional Recurrence Quantification Analysis. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (CHI '19), 342:1--342:14.

[114] Basil Wahn, Jessika Schwandt, Matti Krüger, Daina Crafa, Vanessa Nunnendorf, and Peter König. 2016. Multisensory teamwork: using a tactile or an auditory display to exchange gaze information improves performance in joint visual search. *Ergonomics* 59, 6 (2016), 781–795. DOI:https://doi.org/10.1080/00140139.2015.1099742

[115] Lynne Wainfan and Paul K Davis. 2004. *Challenges in virtual collaboration: Videoconferencing, audioconferencing, and computer-mediated communications*. Rand Corporation.

[116] Sebastian Wallot. 2017. Recurrence quantification analysis of processes and products of discourse: A tutorial in R. *Discourse Process.* 54, 5–6 (2017), 382–405.

[117] Sebastian Wallot, Andreas Roepstorff, and Dan Mønster. 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. *Front. Psychol.* 7, (2016), 1835.

[118] Joseph B. Walther. 1992. Interpersonal Effects in Computer-Mediated Interaction: A Relational Perspective. *Communic. Res.* (1992). DOI:https://doi.org/10.1177/009365092019001003

[119] Charles L Webber Jr and Joseph P Zbilut. 2005. Recurrence quantification analysis of nonlinear dynamical systems. *Tutorials Contemp. nonlinear methods Behav. Sci.* (2005), 26–94.
[120] Hadley Wickham. 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. Retrieved from http://ggplot2.org
[121] Nancy Yao, Jeff Brewer, Sarah D'Angelo, Mike Horn, and Darren Gergle. 2018. Visualizing Gaze Information from Multiple Students to Support Remote Instruction. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, LBW051.
[122] Joseph P Zbilut, Alessandro Giuliani, and Charles L Webber Jr. 1998. Detecting deterministic signals in exceptionally noisy environments using cross-recurrence quantification. *Phys. Lett. A* 246, 1–2 (1998), 122–128.
[123] Yanxia Zhang, Ken Pfeuffer, Ming Ki Chong, Jason Alexander, Andreas Bulling, and Hans Gellersen. 2017. Look together: using gaze for assisting co-located collaborative search. *Pers. Ubiquitous Comput.* 21, 1 (2017), 173–186.
[124] Jun Zheng, Nathan Bos, Judith S. Olson, and Gary M. Olson. 2001. Trust without touch: Jump-start trust with social chat. *Conf. Hum. Factors Comput. Syst. - Proc.* January (2001), 293–294. DOI:https://doi.org/10.1145/634067.634241
[125] Hui Zhou and Tingqin Zhang. 2013. Body language in business. *Body Lang. Bus.* 3, 2 (2013), 1. DOI:https://doi.org/10.1057/9780230292291
[126] C Lawrence Zitnick, Jim Gemmell, and Kentaro Toyama. 1999. Manipulation of video eye gaze and head orientation for video teleconferencing. *Microsoft Res. Tech. Rep.* (1999).

Appendix

Table 5 Dyad-level linear regressions: Joint score

	Joint Score		Joint Score		Joint Score		Joint Score		Joint Score		Joint Score		Joint Score	
Predictors	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*
Spatio-temporal patterns														
Mutual gaze	-0.01	0.966												
Joint attention			0.42	**0.013**										
Gaze aversion					-0.54	**0.001**								
Gaze proportions														
Score Table							0.4	0.053						
Partner's face									-0.34	0.052				
Auxiliary area											-0.02	0.898		
Simultaneous patterns														
Mutual gaze													-0.17	0.333
Covariates														
Condition: Cooperative failed	0.13	0.493	0.17	0.31	0.13	0.378	0.17	0.328	0.19	0.271	0.13	0.484	0.16	0.373
Condition: Cooperative passed	0.03	0.89	0.1	0.57	-0.04	0.803	0.06	0.739	0.04	0.825	0.03	0.864	0.02	0.903
Dyad: Male-only	0.16	0.398	0.23	0.182	0.31	0.057	0.23	0.201	0.25	0.167	0.16	0.396	0.21	0.275
Dyad: Mixedgender	0.28	0.141	0.27	0.114	0.37	**0.022**	0.26	0.146	0.31	0.08	0.28	0.141	0.28	0.131
Data validity	0.25	0.172	0.14	0.396	0.19	0.192	0.01	0.945	0.3	0.084	0.25	0.179	0.23	0.186
Observations	37		37		37		37		37		37		37	
R^2 / adjusted R^2	0.161 / -0.007		0.319 / 0.183		0.428 / 0.314		0.261 / 0.113		0.262 / 0.114		0.161 / -0.006		0.187 / 0.025	

Table 6 Dyad-level negative binomial regressions: Time to initial agreement

	Time to Initial Agreement		**Time to Initial Agreement**		**Time to Initial Agreement**		**Time to Initial Agreement**		**Time to Initial Agreement**		**Time to Initial Agreement**		**Time to Initial Agreement**	
Predictors	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*	*Incidence Rate Ratios*	*p*
(Intercept)	518.34	**<0.001**	575.17	**<0.001**	451.85	**<0.001**	593.96	**<0.001**	487.29	**<0.001**	559.93	**<0.001**	499.28	**<0.001**
Spatio-temporal patterns														
Mutual gaze	1.03	0.45												
Joint attention			0.99	0.092										
Gaze aversion					1.03	**0.035**								
Gaze proportions														
Score Table							0.58	0.442						
Partner's face									3.63	**0.039**				
Auxiliary area											0.16	**0.037**		
Simultaneous patterns														
Mutual gaze													2.85	0.247
Covariates														
Condition: Cooperative failed	0.88	0.281	0.87	0.21	0.89	0.302	0.88	0.288	0.85	0.153	0.96	0.709	0.86	0.219
Condition: Cooperative passed	1	0.993	0.95	0.774	1.03	0.855	0.98	0.898	0.97	0.85	1.08	0.654	0.99	0.941
Dyad: Male-only	0.96	0.786	0.92	0.582	0.89	0.435	0.95	0.739	0.9	0.499	0.97	0.85	0.93	0.671
Dyad: Mixedgender	1	0.976	0.99	0.949	0.95	0.636	0.99	0.941	0.96	0.72	0.98	0.841	0.99	0.919
Data validity	1.55	0.274	1.77	0.158	1.63	0.204	1.89	0.195	1.33	0.461	1.9	0.11	1.59	0.245
Observations	37		37		37		37		37		37		37	
Nagelkerke's R^2	0.092		0.169		0.236		0.092		0.216		0.219		0.119	

Table 7 Dyad-level linear regressions: Subjective Value Inventory (SVI)

	SVI		SVI		SVI		SVI		SVI		SVI		SVI	
Predictors	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*	*β*	*p*
Spatio-temporal patterns														
Mutual gaze	-0.02	0.921												
Joint attention			0.10	0.600										
Gaze aversion					-0.31	0.095								
Gaze proportions														
Score Table							0.06	0.799						
Partner's face									-0.23	0.237				
Auxiliary area											0.03	0.891		
Simultaneous patterns														
Mutual gaze													-0.12	0.523
Covariates														
Condition: Cooperative failed	-0.01	0.947	-0.01	0.975	-0.01	0.949	-0.01	0.96	0.03	0.881	-0.02	0.911	0.01	0.954
Condition: Cooperative passed	0.01	0.963	0.03	0.888	-0.03	0.894	0.02	0.935	0.02	0.92	0.00	0.982	0.01	0.966
Dyad: Male-only	0.10	0.621	0.11	0.574	0.18	0.357	0.11	0.599	0.16	0.433	0.10	0.622	0.13	0.524
Dyad: Mixedgender	0.02	0.939	0.01	0.943	0.07	0.717	0.01	0.946	0.04	0.836	0.02	0.932	0.02	0.926
Data validity	0.08	0.680	0.05	0.784	0.05	0.787	0.04	0.847	0.11	0.546	0.07	0.723	0.07	0.709
Observations	37		37		37		37		37		37		37	
R^2 / adjusted R^2	0.018 / -0.178		0.027 / -0.168		0.107 / -0.072		0.020 / -0.176		0.063 / -0.124		0.018 / -0.178		0.031 / -0.162	

Table 8 Spearman's correlation between experiment outcomes (n = 37 dyads).

	Joint Score	Time to Initial Agreement
Joint Score		
Time to Initial Agreement	-0.45 (p = 0.005)	
Subjective Value Inventory	0.51 (p = 0.001)	-0.44 (p = 0.006)